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Integrating contextual and commonsense information for automatic discourse understanding : contributions to temporal relation classification and bridging anaphora resolution

Onkar Pandit

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et du centre de recherche Inria Lille - Nord Europe

Onkar Pandit

Integrating Contextual and Commonsense Information for Automatic Discourse Understanding

Contributions to Temporal Relation Classification and Bridging Anaphora Resolution

---

Intégration d'informations contextuelles et de sens commun pour la compréhension automatique du discours

Contributions à la classification des relations temporelles et à la résolution des anaphores associatives

sous la direction de Prof. Marc Tommasi
et l'encadrement des Dr. Pascal Denis et Prof. Liva Ralaivola

---

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To my parents

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Résumé

Etablir l'ordre temporel entre les événements et résoudre les anaphores associatives sont cruciaux pour la compréhension automatique du discours. La résolution de ces tâches nécessite en premier lieu une représentation efficace des événements et de mentions d'entités. Cette thèse s'attaque directement à cette problématique, à savoir la conception de nouvelles approches pour obtenir des représentations d'événements et de mentions plus expressives.

Des informations contextuelles et de sens commun sont nécessaires pour obtenir de telles représentations. Cependant, leur acquisition et leur injection dans les modèles d'apprentissage est une tâche difficile car, d'une part, il est compliqué de distinguer le contexte utile à l'intérieur de paragraphes ou de documents plus volumineux, et il est tout aussi difficile au niveau computationnel de traiter de plus grands contextes. D'autre part, acquérir des informations de sens commun à la manière des humains reste une question de recherche ouverte. Les tentatives antérieures reposant sur un codage manuel des représentations d'événements et de mentions ne sont pas suffisantes pour acquérir des informations contextuelles. De plus, la plupart des approches sont inadéquates pour capturer des informations de sens commun, car elles ont à nouveau recours à des approches manuelles pour acquérir ces informations à partir de sources telles que des dictionnaires, le Web ou des graphes de connaissances. Dans notre travail, nous abandonnons ces approches inefficaces d'obtention de représentations d'événements et de mentions.

Premièrement, nous obtenons des informations contextuelles pour améliorer les représentations des événements en fournissant des n-grams de mots voisins de l'événement. Nous utilisons également une représentation des événements basée sur les caractères pour capturer des informations supplémentaires sur le temps et l'aspect de la structure interne des têtes lexicales des événements. Nous allons aussi plus loin en apprenant les interactions sur ces représentations d'événements pour obtenir des représentations riches de paires d'événements. Nous constatons que nos représentations d'événements améliorées démontrent des gains substantiels par rapport à une approche qui ne repose que sur les plongements de la tête lexical de l'événement. De plus, notre étude

d'ablation prouve l'efficacité de l'apprentissage d'interactions complexes ainsi que le rôle des représentations basées sur les caractères.

Ensuite, nous sondons les modèles de langage de type *transformer* (par exemple BERT) qui se sont révélés meilleurs pour capturer le contexte. Nous étudions spécifiquement les anaphores associatives pour comprendre la capacité de ces modèles à capturer ce type de relation inférentielle. Le but de cette étude est d'utiliser ces connaissances pour prendre des décisions éclairées lors de la conception de meilleurs modèles de *transformer* afin d'améliorer encore les représentations des mentions. Pour cela, nous examinons individuellement la structure interne du modèle puis l'ensemble du modèle. L'examen montre que les modèles pré-entraînés sont étonnamment bons pour capturer des informations associatives et que ces capacités dépendent fortement du contexte, car elles fonctionnent mal avec des contextes déformés. De plus, notre analyse qualitative montre que BERT est capable de capturer des informations de base de sens commun mais ne parvient pas à capturer des informations sophistiquées, qui sont nécessaires pour la résolution des anaphores associatives.

Enfin, nous combinons à la fois des informations contextuelles et de sens commun pour améliorer encore les représentations des événements et des mentions. Nous injectons des informations de sens commun à l'aide de graphes de connaissances pour les tâches de classification des relations temporelles et de résolution d'anaphores associatives. Notre approche pour acquérir de telles connaissances se fonde sur des plongements de nœuds de graphe appris sur des graphes de connaissances pour capturer la topologie globale du graphe, obtenant ainsi des informations externes plus globales. Plus précisément, nous combinons des représentations basées sur des graphes de connaissances et des représentations contextuelles apprises avec des plongements uniquement textuels pour produire des représentations plus riches en connaissances. Nous évaluons notre approche sur des jeux de données standard comme ISNotes, BASHI et ARRAU pour la résolution des anaphores associatives et MATRES pour la classification des relations temporelles. Nous observons des gains substantiels de performance par rapport aux représentations uniquement textuelles sur les deux tâches démontrant l'efficacité de notre approche.

Abstract

Establishing temporal order between events and resolving bridging references are crucial for automatic discourse understanding. For that, effective event and mention representations are essential to accurately solve temporal relation classification and bridging resolution. This thesis addresses exactly that and designs novel approaches to obtain more expressive event and mention representations.

Contextual and commonsense information is needed for obtaining such effective representations. However, acquiring and injecting it is a challenging task because, on the one hand, it is hard to distinguish useful context itself from bigger paragraphs or documents and also equally difficult to process bigger contexts computationally. On the other hand, obtaining commonsense information like humans acquire, is still an open research question. The earlier attempts of hand engineered event and mention representations are not sufficient for acquiring contextual information. Moreover, most of the approaches are inadequate at capturing commonsense information as they again resorted to hand-picky approaches of acquiring such information from sources like dictionaries, web, or knowledge graphs. In our work, we get rid of these inefficacious approaches of getting event and mention representations.

First, we obtain *contextual* information to improve event representations by providing neighboring n-words of the event. We also use character-based representation of events to capture additional tense, and aspect information from the internal structure of event headwords. We also go a step further and learn interactions over these event representations to get rich *event-pair* representations. We find that our improved event representations demonstrate substantial gains over an approach which relied only on the event head embeddings. Also, our ablation study proves the effectiveness of complex interaction learning as well as the role of character-based representations.

Next, we probe transformer language models (e.g. BERT) that are proved to be better at capturing *context*. We investigate specifically for bridging inference to understand the capacity of these models at capturing it. The purpose of this investigation is to use these understandings for making informed decisions at designing better transformer models to further improve mention representations. For that, we examine the model's internal structure individually and then the whole model. The investigation shows that pre-trained models are surprisingly good at capturing bridging information and these capabilities are highly context dependent, as they perform poorly with distorted contexts. Further, our qualitative analysis shows that BERT is capable of capturing basic commonsense

information but fails to capture sophisticated information which is required for bridging resolution.

Finally, we combine both *contextual* and *commonsense* information for further improving event and mention representations. We inject commonsense information with the use of knowledge graphs for both temporal relation classification and bridging anaphora resolution tasks. We take a principled approach at acquiring such knowledge where we employ graph node embeddings learned over knowledge graphs to capture the overall topology of the graph as a result gaining holistic external information. Specifically, we combine knowledge graph based representations and contextual representations learned with text-only embeddings to produce knowledge-aware representations. We evaluate our approach over standard datasets like ISNotes, BASHI, and ARRAU for bridging anaphora resolution and MATRES for temporal relation classification. We observe substantial gains in performances over text-only representations on both tasks proving the effectiveness of our approach.

Table of contents

List of figures xiii

List of tables xv

1 Introduction 1

1.1 Automatic discourse understanding . . . 1
1.2 Temporal processing and bridging resolution . . . 3
1.3 Event and mention representations . . . 5
1.4 Research questions and contributions . . . 7
1.5 Organization of the dissertation . . . 10

2 Background 11

2.1 Tasks . . . 12
2.1.1 Temporal relation classification . . . 12
2.1.1.1 Definition . . . 12
2.1.1.2 Supervised learning approach . . . 16
2.1.1.3 Corpora . . . 17
2.1.1.4 Evaluation . . . 21
2.1.2 Bridging anaphora resolution . . . 24
2.1.2.1 Definition . . . 24
2.1.2.2 Supervised learning approach . . . 26
2.1.2.3 Corpora . . . 27
2.1.2.4 Evaluation . . . 28
2.2 Artificial neural networks . . . 28
2.3 Representation learning . . . 32
2.4 Word representations . . . 35
2.4.1 Distributed representations . . . 36
2.4.1.1 Word2vec . . . 37
2.4.1.2 Global vector (Glove) . . . 40

2.4.1.3 FastText . . . 41
2.4.2 Contextual word representations . . . 42
2.4.2.1 ELMo . . . 42
2.4.2.2 BERT . . . 43
2.5 Composing word representations . . . 48
2.5.1 Fixed composition functions . . . 49
2.5.2 Learned composition functions . . . 50
2.6 Knowledge graphs and representations . . . 51
2.6.1 Knowledge graphs . . . 51
2.6.1.1 WordNet . . . 53
2.6.1.2 TEMPROB . . . 53
2.6.2 Graph node embeddings . . . 56
2.6.2.1 Unified framework . . . 57
2.6.2.2 Matrix factorization based approaches . . . 58
2.6.2.3 Random walk based approaches . . . 59
2.7 Summary . . . 60

3 Related Work 61
3.1 Temporal relation classification . . . 61
3.1.1 Work on event representations . . . 62
3.1.1.1 Manually designed representations . . . 62
3.1.1.2 Automatic representation learning . . . 63
3.1.2 Work on models and inference . . . 66
3.1.3 Summary . . . 68
3.2 Bridging anaphora resolution . . . 69
3.2.1 Work on mention representation . . . 70
3.2.1.1 Manually designed representation . . . 70
3.2.1.2 Automatic representation learning . . . 73
3.2.2 Work on models and inference . . . 74
3.2.3 Summary . . . 75

4 Learning Rich Event Representations and Interactions 77
4.1 Introduction . . . 77
4.2 Effective event-pair representations . . . 78
4.3 Method . . . 81
4.3.1 Representation Learning . . . 81
4.3.2 Interaction Learning . . . 82

4.4 Experiments . . . 83
4.4.1 Datasets and Evaluation . . . 83
4.4.2 Training details . . . 83
4.4.3 Baseline systems . . . 84
4.4.4 Ablation setup . . . 85
4.5 Results . . . 85
4.5.1 Comparison to baseline Systems . . . 85
4.5.2 Comparison with state-of-the-art . . . 86
4.6 Ablation study . . . 87
4.7 Conclusions . . . 88

5 Probing for Bridging Inference in Transformer Language Models 91
5.1 Introduction . . . 92
5.2 Probing transformer models . . . 94
5.2.1 Probing for relevant information . . . 95
5.2.2 Probing approaches . . . 95
5.3 Methodology . . . 96
5.4 Probing individual attention heads . . . 97
5.4.1 Bridging signal . . . 97
5.4.2 Experimental setup . . . 98
5.4.3 Results with only Ana-Ante sentences . . . 98
5.4.4 Results with all sentences . . . 100
5.4.5 Discussion . . . 100
5.5 Fill-in-the-gap probing: LMs as Bridging anaphora resolvers . . . 102
5.5.1 *Of-Cloze test* . . . 102
5.5.2 Experimental setup . . . 103
5.5.3 Results and Discussion . . . 103
5.5.3.1 Results on candidates scope . . . 103
5.5.3.2 Results on Ana-Ante distance . . . 104
5.6 Importance of context: *Of-Cloze test* . . . 105
5.6.1 Experimental setup . . . 105
5.6.2 Results on different contexts . . . 106
5.7 Error analysis: *Of-Cloze test* . . . 107
5.8 Conclusions . . . 108

6 Integrating knowledge graph embeddings to improve representation 109
6.1 Introduction . . . 110
6.2 Commonsense knowledge . . . 111
6.2.1 Significance for effective representation . . . 114
6.2.2 Challenges in integration . . . 116
6.3 Our approach . . . 118
6.3.1 Knowledge graphs: WordNet and TEMPROB . . . 118
6.3.1.1 WordNet . . . 119
6.3.1.2 TEMPROB . . . 121
6.3.2 Normalization: Simple rules and lemma . . . 122
6.3.3 Sense disambiguation: Lesk and averaging . . . 123
6.3.4 Absence of knowledge: Zero vector . . . 124
6.4 Improved mention representation for bridging resolution . . . 124
6.4.1 Knowledge-aware mention representation . . . 124
6.4.2 Ranking model . . . 125
6.4.3 Experimental setup . . . 126
6.4.4 Results . . . 128
6.4.5 Error analysis . . . 132
6.4.5.1 Mention normalization and sense disambiguation . . . 132
6.4.5.2 Anaphor-antecedent predictions . . . 132
6.5 Improved event representation for temporal relation classification . . . 134
6.5.1 Knowledge-aware event representations . . . 135
6.5.2 Neural model . . . 136
6.5.2.1 Constrained learning . . . 136
6.5.2.2 ILP Inference . . . 138
6.5.3 Experimental setup . . . 139
6.5.4 Results . . . 141
6.5.5 Discussion . . . 144
6.6 Conclusion . . . 145

7 Conclusions 147

References 151

List of figures

2.1 Temporal relation identification over a sample text. 14
2.2 Example of a transitivity rule over temporal relations. 14
2.3 Three equavalent but different temporal graphs. 21
2.4 Two evaluation schemes: Reference graph K and predicted graph G. 23
2.5 Bridging resolution over a sample text. 25
2.6 Artificial Neural Network. 29
2.7 Word2vec: continous bag-of-words (CBOW) and skip-gram. 38
2.8 Hierarchical softmax. 40
2.9 BERT architecture. 44
2.10 Internal components of encoder. 45
2.11 A subset of WordNet related to the four senses of *book*. 52
2.12 Overview of graph node embeddings: A conceptual encoder-decoder framework. 56

4.1 Architecture of our proposed model. 81

5.1 Bridging signals in the pre-trained BERT-base-cased model. 99

List of tables

2.1 Allen's interval temporal relations. 13
2.2 TimeML temporal relations and corresponding Allen's interval relations. . . 18
2.3 Temporal relation classification: Corpora details. 19
2.4 Ambiguous as well as rare relations mapped to coarse-grained relations. . . 20
2.5 Temporal relation classification: Evaluation results with two different schemes. 23
2.6 Briading anaphora resolution: Corpora details 27
2.7 A portion of TEMPROB. 54

4.1 Results of baseline and state-of-the-art systems 86
4.2 Ablation study. 88

5.1 Examples of easy and difficult bridging relations for the prominent heads. . 101
5.2 Result of selecting antecedents for anaphors. 104
5.3 Anaphor-antecedent distance-wise accuracy. 105
5.4 Accuracy of selecting antecedents with different types of context. 106

6.1 Results of our experiments and state-of-the-art models. 129
6.2 Number of mentions from the datasets and proportion of them absent in WordNet. 132
6.3 Few examples of mention mapping and mention sense selection. 133
6.4 Composition rules on end-point relations present in MATRES dataset. . . . 138
6.5 Results of the experiments over MATRES. 142

Chapter 1

Introduction

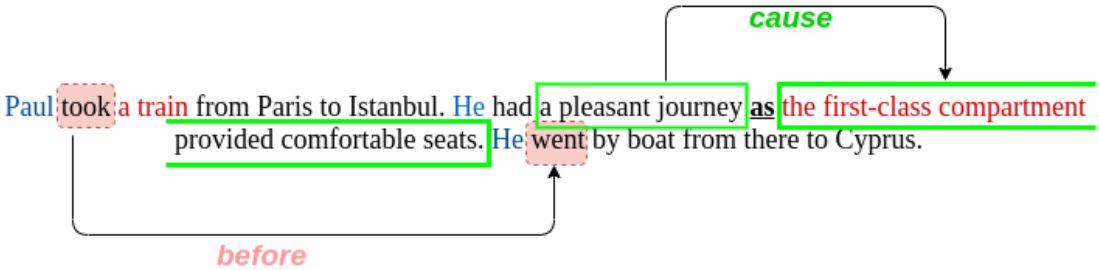
1.1 Automatic discourse understanding

Discourse is a bigger chunk of language than a sentence such as paragraph, document, etc., which often comprises multiple sentences. The sentences can be uttered by a single person or multiple people with the constraint that discourse as a unit produces coherent communication (Hobbs, 1979; Scha et al., 1986). A coherent communication conveys a single core subject with multiple discourse elements producing continuous sense by relating to previously mentioned elements. On the contrary, a random sequence of sentences that does not possess such continuity of senses can not be a discourse (De Beaugrande and Dressler, 1986; Mann and Thompson, 1986). A discourse can be between writer–reader (text) or speaker–listener (dialogue). In this work, we concentrate on the written text so that discourses are monologues that communicate with the reader.

In discourse, linguistic units are connected by different relations to maintain coherence and deciphering these relations is a part of discourse understanding (Stede, 2011; Webber, 2019). The linguistic units such as sentences, clauses, or *events* (smaller linguistic units that indicate situations within clauses) can be *temporally* related to each other (Bramsen et al., 2006). *Temporal relations* between them denote the chronological order in which they occur (e.g. precedence, succession, concurrence, etc.). In addition to temporal relations, a relation on a semantic or pragmatic level can link clauses, sentences, or larger portions of discourse to each other. These relations are known as *discourse relations* (also called as *coherence* or *rhetorical relations*). The exact number of discourse relations varies depending on the postulated granularity but generally they indicate consequence, explanation, elaboration, or contrast between discourse units (Carlson et al., 2001; Prasad et al., 2008; Stede, 2011). Apart from these relations, there can be expressions in different sentences which link to previously mentioned expressions either directly or indirectly.

We are talking specifically about *mentions* that refer to real or abstract entities. Mentions are either named (e.g. Barack Obama), nominal (e.g. the chairman, a car, the driver) or pronominal (e.g. he, she) expressions. They exhibit certain relations with each other. Mentions can hold either *bridging relation* where mentions refer to different entities but are associated with each other (e.g. the driver-a car) or *coreference relation* where mentions refer to the same entity (e.g. He-Barack Obama).

Let us explain this further with a following simple discourse (modified from Hobbs (1979)):



This discourse tells a reader that *Paul traveled in the first-class compartment of the train from Paris to Istanbul and he enjoyed the ride. After that Paul traveled in a boat to reach Cyprus.* This understanding is possible because a human reader unravels various relations from the discourse:

- "the first-class compartment" indicates *the first-class of the train in which Paul traveled.* (**bridging relation** between "a train" and"the first-class compartment")
- Both instances of the pronouns, "He", "He" refer to "Paul". (**Coreference relation**)
- Paul's journey was pleasant "because" the seats were comfortable. (*causal* **Discourse relation**)
- Paul traveled to Cyprus "after" the train journey from Paris to Istanbul. (**Temporal relation**)

Uncovering these relations is essential for automatic discourse understanding. Out of these relations, temporal and bridging relations are relatively less studied in NLP than discourse relations (Braud and Denis, 2015; Dai and Huang, 2018; Ji and Eisenstein, 2015; Lin et al., 2009; Liu et al., 2020; Liu and Li, 2016; Marcu and Echihabi, 2002; Pitler et al., 2008; Saito et al., 2006; Shi and Demberg, 2019; Varia et al., 2019; Wang and Lan, 2015; Wellner et al., 2006) and coreference relations (Clark and Manning, 2015, 2016a,b; Daumé III and Marcu, 2005; Denis and Baldridge, 2008; Durrett and Klein, 2013; Finkel

and Manning, 2008; Joshi et al., 2020; Lee et al., 2017; Luo et al., 2004; Soon et al., 2001; Wiseman et al., 2015, 2016; Zhang et al., 2019a). Consequently, we specifically concentrate on *temporal relation classification* and *bridging resolution* tasks, which automatically detect the temporal and bridging relations from text. The following sections discuss in detail about them.

1.2 Temporal processing and bridging resolution

Temporal processing Automatic temporal analysis is critical to perform automatic processing and understanding of discourse. Detecting temporal relations between events accurately unravels the intended meaning conveyed by the writer. For instance, consider two events from a discourse: *people were furious* and *police used water canons*. Assigning two different temporal relations to them affects the meaning of the discourse: *police used water canons* before *people were furious* means *people became furious because of police's action*, whereas *police used water canons* after *people were furious* conveys *police used water canons to placate angry people*. Additionally, the temporal relations help to establish discourse relations between clauses (Wang et al., 2010), which can be seen from the previous example, where *police used water canons* causes *people were furious* given that it happens before, whereas after temporal relation reverses causality. This shows a clear need to establish accurate temporal relations to extract the overall intended meaning out of discourse.

Besides its significance in discourse understanding, temporal analysis has important practical implications. In document summarization, knowledge about the temporal order of events can enhance both the content selection and the summary generation processes (Barzilay et al., 2002; Ng et al., 2014). In question answering (QA), temporal analysis is needed to determine "when" or "how long" a particular event occurs and temporal order between them (Meng et al., 2017; Prager et al., 2000). The temporal modeling can also help machine translation systems (Horie et al., 2012). In addition, temporal information is highly beneficial in the clinical domain for applications such as patient's timeline visualization, early diagnosis of disease, or patients selection for clinical trials (Augusto, 2005; Choi et al., 2016; Jung et al., 2011; Raghavan et al., 2014).

For a given discourse, the temporal processing task can be divided into two main parts: 1. Detecting temporal entities such as *events* and *time expressions* (TimEx)[1], and 2. Establishing temporal ordering between these temporal entities. The latter task is

[1]Time expressions are phrases that indicate moment, intervals or other time regions. The phrases such as *15 Aug. 1947*, *two weeks* or *today* fall into this category. We detail this in the next chapter.

called *temporal relation classification* which particularly determines temporal relations between *event-event*, *event-TimEx* and *TimEx-TimEx* pairs. In this work, we are focusing on the temporal relation classification for *event-event* pairs because it is challenging in comparison to other pairs. But, the proposed methods can be easily extended for determining relations between the other two pairs as well.

Bridging resolution *Mentions* also possess certain relations between each other like temporal relations between sentences, clauses, or events. Specifically, an *anaphor* is a special *mention* that depends on previously appeared *mention(s)*, referred to as *antecedent(s)*, for its complete interpretation. As stated previously, anaphor-antecedent can be related to each other either by a bridging or coreference relation. Bridging relation indicates an association between *anaphor* and *antecedent* but non-identical relation (e.g. *the first-class compartment–a train*) whereas coreference denotes identical relation (e.g. *He–Paul*). Automatically identifying bridging relations is more challenging than coreference resolution as bridging encodes various abstract relations between mentions as opposed to identical relations in coreference. These context-dependent abstract relations also require world knowledge to make a connection between them. Additionally, the annotated corpora for bridging are smaller in comparison increasing the difficulty level further. Bridging relations are the second topic of focus in this work, as even though difficult, realizing bridging relations is crucial for discourse comprehension.

Identifying bridging relations is also beneficial for various tasks such as textual entailment, QA, summarization, and sentiment analysis. Textual entailment establishes whether a *hypothesis* can be inferred from *a particular text*, and bridging can be used in determining this inference (Mirkin et al., 2010). For QA system, (Harabagiu et al., 2001) resolved a subset of bridging relations (meronymic) in the context for better accurately identifying answers. Resolving bridging relations is important for summarization, as different sentences can be combined based on it (Fang and Teufel, 2014). Bridging resolution is also of help in aspect-based sentiment analysis (Kobayashi et al., 2007), where the aspects of an object, for example, the zoom of a camera, are often bridging anaphors.

Computational task for identifying bridging relations is called *bridging resolution*. That can be further broken into two main tasks: *bridging anaphora identification* which identifies bridging anaphors from documents, and *bridging anaphora resolution* which links them to appropriate antecedents. This work focuses on the second task of anaphora resolution.

1.3 Event and mention representations

Importance of context and commonsense information Automatic processing of temporal and bridging relations is difficult which can be seen from the low state-of-the-art results. However, humans perform these tasks very easily. We hypothesize that the reasons might be that human readers can access contextual information from the given discourse itself as well as use their prior experience in the form of commonsense knowledge to figure out these relations.

A context[2] is important for establishing temporal ordering between linguistic units and making bridging associations. In fact, it is crucial for overall discourse understanding, for instance, in the previous example, we can not understand "from where he went to Cyprus?" if the last sentence "He went by boat from there to Cyprus" is read without the earlier sentences. To specifically see the importance of context for temporal relations, let us look at the following examples that are adapted from Lascarides and Asher (1993):

(1) Max switched$_{e_1}$ *on* the light. The room was pitch dark$_{e_2}$.

(2) Max switched$_{e_1}$ *off* the light. The room was pitch dark$_{e_2}$.

From the discourse in example 1, a human reader can understand that *the room was dark* <u>before</u> *Max switched on the light.* But, in example 2, *the room was dark* <u>after</u> *Max switched off the light.* The chronology of events *switching* and *room becoming dark* is changed depending on the context in which they are used.

Similarly, context is significant for establishing bridging relations, which can be understood from the following examples:

(3) <u>A car</u> is more fuel efficient than a rocket as **the engine** requires *less* fuel.

(4) A car is more fuel efficient than <u>a rocket</u> as **the engine** requires *more* fuel.

In example 3, *the engine* refers to *the car engine* as it requires less fuel and we said that cars are more fuel efficient that rockets. But, because of change in the context, when we say *the engine requires more fuel* in 4, here, *the engine* refers to *the rocket engine* and not *the car engine.*

[2]Throughout this thesis, context refers to *linguistic context.* Context can be derived from different sources such as *physical context* depends on the place of discourse deliverance, participants in communication having similar background knowledge share *epistemic context,* or *social context* is derived from same social conducts of participants. But, here we are referring to *linguistic context* where communication is built on the previous text and a meaning is derived from them.

Commonsense[3] information is equally important as contextual information for determining temporal and bridging relations. This is especially useful when there are no explicit surface clues present in the context. Let us see some examples:

(5) A thief *robbed*$_{e_3}$ the national bank. The *investigation*$_{e_4}$ showed that $1 million are stolen.

(6) *The driver* rushed out of his car as **the diesel tank** was leaking.

In example 5, to determine the temporal ordering of events *robbery* and *investigation*, it is crucial to possess the commonsense information that an investigation happens after the crime has been committed. Hence, e_4 is *after* e_3. Similarly for bridging relation in example 6, *the diesel tank* refers to *the diesel tank of his car* as generally cars have diesel tanks and not related to the previous expression – *The driver*.

Effective representation learning A representation associates linguistic objects to typically a high-dimensional vector. Obtaining this representation of events and mentions is essential for automatic identification of temporal and bridging relations because machine learning models used to solve them require a mathematical object (typically a vector) as an input. More than just a mathematical object, the representation should also capture as much relevant information needed to solve these tasks. Following the discussion from the last section, we believe contextual and commonsense information should be encoded in the representation for being effective.

Identifying the relevant features required for the task is a challenging aspect in getting an effective representation. One way of obtaining these features is with the use of human expertise and prior knowledge about the task. The earlier approaches for temporal relation classification (Bethard, 2013; Bethard et al., 2007; Boguraev and Ando, 2005; Chambers; D'Souza and Ng, 2013; Laokulrat et al., 2013; Lapata and Lascarides, 2004; Mani et al., 2003, 2006) and for bridging anaphora resolution (Lassalle and Denis, 2011; Poesio et al., 2004; Poesio and Vieira, 1998; Poesio et al., 1997) used hand-engineered features. However, manually designing features is labor-intensive and tedious work that requires task-specific knowledge. Also, there is a possibility of error in obtaining such features because of noisy data. Moreover, if the domain of the data is changed the effort of obtaining relevant features needs to be repeated. For example, the wording used in finance, sports, or law differs subtly and can require a different set of features to solve the task. The problem

[3] We refer to any knowledge that can not be easily derived from the given text as *commonsense* knowledge. This means, it encompasses both linguistic knowledge (e.g. lexical semantic knowledge) as well as world knowledge (e.g. factual or encyclopedic knowledge).

of designing features becomes more difficult if the language of the text is changed. As a result, it is critical to learn these relevant features rather than relying on manually designed representation.

The recent approaches based on neural networks attempt to remedy issues of manually designed features by automatically learning these representations but these approaches are few. In the case of temporal relation classification, either approaches ignored context completely (Mirza and Tonelli, 2016) or added syntactic tree preprocessing burden to encode contextual information (Cheng and Miyao, 2017; Choubey and Huang, 2017; Meng et al., 2017) [4]. Also, the approaches proposed to encode commonsense information relied on certain hand-designed features (Ning et al., 2018a) or used a portion of knowledge source (Ning et al., 2019). Similarly, for bridging anaphora resolution recently proposed bridging-specific embeddings (Hou, 2018a,b) ignored context whereas BERT based approaches (Hou, 2020a; Yu and Poesio, 2020) neglected commonsense information.

As stated earlier, an effective representation learning should capture contextual and commonsense information as they are important for both tasks, but incorporating these two types of information poses various challenges. The major problem in injecting contextual knowledge is to understand what kind of context to provide and how much. It is possible, that humans derive context from previous sentences, paragraphs, or even documents. But including this context in the learning models is difficult because of the limited processing abilities of the models as well as the overall capacity to decipher the useful context. On the other hand, commonsense information inclusion poses other type of problems. Since humans acquire commonsense knowledge from various sources, in general from their world experiences, it is not easy to replicate them in computational approaches. In recent years, studies based on both contextual and commonsense knowledge are gaining traction, as approaches using various sources of external knowledge like knowledge graphs (Faruqui et al., 2015; Mihaylov and Frank, 2018; Shangwen Lv and Hu, 2020), images (Cui et al., 2020; Li et al., 2019; Rahman et al., 2020), videos (Huang et al., 2018; Palaskar et al., 2019), or crowdsourced resources (Krishna et al., 2016) have been proposed.

1.4 Research questions and contributions

From this discussion, we see that the previously proposed approaches fail to simultaneously capture both contextual information and commonsense information effectively.

[4] We are talking about the period before the proposal of our system (Pandit et al., 2019), significant improvements have been made since then.

We intend to fill this gap. Our aim in this thesis is to design efficient approaches for learning effective event representations for temporal relation classification and mention representations for bridging anaphora resolution. We include both contextual as well as commonsense knowledge because of their importance in these representations. We argue that the amount of commonsense information that can be learned from only text-based approaches is limited. Hence, there is a need to complement text-based information with commonsense information learned from external knowledge sources. This understanding leads to different objectives and contributions:

Contextual event representation We encode the contextual information present in the neighboring words of events to improve event representation. We believe this context can capture the important tense, aspect, and necessary temporal information. We develop a Recurrent Neural Network (RNN) based model to learn this representation. We provide a context in the window of n-words of event head to RNN where each word is represented with distributed word embeddings. To complement this contextual information, we also inject morphological information into the representation. For that, we concatenate these embeddings with character-based embeddings of the event-head word to capture morphology information of the event. We empirically show the effectiveness of the approach on the standard datasets.

Complex event interactions Besides event representations, combined representation of event pairs was not explicitly studied barring the exception of Mirza and Tonelli (2016) where they used deterministic functions to get interactions between events. We argue that complex interactions between event representations can capture effective event-pair representations. To achieve that, we proposed a Convolution Neural Network (CNN) based approach to capture these event interactions to produce rich event-pair representation. Our analysis shows that this approach is more effective than obtaining simple linear interactions.

Investigation of transformer language models for bridging inference The recently proposed transformer-based language models (e.g. BERT) are potent at capturing required contextual information (Devlin et al., 2019; Liu et al., 2019b). The previously proposed approaches based on BERT (Hou, 2020a; Yu and Poesio, 2020) proved to be effective at bridging anaphora resolution. But the specific reasons behind the success of transformer language models are still unknown. This lack of understanding hampers the further efficient improvement of the architecture. Hence, we believe it is an essential initial step to

investigate these transformer models for bridging information because with that understanding mention representations can be further improved. Specifically, we want to probe how capable are these transformer models at capturing bridging inference and which layers of these big models are focusing on bridging. Importantly, we also check what kind of context is required for these models to produce decent results. We design our probing methods keeping these objectives in mind.

We employ two approaches for this investigation. First, we probe individual attention heads of the transformer models for bridging inference. Our investigation shows that the higher layers better capture bridging information than the middle and lower layers. Second, we go a step further to investigate whole transformer model so as to understand how effectively they perform cumulatively. We design a novel *Of-Cloze test*, a fill-in-the-blank test that scores candidate antecedents for each anaphor and selects the highest scoring mention as predicted antecedent. This *Of-Cloze* formulation produces competitive results for bridging anaphora resolution indicating transformer models' ability at capturing bridging information. Finally, we investigate the importance of context by providing a different set of contexts to *Of-Cloze test*. We also, qualitatively investigate BERT to assess its ability at capturing commonsense information required for bridging, which shows insufficiency of BERT at them.

Knowledge-aware mention and event representation Our investigation of transformer language models suggests that they are good at capturing contextual information but inadequate at capturing commonsense information which is in line with the previous studies (Da and Kasai, 2019; Park et al., 2020). So, we design approaches to inject such knowledge for mention and event representations, and propose to use knowledge graph node embeddings for this purpose. We claim that this way of injecting knowledge is more effective than designing features based on external knowledge. However, this approach poses a few challenges: First, mapping mentions or events to graph nodes is a non-trivial task as they are inherently different objects (nodes can be abstract concepts whereas mentions are linguistic units containing tokens). Second, the mapping can lead to multiple nodes (due to the several meanings of the word) or no node at all (due to the absence of knowledge from the graph). We propose simple approaches to address these questions that can be applied over for any knowledge graph. Specifically, we use two knowledge graphs separately, WordNet (Fellbaum, 1998), and TEMPROB (Ning et al., 2018a), and empirically show the effectiveness of these proposed methods for both tasks, followed by analysis for a better understanding.

1.5 Organization of the dissertation

The remainder of the document is mainly divided into three parts. First, we introduce the background information and prior work. The next three chapters detail our contributions and finally, we conclude by noting down our findings and future directions.

Chapter 2 describes necessary task definitions, the corpora used in the experiments, and evaluation strategies. Further, we briefly introduce artificial neural networks that are used extensively in the thesis as a base model. Next, the chapter details the different word representation approaches that are central to our work. Finally, we describe different knowledge graphs, and graph node embeddings framework.

Chapter 3 explores related work for both temporal relation classification and bridging resolution. For both tasks, we focus on the previous event and mention representation approaches while briefly discussing model and inference related work.

Chapter 4 details our rich event representation and complex interaction learning approach used for temporal relation classification. We understand from previous studies that less attention is given to capture context for event representations. To remedy that, we propose RNN based model to get event representation and CNN to capture complex interactions. We detail our proposed neural model in this chapter, and we present results from experiments to prove the efficacy of our approach. We also provide ablation studies to understand the importance of different components in our system.

Chapter 5 focuses on the probing of transformer models for bridging inference. This chapter talks about three important things: first, the ability of individual attention heads at capturing bridging signal, second, our novel *Of-Cloze test* that checks the potency of the whole transformer model, and third, the effect of context on their ability of understanding bridging. The detailed error analysis is also done to understand the shortcomings of transformer models as well as of our formulation.

Chapter 6 proposes an approach for obtaining knowledge-aware mention and event representations. We first describe the challenges posed by the process of injecting commonsense information with the use of knowledge graphs. Then we propose a unifying strategy to inject such knowledge for bridging anaphora resolution and temporal relation classification. We provide empirical evidence of the effectiveness of our approach and a detail analysis of our results.

Finally, Chapter 7 provides a formal conclusion of the thesis and a discussion of promising future directions.

Chapter 2

Background

This chapter serves as a background for the rest of the thesis. It describes three important items: (i) task definitions of both temporal relation classification and bridging anaphora resolution, components of supervised approaches used to solve them including essential factors: event, and mention representation, corpora used in the work, and evaluation strategies, (ii) artificial neural networks which are popularly used for representation learning and modeling, and (iii) representation learning and related fields, previously proposed approaches to learn word representations, several composition functions over them to obtain representations of word sequences (phrases, sentences, or paragraphs), and knowledge graphs and graph node representations.

Section 2.1 details two central tasks of the thesis: temporal relation classification and bridging anaphora resolution. For both tasks, we first provide formal definitions, then specify three main components of supervised learning approaches used to solve them: event and mention representations, models, and inference strategies. Further, we detail corpora used for training and evaluating proposed approaches, and evaluation schemes.

In recent years, Artificial neural networks have been used ubiquitously for representation learning as well as modeling. Due to their potency, we also used them to improve representations and for modeling. Therefore, we provide brief introduction of them in Section 2.2. We explain the fundamental element of these models (neuron), activation functions, hyperparameters, and optimization strategies. Further, we describe some of the regularly used neural network architectures such as Feed-forward neural networks (FFNN), Recurrent neural networks (RNN), and Convolutional neural networks (CNN).

The remaining chapter focuses on representation learning and various popularly employed approaches to learning representations of words, word sequences, and graph nodes. Section 2.3 discusses representation learning and related fields like metric learning, and dimensionality reduction. Next, in section 2.4 we look at different distributional

and contextual approaches of obtaining word representations. We first describe popular distributional embeddings such as Word2vec (Mikolov et al., 2013a), Glove (Pennington et al., 2014), and FastText (Bojanowski et al., 2017) which are used in the thesis, followed by recently proposed contextual embeddings like ELMo (Peters et al., 2018), and BERT (Devlin et al., 2019). Further, in section 2.5 we look at different ways of combining these word embeddings to obtain representations of word sequences i.e. bigger chunks of language than words like phrases, sentences, paragraphs, or documents. At last, we brief about knowledge graphs and describe WordNet (Fellbaum, 1998) and TEMPROB (Ning et al., 2018a), followed by details of conceptual framework and two broad families of node embeddings approaches in Section 2.6.

2.1 Tasks

In this thesis, we focus on two discourse tasks: temporal relation classification and bridging anaphora resolution. We detail about them in this section.

2.1.1 Temporal relation classification

Time is a critical part of a language that is grasped from either explicitly or implicitly present temporal information in the text, and automatically extracting such temporal information is necessary for discourse understanding. In a discourse, various types of linguistic units can be related temporally to each other such as sentences, clauses, or smaller linguistic units like *events*, and expressions (TimEx) (Bramsen et al., 2006). Events and TimEx, the granular units compared to sentences and clauses, are fundamental for temporal information in language (Moens and Steedman, 1988). Hence, all recent approaches consider these *temporal entities*, events and TimEx, as the ordering units for establishing temporal relations (Bethard, 2013; Bethard et al., 2007; Chambers; D'Souza and Ng, 2013; Laokulrat et al., 2013). We also follow a similar definition in our work.

In the following sections, we formally define temporal relation classification task (Section 2.1.1.1), describe main components of common supervised learning approaches used to solve them (Section 2.1.1.2), detail on corpora used in the experiments (Section 2.1.1.3), and specify evaluations schemes (Section 2.1.1.4).

2.1.1.1 Definition

Temporal relation classification establishes *temporal relations* between temporal entities such as events, and time expressions (TimEx) present in the given document. Events

Relation	Symbol	Symbol for inverse	Pictorial view
X *before* Y	b	a	XXX YYY
X *meets* Y	m	mi	XXXYYY
X *overlaps* Y	o	oi	XXX YYY
X *during* Y	d	di	XXX YYYYYY
X *starts* Y	s	si	XXX YYYYY
X *finishes* Y	f	fi	XXX YYYYY
X *equal* Y	=	=	XXX YYY

Table 2.1 Allen's interval temporal relations (Allen, 1983).

denote actions, occurrences, or reporting and can last for longer period of time or complete in a moment (Pustejovsky et al., 2003b). Events are often expressed with verbs (e.g. *raced*, *declared*), and sometimes with noun phrases (e.g. *deadly explosion*), statives (e.g. he is an *idiot*), adjectives (e.g. the artist is *active*), predicatives (e.g. Biden is the *president*), or prepositional phrases (e.g. soldiers will be present *in uniform*) may also indicate events (Steedman, 1982). The second temporal entity, TimEx denotes exact or relative pointer of time (e.g. *now*, *last week*, *26 Jan. 1950*). It can be a moment, or an interval that can state unambiguous time like *26 Jan. 1950* or a reference from the utterance such as *last week*, *now*.

In this thesis, we consider temporal entities (events and TimEx) as intervals of time that have start-point and end-point where start-point occurs before end-point (Hobbs and Pan, 2004). This interval perspective holds true even in the case of a moment because it still has start-point and end-point, albeit, not far from each other. Based on this interval notion of temporal entities, Allen (1983) defined 13 possible temporal relations that can be assigned between pair of temporal entities as shown in Table 2.1.

For the given document, temporal relations between temporal entities can be presented with the use of a graph where nodes are temporal entities and edges denote temporal relations between them. This graph formed over temporal entities with temporal relations between them is called *temporal graph*. Figure 2.1 shows the temporal graph generated over a sample text. The figure also illustrates the complete process of temporal

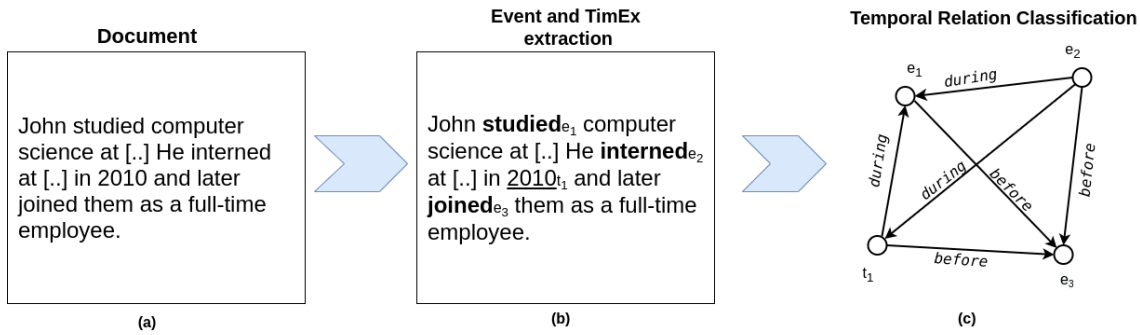


Fig. 2.1 Temporal relation identification over a sample text. From the given text (a), events and TimEx are extracted (b), bold-faced words denote events and underlined words are TimEx and then, temporal relations are assigned between events/TimEx to create a *temporal graph* (c) with nodes as event or TimEx and edge denoting temporal relation. Temporal graph shows edges as *John studied* (e_1) *before joined* (e_3), *interned* (e_2) *during* in *2010* (t_1) where both these happened `during` *studied* (e_1).

relation extraction, first from the given raw text events and are extracted and then, a temporal graph is formed over them.

Over these temporal relations, logical rules like symmetry and transitivity can be applied as they possess algebraic properties (Allen, 1983). Suppose A, B and C are some arbitrary events, then the rule of symmetry over temporal relations states that if A is *before* B then B must be *after* A, because *before* and *after* are inverse temporal relations. This symmetric rule can be generalized to other relations and their inverse relations mentioned in Table 2.1. Formally, a symmetry rule $S_{i,j}$ between a $r, \bar{r}$ inverse relation pair can be given as:

$$S_{i,j} : r_{i,j} \rightarrow \bar{r}_{j,i} \tag{2.1}$$

where i, j denote any temporal interval and $r_{i,j}$, $\bar{r}_{j,i}$ denote respectively temporal relations r, $\bar{r}$ between i, j and j, i.

In addition to rules of symmetry, several transitivity rules can be applied over temporal relations, for instance, if A *meets* B and B *overlaps* C, then A must be *before* C as illustrated in Fig. 2.2. Here, we mentioned single transitivity rule over a specific pair of temporal

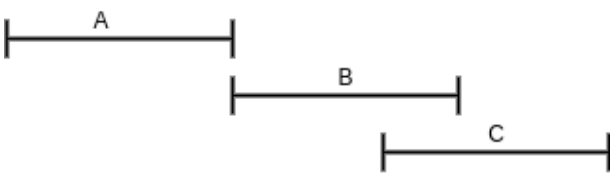


Fig. 2.2 $(A \text{ m } B) \wedge (B \text{ o } C) \rightarrow (A \text{ b } C)$.

relations: *meets*, and *overlaps*, but similar transitivity rules can be applied over all possible

pairs of relations which is detailed in (Allen, 1983). Formally, a generic transitivity rule $T_{i,j,k}$ can be given as:

$$T_{i,j,k} : r_{i,j} \wedge \hat{r}_{j,k} \rightarrow r'_{i,k} \tag{2.2}$$

where i, j, k are any temporal intervals and $r_{i,j}, \hat{r}_{j,k}, r'_{i,k}$ respectively denote temporal relations $r, \hat{r}, r'$ between $i - j$, $j - k$, and $i - k$, and r' is the relation obtained by composing r and $\hat{r}$.

Unknown temporal relations can be inferred from other known relations with the application of these logical rules. Consider the above example, if the temporal relation between A and C was unknown, then the transitivity rule over known relations between A-B and B-C could easily tell us that A occurs *before* C. The process of applying these transitivity rules to infer all the possible temporal relations from a temporal graph is known as *temporal graph saturation* or *temporal closure*. As a consequence, temporal relations between certain pair dictate relations between all other pairs because of propagation of constraints (Allen, 1983). Therefore, it is mandatory for a pair present in the temporal graph to obey the constraints put by other pairs. The temporal graph which follows all the constraints is called *consistent temporal graph*. Conversely, if some of the constraints can not be enforced in the temporal graph then such a graph is called *inconsistent temporal graph*. The inconsistent temporal graph is practically useless for any downstream task as it can not convey any useful information. Also, given an inconsistent temporal graph, it is impossible to point out the wrong temporal relation that introduced inconsistency. To illustrate that, let us again consider the previous example, suppose now a temporal graph shows A *meets* B and B *overlaps* C but A is *after* C, then all the temporal orderings are useless as it is impossible to find out the wrong relation from them.

Formally, suppose a given document D contains set of events, $\mathscr{E} = \{e_1, e_2, \cdots, e_{n_e}\}$, TimEx, $\mathscr{T} = \{t_1, t_2, \cdots, e_{n_t}\}$, and $\mathscr{R} = \{r_1, r_2, \cdots, r_{n_r}\}$ be the set of possible temporal relations. Then the temporal relation classification generates a consistent temporal graph $G = (V, E)$ where V, E are nodes and edges such that $V = \mathscr{E} \cup \mathscr{T}$ and $E = \{(i, j, r_{ij}) | i, j \in V, r_{ij} \in \mathscr{R}\}$ with the condition that all the temporal constraints $\mathscr{C}$ are obeyed in G, where $\mathscr{C} = \{S_{i,j}, T_{i,j,k} | \forall i, j, k \in V\}$, $S_{i,j}$ denote symmetry constraints as shown in Eq. 2.1, and $T_{i,j,k}$ denote set of transitivity constraints similar to Eq. 2.2.

Even though the complete definition of temporal relation classification involves finding relations between event-event, TimEx-TimEx, and event-TimEx pairs, previously proposed approaches frequently concentrated only on event-event pair relation assignments, as it is the most challenging task among them. Besides the solution proposed for it can be easily extended to other temporal entity pairs (Ning et al., 2017). Thus, going

forward we only target event pairs with the assumption that the solution proposed for them can be extended to TimEx-event as well as TimEx-TimEx pairs.

2.1.1.2 Supervised learning approach

In our proposed approach, we cast temporal relation classification as a supervised learning problem. It consists of three main components: event and event-pair representations, models, and inference. We discuss them in the following paragraphs.

Event and event-pair representation The essential part of supervised learning approaches for temporal relation classification is a representation of events. Event representations associate a set of events present in a document to a real-valued vector, which acts as an input for the models. A generic function $\mathcal{Z}_E$ is designed to map an events to a d_e-dimensional vector:

$$\begin{aligned} \mathcal{Z}_E &: \mathcal{E} \rightarrow \mathbb{R}^{d_e} \\ e_i &\mapsto \mathcal{Z}_E(e_i) \end{aligned} \tag{2.3}$$

where $e_i \in \mathcal{E}$.

Next, it is equally important to combine the event representations to get event-pair representations, as temporal relation is a binary relation (between pair of events). Suppose for $e_i, e_j \in \mathcal{E}$ representations obtained with $\mathcal{Z}_E$ are $\mathbf{e_i} := \mathcal{Z}_E(e_i), \mathbf{e_j} := \mathcal{Z}_E(e_j)$, then an effective event-pair representations is modeled as:

$$\begin{aligned} \mathcal{Z}_P &: \mathbb{R}^{d_e} \times \mathbb{R}^{d_e} \rightarrow \mathbb{R}^{d'_e} \\ (\mathbf{e_i}, \mathbf{e_j}) &\mapsto \mathcal{Z}_P(\mathbf{e_i}, \mathbf{e_j}) \end{aligned} \tag{2.4}$$

In this thesis, we learn these functions $(\mathcal{Z}_E, \mathcal{Z}_P)$ to obtain better event and event-pair representations to solve the task more accurately. In the next chapter (Section 3.1.1), first we detail about the previously proposed approaches to obtain these functions and then in Chapters 4 and 6 we present our approach.

Models To solve temporal relation classification task, commonly two types of models are used: *local models* and *global models*. The *local models* learn model parameters without considering temporal relation between other pairs (Chambers et al., 2007; Mani et al., 2006). This makes the task a pairwise classification problem where a confidence score corresponding to each temporal relation is predicted for a given pair of events. Generally a

local model learns a function of the form: $\mathscr{P}_{L,\theta}: \mathbb{R}^{d'_e} \rightarrow \mathbb{R}^{|\mathscr{R}|}$ where d'_e-dimensional vector representation obtained from $\mathscr{Z}_P$, and $\mathscr{R}$ is a set of possible temporal relations. On the contrary, *global models* learn parameters globally while considering temporal relations between other pairs, thus, the learning function takes all event-pair representations and outputs confidence scores corresponding to each pair, modeled as: $\mathscr{P}_{G,\phi}: \mathbb{R}^{n \times d'_e} \rightarrow \mathbb{R}^{n \times |\mathscr{R}|}$ where n is number of event pairs.

Inference Both these models produce a confidence score corresponding to each temporal relation for all the event pairs. Therefore, a strategy must be designed to get the temporal graph from these scores. The most straightforward strategy is to choose the temporal relation for a pair that has the highest confidence score. But, this strategy may lead to inconsistent temporal graph prediction. Therefore, a more global strategy needs to be designed. Initially, *greedy* approaches (Mani et al.; Verhagen and Pustejovsky, 2008) were used. These strategies start with the empty temporal graph, then either add a node or an edge while maintaining the temporal consistency of the graph. Though they produce temporally consistent graphs, they fail to produce optimal solutions. For this, the constraints were converted into Integer Linear Programming (ILP) problem and an optimization objective is solved to produce the graph (Denis and Muller, 2011; Mani et al., 2006; Ning et al., 2017).

In our work, we used a local model with a simple inference strategy to obtain rich event-pair representations in Chapter 4, and a global model with ILP based inference approach in Chapter 6 where commonsense knowledge is integrated with contextual information. We also briefly discuss several previously proposed approaches for modeling and inference in the next chapter in Section 3.1.2.

2.1.1.3 Corpora

The corpora for temporal relation classification is annotated with events, time expressions (TimEx), and temporal relations between them. TimeML (Pustejovsky et al., 2003b) is the most widely used annotation scheme for denoting this temporal information in documents. Popular corpora that are used in the thesis such as TimeBank (Pustejovsky et al., 2003a), AQUAINT (Graff, 2002), TimeBank-Dense (Cassidy et al., 2014), TE-Platinum (Uz-Zaman et al., 2013), and MATRES (Ning et al., 2018b) are all based on TimeML annotation scheme that contains three core data elements `EVENT`, `TIMEX`, and `TLINK`[1]. Event tokens present in the document are denoted by `EVENT` whereas time expressions are denoted

[1] There are other elements defined by TimeML such as `SIGNAL`, `SLINK`,etc. which are not widely used for the task.

TimeML Relations	Allen's Interval Relations
BEFORE	*before*
AFTER	*after*
INCLUDES	*contains*
IS_INCLUDED	*during*
IBEFORE	*meets*
IAFTER	*met by*
BEGINS	*starts*
BEGUN_BY	*started by*
ENDS	*ends*
ENDED_BY	*ended by*
DURING	*during* | *equals*
DURING_INV	*contains* | *equals*
SIMULTANEOUS	*equals*
IDENTITY	*equals*

Table 2.2 TimeML temporal relations and corresponding Allen's interval relations. Note that there is no equivalent of Allen's *overlaps* and *overlapped by* relations in TimeML.

by `TIMEX`, and temporal relations between them are denoted by `TLINK`. In the scheme, events and TimEx are represented as time intervals, so temporal relations can have thirteen possible types that almost resemble Allen's interval relations, Table 2.2 shows the correspondence between them. Now, with this brief understanding of TimeML annotation scheme, let us look at several corpora that are used in the thesis.

TimeBank TimeBank (Pustejovsky et al., 2003a) is the largest dataset available for temporal relation classification containing 183 news documents (the New York Times, Wall Street Journal, Associated Press). It is a human annotated dataset based on TimeML annotation scheme with 7935 `EVENT`s, and 6418 `TLINK`s, Table 2.3 shows further distribution over each temporal relation.

AQUAINT AQUAINT (Graff, 2002) contains 73 documents and have similar temporal relations annotated as TimeBank. It contains 4431 `EVENT`s and 5977 `TLINK`s. The distribution of `TLINK`s with different temporal relations can be seen in column 3 of Table 2.3.

TE-Platinum TempEval-3 (UzZaman et al., 2013) provided TE-Platinum dataset containing twenty documents for evaluating the systems. This is also a human annotated corpus based on TimeML, similar to previous two datasets (Table 2.3 Column 4).

	TimeBank	AQUAINT	TE-PT	TimeBank-Dense	MATRES
Documents	183	73	20	36	276
Events	7935	4431	748	1729	12366
TLINK s	6418	5977	889	12715	13558
– BEFORE	1408	2507	330	2590	6874
– AFTER	897	682	200	2104	4570
– INCLUDES	582	1051	89	836	–
– IS_INCLUDED	1357	1172	177	1060	–
– SIMULTANEOUS	671	63	93	215	470*
– VAGUE	0	0	0	5910	1644
– IDENTITY	743	283	15	–	–
– DURING	302	37	2	–	–
– ENDED_BY	177	22	2	–	–
– ENDS	76	17	3	–	–
– BEGUN_BY	70	22	3	–	–
– BEGINS	61	65	2	–	–
– IAFTER	39	17	10	–	–
– IBEFORE	34	39	8	–	–
– DURING_INV	1	0	1	–	–

Table 2.3 Corpora statistics. *MATRES contains EQUAL temporal relation and not SIMULTANEOUS but both are treated as equivalent.

These three datasets are annotated with the same fourteen temporal relations (Table 2.3). However, recently proposed systems have classified temporal relations over a truncated set of relations instead of all the annotated relations (Chambers et al., 2014; Mirza and Tonelli, 2016; Ning et al., 2017). They obtained this truncated list of possible temporal relations by mapping a few relations to their corresponding approximate relations. Temporal relations mentioned after the dashed line in Table 2.3 are mapped to the temporal relations from the set of relations above the dashed line as shown in Table 2.4. The main reason for these mappings is the rarity of annotations of such relations which leads to class-imbalance making the classification difficult. For instance, distinguishing between relations like BEFORE and IBEFORE (immediately before), AFTER and IAFTER (immediately after) can complicate an already difficult task. In these cases, IBEFORE , IAFTER can be respectively considered as special cases of BEFORE and AFTER . Similarly, relations such as ENDS and BEGINS are special cases of IS_INCLUDED whereas ENDED_BY and BEGUN_BY are mapped to INCLUDES . Besides, added benefits of using these fine-grained temporal relations are not clear (Chambers et al., 2014). Next, TimeML IDENTITY relation indicates event coreference which means the two events are mentions

Original Relation	Mapped To
ENDED_BY	INCLUDES
BEGUN_BY	INCLUDES
ENDS	IS_INCLUDED
BEGINS	IS_INCLUDED
IAFTER	AFTER
IBEFORE	BEFORE
IDENTITY	EQUAL
SIMULTANEOUS	EQUAL
DURING	EQUAL
DURING_INV	EQUAL

Table 2.4 Ambiguous as well as rare relations mapped to coarse-grained relations.

of the same event, whereas SIMULTANEOUS relation indicates that two events are occurring at the same time. These two relations are mapped to EQUAL. At last, DURING and DURING_INV relations intuitively seem closer to IS_INCLUDED and INCLUDES , but are not clearly defined (Chambers et al., 2007; Derczynski, 2016; Derczynski et al., 2013), and are interpreted as SIMULTANEOUS (UzZaman et al., 2013).

TimeBank-Dense While annotating previously mentioned corpora such as TimeBank, AQUAINT, annotators were not asked to annotate all the temporal entity pairs. This leads to sparse temporal relation annotations which can be problematic, as it makes temporal relation extraction difficult because of class imbalance as annotators frequently annotated BEFORE or IS_INCLUDED relations than any other relations (Table 2.3). Besides that, systems trained on such a dataset can be penalized at the evaluation step for predicting relations that annotators might have missed. To solve this issue, Cassidy et al. (2014) annotated relations between all events within a certain token window over 36 documents from TimeBank corpus. Following the argument from the previous paragraphs, they considered the truncated set of temporal relations: BEFORE , AFTER , INCLUDES , IS_INCLUDED , and SIMULTANEOUS . They also annotated pairs with VAGUE relation if no relation can be assigned from this list. The details of these annotations can be seen in column 5 of Table 2.3.

MATRES The low inter-annotator agreement in TimeBank, AQUAINT, and the large number of VAGUE relations in TimeBank-Dense, indicate ambiguity of temporal relations between certain pairs. Ning et al. (2018b) reason that some of the pairs are not temporally related which leads to this ambiguity. They propose a multi-axis annotation scheme to

solve these problems. The first step of their annotation scheme involves anchoring events depending on their types to a specific axis such as main axis, intention axis, opinion axis, etc. Next, only events that are on the same axis and in the window of two sentences are eligible for assigning temporal relations. Also, their annotations differ from the previous datasets, as they assign temporal relation between start-points of the events instead of the whole time intervals of events. As a result, possible temporal relations in the dataset are BEFORE , AFTER , EQUAL or VAGUE, because only these relations can be assigned between *two points*. Additionally, instead of relying on expert annotators, they crowdsourced the annotation effort. They initially annotated only 36 documents from TimeBank-Dense dataset but recently extended annotations over all the documents from TimeBank, AQUAINT, and TE-Platinum. As a result, MATRES contains 276 documents and cumulative EVENTs as shown in Table 2.3.

2.1.1.4 Evaluation

The obvious way of evaluating temporal relation classification systems is a direct comparison of system predicted relations with reference relations i.e. for a given pair of events from the gold annotations, predicted relation of the same event pair is compared. But, evaluating a temporal classification system based on this simple assessment is not sufficient as the same temporal information can be presented in different ways. This makes the evaluation of temporal systems non-trivial.

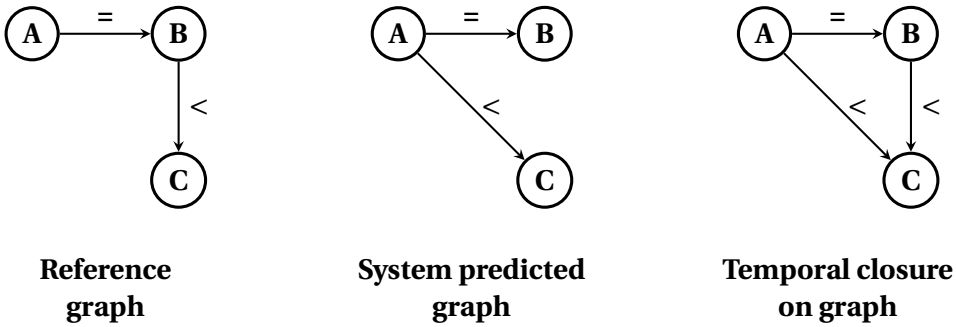


Fig. 2.3 Three equavalent but different representations (Setzer et al., 2002).

Consider the case presented in Fig 2.3 where the human annotated reference graph contains temporal relations which says events $A-B$ are occurring *simultaneously* and $\underline{B}$ occurs *before* C and certain system asserted that $A-B$ are are occurring *simultaneously* but $\underline{A}$ is *before* C. Here, if we measure the system's performance only by the direct comparison of the graphs, the system will get a non-perfect evaluation score despite predicting all relations correctly. Because, from the annotated relations B occurs before C can be easily

inferred with transitivity. This demonstrates that evaluation schemes must do more than just a pairwise comparison to assess a system.

Due to which several evaluation schemes have been proposed. Earliest work (Setzer et al., 2002) proposed a graph based evaluation for limited number of relations such as *before*, *simultaneous* and *includes*. They performed graph closure over both system predicted graph and reference graph to calculate recall and precision. This method was generalized over all temporal relations in (Muller and Tannier, 2004) due to which system with all Allen's relations can be evaluated with this measure. In SemEval'07 campaign (Verhagen et al., 2007) proposed another temporal evaluation metric which was very specific to the dataset used in the shared tasks. After that, Tannier and Muller (2011) proposed a promising evaluation scheme that compares transitively reduced temporal graphs over the end-points of events. Further, temporal awareness evaluation metric is proposed by UzZaman et al. (2013) which is widely used for evaluating temporal relation classification systems.

In our work, for direct comparison of our systems with previous approaches, we evaluated our systems with the same two evaluation schemes that they used (Mirza and Tonelli, 2016; Ning et al., 2017): *direct evaluation* and *temporal awareness*. We discuss them in the following paragraphs. While explaining these evaluation schemes, we use common notations where for a given document, we denote the true reference (gold-annotated) temporal graph as K and system predicted temporal graph as G. The total number of edges of the graph x are denoted as $|x|$ and $|x \cap y|$ denote the number of common edges in the two graphs x, y.

Direct Evaluation This is the most straightforward evaluation metric that measures the precision of a system as a ratio of the number of pairs with correct temporal relation predictions to the number of all the pairs for which temporal relation is predicted. Next, it calculates the recall as a ratio of the number of pairs with correct temporal relations predictions to the number of pairs with true reference relations. Finally, F_1-score is calculated by considering the harmonic mean of precision and recall as:

$$P = \frac{|G \cap K|}{|G|} \qquad R = \frac{|G \cap K|}{|K|} \qquad F_1 = \frac{2PR}{P+R} \tag{2.5}$$

Temporal Awareness Similar to the previously proposed approaches (Setzer et al., 2002; Tannier and Muller, 2008), temporal awareness evaluation (UzZaman et al., 2013) also performs temporal closure over reference and system predicted graphs but do not compare these graphs directly. Instead, it compares the accuracy of *core relations*, relations which

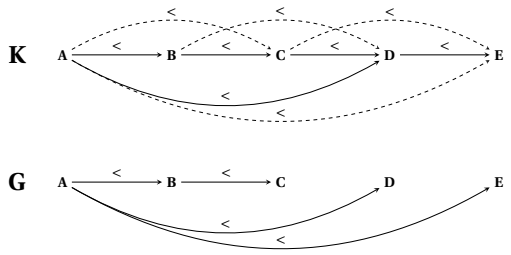


Fig. 2.4 Reference graph K and predicted graphs G. In the graphs thick connected edges show actual annotation, whereas dotted lines denote inferred relations, and the symbol < indicates *before* relation.

Evaluation scheme	P	R	F1
Direct Evaluation	75.0	60.0	66.67
Temporal Awareness	100.0	50.0	66.67

Table 2.5 Evaluation results of G with respect to K with two different schemes.

can not be derived from other relations. It performs graph closure over system produced graph G and reference graph K to get G^+, K^+, respectively. Conversely, the redundant relations are removed from the original graphs G and K to construct reduced graphs as G^-, K^-, respectively, that contain only *core relations*.

Then, precision calculates the percentage of core relations identified accurately, and recall checks the percentage of actual core relations identified by the system. Finally, compact temporal awareness score is calculated as F_1-score:

$$P = \frac{|G^- \cap K^+|}{|G^-|} \qquad R = \frac{|G^+ \cap K^-|}{|K^-|} \qquad F_1 = \frac{2PR}{P+R} \tag{2.6}$$

Difference of evaluation schemes The difference between these two evaluation schemes can be illustrated with a simple example shown in Fig. 2.4. Suppose, we are given annotated document $\mathscr{D}$ containing five temporal entities: A, B, C, D, and E, and true temporal relations between them. Let the graph K shown in Fig. 2.4 be the reference graph obtained from $\mathscr{D}$, and G be the predicted temporal graph from some arbitrary system. In the graphs, actual annotations are shown with thick edges, whereas inferred relations are denoted with dotted lines. The evaluation of graph G with the two evaluation schemes, Direct Evaluation (DE) and Temporal Awareness (TA) is shown in Table 2.5. We see, precision drops with DE even though all the predictions are accurate, because without temporal closure of graph K, the relation between $A-E$ can not be determined. Next, recall scores are also different as DE considers all five annotated relations (thick lines in K) equally important and calculates recall 60% as only 3 out of 5 relations are predicted accurately. On the other hand, TA calculates recall as 50% as it assigns no score for predicting temporal relations between $A-D$, $A-E$ as they can be inferred from other temporal relations.

2.1.2 Bridging anaphora resolution

Bridging is an essential part of discourse understanding (Clark, 1975). The reader may have to *bridge* the currently encountered expression to a previously known information either from the text or from her memory. In his pioneering work, Clark (1975) considered this broad phenomenon as *bridging*, which connects any expressions that can not be understood without the context to previously appearing phrases. The expression which can not be interpreted without the context is called as *anaphor*, and the phrase on which it depends for meaning is referred to as *antecedent*. The earlier definition of bridging included an identical relation between anaphor and antecedent, which is commonly known as *coreference*. But, over the period, the scope of bridging has changed, so now bridging refers to any *association* between anaphor and antecedent except *coreference*. Also, another difference is that, in bridging defined by Clark (1975), an antecedent can be a sentence or a clause that can be useful for interpretation of an anaphor. But, in this work, we are considering only those anaphor-antecedent pairs which are noun phrases (NP) (as practiced by recent researchers). Apart from Clark, Hawkins (1978); Prince (1981, 1992) also studied bridging but referred to this phenomenon differently. Hawkins (1978) termed it as *associative anaphora* and only considered definite NPs as anaphors, whereas Prince (1981) referred to anaphors which can be inferred from previously mentioned expressions as *inferrables*.

With this understanding of bridging, we describe the computational task which identifies it automatically: *bridging anaphora resolution*, in the coming sections. Section 2.1.2.1 formally defines the task, Section 2.1.2.2 discusses main components of supervised learning approaches of solving it, next Section 2.1.2.3 details corpora used in this work, and finally, Section 2.1.2.4 presents an evaluation metric.

2.1.2.1 Definition

Bridging resolution is the computational task corresponding to the bridging phenomenon. It consists of two tasks, bridging anaphora *recognition* which identifies all the bridging anaphors from a given document, and bridging anaphora *resolution* which connects these bridging anaphors to their antecedents. We are solving the latter task.

Mention is a term used to denote named entities, and NPs, or pronominals that refer to entities. For instance, entity such as *Barack Obama*, and NP references like *the president*, *the senator*, or pronominal reference like *he, him*, are mentions. We are considering only those anaphors and antecedents that can be NPs in our work, so can be considered as sub-type of *mentions*. Consequently, bridging resolution task can be visualized as

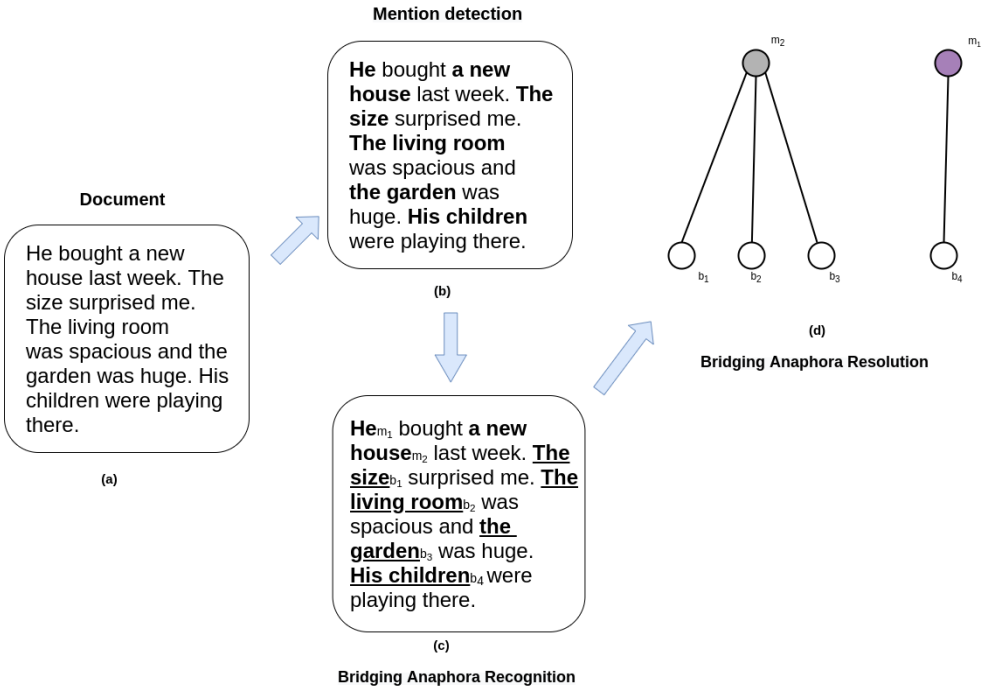


Fig. 2.5 Bridging resolution over a sample text. From the given text (a), all the mentions are detected (b), bold-faced words denote mentions, in next step bridging anaphors are found out (c), the underlined words are bridging anaphors and finally, bridging anaphora resolution is executed to link these anaphors to antecedents (d). In the generated graph (d) thick line denotes bridging relation. *The size, the living room* and *the garden* are all specifically related to *a new house*. So, bridging anaphors b_1, b_2, b_3 are linked to the same antecedent m_2. Then another bridging anaphor *his children* are related to the person who bought the house, *He*, thus, showing bridging relation between b_4 and m_1. Note that there is no bridging relation between antecedents m_1 - m_2 as well as between bridging anaphors - b_1, b_2, b_3, b_4.

pipeline where first mentions are detected, from this set of mentions bridging anaphors are identified in bridging anaphora *recognition*, and finally bridging anaphora *resolution* connects these anaphors to corresponding antecedents. This is depicted with a sample text in Fig. 2.5.

Formally, let D be a given document containing set of mentions: $\mathscr{M} = \{m_1, m_2, \cdots, m_{n_m}\}$, and bridging anaphors :$\mathscr{A} = \{a_1, a_2, \cdots, a_{n_a}\}$. Then the bridging anaphora resolution generates a set of anaphor and predicted antecedent pairs as: $\{(a_i, y_i) | \forall a_i \in \mathscr{A}, y_i \in \mathscr{M}\}$.

2.1.2.2 Supervised learning approach

Similar to temporal relation classification, in this task as well we are taking supervised learning approach to solve bridging anaphora resolution. This involves three important components: mention representations, models and inference. We detail them here.

Mention representations As both anaphors and antecedents are assumed to be a subset of mentions, obtaining mention representations becomes essential. For that, a generic function $\mathcal{Z}_M$ is found out as follows:

$$\begin{aligned} \mathcal{Z}_M &: \mathcal{M} \rightarrow \mathbb{R}^{d_m} \\ m_i &\mapsto \mathcal{Z}_M(m_i) \end{aligned} \tag{2.7}$$

where $m_i \in \mathcal{M}$. We develop an approach to learn this function where contextual and commonsense information is acquired (Chapter 6). Before that, in the next chapter, we detail previously proposed approaches to get this function in Section 3.2.1.

Models Similar to temporal relation classification, *local models* and *global models* are used for bridging anaphora resolution as well. In the local models for bridging anaphora resolution, a confidence score for bridging anaphor and a previously occurring mention is predicted (Markert et al., 2003; Poesio et al., 2004). Formally, these models learn a function of the form: $\mathcal{B}_{L,\theta}: \mathbb{R}^{d_m} \times \mathbb{R}^{d_m} \rightarrow \mathbb{R}$. On the contrary, global models find corresponding antecedents for anaphors simultaneously (Hou et al., 2013b). This work with global modeling approach did not explicitly find the mention representations but employed Markov Logic Networks (MLN) (Domingos and Lowd, 2009) for global inference.

Inference In bridging anaphora resolution, infererence is not as complicated as in temporal relation classification, as it does not follow any complex symmetry or transitivity constraint. The inference step in local models is similar to the *best-first clustering*. Initially, antecedent candidates are arranged depending on the confidence scores predicted from the model, then the highest scoring candidate antecedent is selected as the predicted antecedent for the bridging anaphor. In case of a global model, Hou et al. (2013b) put some linguistic constraints such as anaphor have less probability of being antecedent, or antecedents have higher probability for being antecedent for other anaphors, in her inference strategy and obtained global inference with MLN. We provide more details about it in the next chapter.

	ISNotes	BASHI	ARRAU			
			RST	TRAINS	PEAR	GNOME
Documents	50	50	413	114	20	5
Domain	news	news	news	dialogues	spoken narratives	medical
Bridging anaphors	663	459	3777	710	333	692
Mentions	11272	18561	72013	16999	4008	6562

Table 2.6 Bridging corpora used in the thesis.

We used local model to solve bridging anaphora resolution but applied different strategy while learning, instead of casting it as classification problem we employed ranking strategy. Next, we used simple inference strategy where top ranking candidate antecedent is selected from the list of candidates for the anaphor. We detail about this in Section 6.4.2.

2.1.2.3 Corpora

ISNotes Markert et al. (2012) annotates 50 documents from the Wall Street Journal (WSJ) portion of OntoNotes corpus (Weischedel et al., 2013) with bridging information which contains 663 bridging anaphors (Table 2.6). These are all *referential bridging* anaphors which means they strictly require the context for interpretation (Kobayashi and Ng, 2021; Roesiger et al., 2018). All the anaphors are NPs, whereas antecedents are either entities or events (verb phrases (VPs) or clauses). Out of all 663 anaphors, 622 anaphors have NPs as antecedents and the remaining are events. ISNotes also categorizes these anaphor-antecedent pairs based on the relations they possess: set/membership (45), part-of/attribute-of (92), action (16), though most of the relations are unspecified and marked as *Other* (530) relation.

BASHI Roesiger (2018a) annotated 50 documents (different set of documents than ISNotes) from OntoNotes with bridging information (Table 2.6). The corpus contains 459 bridging anaphors where they categorize them as: definite (275), indefinite (114), and comparative (70). Out of these 70 comparative anaphors, 12 have more than one link to antecedents. Also, similar to ISNotes all the anaphors are *referential* type and NPs, whereas antecedents can be entity or event.

ARRAU The first version of ARRAU was created by Poesio and Artstein (2008), recently Uryupina et al. (2019) proposed the latest version. The corpus contains documents from four different domains: news (RST), spoken narratives (PEAR), dialogues (TRAINS), and medical (GNOME). In total it consists of 5512 bridging pairs, Table 2.6 shows division of these pairs. The type of bridging is different than ISNotes and BASHI as most of the anaphors are *lexical bridging* (e.g. Europe-Spain) that do not strictly depend on the context for interpretation whereas some are of *referential* (Kobayashi and Ng, 2021; Roesiger et al., 2018). Also, antecedents are only entities and anaphors are NPs. Bridging pairs from RST portion of the corpus are annotated with relations such as subset, comparative, possessive, element, and inverse of these relations. The pairs which can not be categorized into these relations are marked as *underspecified*. Addition to bridging, ARRAU consists of annotations for coreference as well as discourse deixies.

2.1.2.4 Evaluation

The quality of prediction is assessed with accuracy measure, the ratio of correctly linked anaphors with their respective antecedents to the total number of anaphors. We consider an anaphor linking correct if it is linked to any mention of the true antecedent entity. If there are n_a number of anaphors and out of those, for n_a^c number of anaphors antecedents were correctly found then the accuracy is calculated as:

$$A = \frac{n_a^c}{n_a} \tag{2.8}$$

2.2 Artificial neural networks

So far, we detailed the tasks that are tackled in this thesis. Now, we briefly introduce artificial neural networks which are powerful at learning representations as well as potent at modeling many tasks.

Artificial neural networks are computational systems inspired from the biological neural networks, and *neurons* are the fundamental computation unit in them. A neuron processes inputs by applying pre-designed function (generally, non-linear function known as *activation functions*) to produce output. Further, a number of neurons are aggregated into a layer where the first layer of the network always receives input and the final layer produces output, and there can be any number of layers in between which are called *hidden layers*. The neurons, in turn, layers, are interconnected to produce a network or graph, where neurons are nodes and edges denote a connection between them, hence the name *neural network*. The connections are directed labeled edges that indicate the

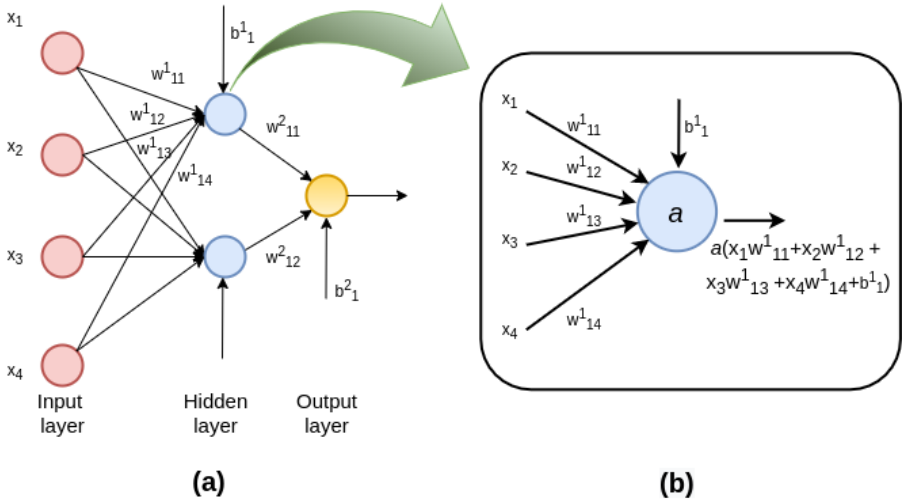


Fig. 2.6 Simple neural network. Fig.(a) shows a simple neural network with three layers - input layer, hidden layer, and output layer where information flows from input layer to hidden layer and finally to output layer. The nodes denote neurons, and edges show a weighted connection between them. A single neuron is detailed in Fig. (b). It takes input from the previous layer and calculates weighted sum which is passed through *activation* function a to produce output.

direction and weight of the signal. These weights control the connection and are adjusted at the training step of the network.

A simple neural network is shown in Fig. 2.6, which contains three layers – *input, hidden, and output layer*, respectively having four, two, and one neurons. A neuron produces output based on the inputs, the associated weights, biases and the *activation function* (Fig. 2.6 (b)), where weights and biases are called *parameters* of the network and are learned at the training step. A neural network can have any number of layers, any number of neurons in them, and different kinds of connections between them. These are *hyperparameters*[2] which depend on the type of problem the neural network solves. In any neural network, the produced output depends on the input and the various transformations applied to it at each layer. Hence, the output $\hat{y}$ obtained from a neural network as a (non-linear) transformation on input x, controlled by parameters θ is given as:

$$\hat{y} = f_\theta(x) \tag{2.9}$$

[2]Learning rate, learning algorithm, epoch (number of iteration of training), activation function, dropout are some other *hyperparameters*.

where f_θ is composition of different (non-linear) transformations at various layers: $f_\theta = f_1 \circ f_2 \circ \cdots \circ f_l$.

Training of neural network determines the values of *parameters*. At the beginning of this step, all the parameters, i.e. weights and biases, are randomly initialized. Then the training adjusts these parameters values so as to produce the desired output. The difference between the desired and actual output is measured with a loss function. Suppose, $\mathscr{D} = \{(x_i, y_i)_{i=1}^n\}$ is training data where x_i denote input features and y_i shows associated label. The cumulative loss is given as:

$$\mathscr{L}(\theta) = \sum_{(x_i, y_i) \in \mathscr{D}} l(y_i, \hat{y}_i) \tag{2.10}$$

where l is a error function which gives difference between true output y_i and predicted output $\hat{y}_i := f_\theta(x_i)$. Then, following optimization objective is solved to get appropriate parameters:

$$\min_\theta \mathscr{L}(\theta) \tag{2.11}$$

The objective function $\mathscr{L}(\theta)$ is non-convex function because of non-linear activation functions and obtaining analytical solution is difficult.

Gradient descent algorithms are commonly used for minimizing this objective. The algorithm updates parameters of the network iteratively and the parameter values are reduced by the value proportional to the gradient of the loss function with respect to the parameter. The update rule at $(t+1)^{th}$ iteration is given as:

$$\theta_{t+1} \leftarrow \theta_t - \gamma \frac{\partial \mathscr{L}(\theta)}{\partial \theta} \tag{2.12}$$

where θ_t denotes the parameters of the neural network at iteration t in gradient descent, and learning rate.

However, obtaining a gradient with respect to each parameter in the network is a computationally expensive operation. *Backpropagation* (backward propagation of errors) algorithm (Goodfellow et al., 2016; Kelley, 1960; Rumelhart et al., 1986b) is used to calculate the gradient of the error function with respect to the neural network's weights. The gradient calculation proceeds in the backward direction, i.e. first the gradient of the error is calculated with the final layer, then, these values are propagated with the chain rule to obtain gradients with parameters from the previous layers. This produces efficient

computation of the gradient at each layer versus the naive approach of calculating the gradient of each layer separately.

Additionally, to speed up the learning process different variants of gradient descent algorithms such as batch, mini-batch, and stochastic gradient descent are used. Recently, various improvements have also been proposed for the gradient descent algorithms: Adagrad (Duchi et al., 2011), Adadelta (Zeiler, 2012), RMSProp (Tieleman and Hinton, 2012), Adam (Kingma and Ba, 2017), etc.

Different types of neural networks produce different transformations of the input data. We describe few popular neural networks that are used in this work as well.

- **Feedforward networks**: In these networks, the information flows from the input neurons to hidden neurons to output neurons (example Fig. 2.6). Formally, the output of ith layer having n_i neurons, $h_i \in \mathbb{R}_i^n$ is given as:

$$h_i = \psi_i(W_i^T h_{i-1} + b_i) \tag{2.13}$$

  where $h_{i-1} \in \mathbb{R}^{n_{i-1}}$ is output from $(i-1)^{th}$-layer, $W_i \in \mathbb{R}^{n_{i-1} \times n_i}, b_i \in \mathbb{R}^{n_i}$ are weights and biases, and ψ_i is activation function for i^{th}-layer. Here, $i \in \{1, 2, \cdots, l\}$ for l-layered feed-forward network and h_0 denotes input to the network.

- **Convolutional neural network (CNN)**: CNN (Lecun et al., 1998) is a special type of feed-forward network which commonly consists of convolution layer, application of non-linear activation function, and followed by pooling-layer. The input is convolved with weight matrices that are learned, called *filters* or *kernels*. Intuitively, in convolution operation, the filter slides over the input, obtains element-wise products, and sums them. Formally, for a given input[3] $X \in \mathbb{R}^{d_h \times d_w}$ and filter $F \in \mathbb{R}^{d_f \times d_f}$, result is given as:

$$R_{m,n} = \sum_i \sum_j X_{(m-i),(n-j)} F_{i,j} \tag{2.14}$$

  where $R \in \mathbb{R}^{d_{c_h} \times d_{c_w}}$, $d_{c_h} = d_h - f + 1$, $d_{c_w} = d_w - f + 1$. Next, non-linear projection with activation is given as:

$$R' = \psi(R) \tag{2.15}$$

[3]CNNs are used often over images that are stored with two or more dimensional data. Hence, we are considering 2-dimensional input, but convolutions over 1-dimensional input can be obtained in the similar way with filter sliding over only one dimension.

Finally, it is passed through pooling-layer φ to get the final output as:

$$Y = \varphi(R') \tag{2.16}$$

commonly, φ is max-pooling layer or average-pooling layer.

- **Recurrent neural network (RNN)**: Unlike feed-forward networks, RNNs (Rumelhart et al., 1986a) have loops. Because of this feedback mechanism, the output depends on the current as well as the previous input which also leads to a sequential behavior where different states produce different outputs. There are many variants of RNNs: Long Short-term Memory (LSTM) (Hochreiter and Schmidhuber, 1997), Gated Recurrent Unit (GRU) (Cho et al., 2014), etc. We present a simple RNN (Elman, 1990; Jordan, 1997) which is extended to produce these more advanced variants.

$$h_t = \psi_h(W_h^T x_t + U_h^T h_{t-1} + b_h) \tag{2.17}$$

$$y_t = \psi_y(W_y^T h_t + b_y) \tag{2.18}$$

where $h_t, h_{t-1} \in \mathbb{R}^{n_h}$ are hidden states at $t, t-1$, respectively, $x_t \in \mathbb{R}^{n_x}$ and $y_t \in \mathbb{R}^{n_y}$ are input and output at time t, $W_h \in \mathbb{R}^{n_x \times n_h}, W_y \in \mathbb{R}^{n_y \times n_h}, U_h \in \mathbb{R}^{n_h \times n_h}$ are weight matrices, $b_h \in \mathbb{R}^{n_h}, b_y \in \mathbb{R}^{n_y}$ are biases, and ψ_h, ψ_y are activation functions.

2.3 Representation learning

In Section 2.1, we detailed task definitions of two tasks that are addressed in this thesis. Then in the previous section, we introduced artificial neural networks which are used widely to solve many tasks especially for learning effective representations. In this section, we discuss representation learning and related fields. This discussion sets a base for the various representation learning approaches described in the next section.

Most NLP models require *real valued vectors* (or *tensors* in general) as an input. These numeric representations of linguistic objects are either designed or automatically learned for the purpose of inputting to machine learning models. Converting any type of data into vectors, i.e. obtaining *representation*, is an important part of the whole process of applying a machine learning algorithm. Not only that, it is crucial to obtain a *good* representation so that the task of the machine learning algorithm in the pipeline becomes easier. A *good* representation should capture as many relevant features present in the original data that are required for solving the underlying NLP task.

Feature engineering is one way of obtaining such relevant features which are designed by experts of the field. But, feature engineering is an arduous job which requires *task-specific* knowledge and immense human effort. Besides, the noisy data can induce errors in obtaining such features. Moreover, changes in the domain of underlying data can lead to a repetition of efforts on the new data. This is especially severe for NLP tasks where domain changes are quite frequent. For instance, wordings used in a political discourse are different from a corporate discourse which is again different from a medical discourse, as a result, the solutions designed for one domain may not be effective for other domains. The problem aggravates in the case of language change which may require different experts of the language to design new features. To address these drawbacks of feature engineering, it is necessary to automatically discover features. *Representation learning* or *feature learning* does exactly that and retrieves relevant features from the data automatically without the need of any human expert.

Representation learning approaches for text can be divided into two categories: 1. Supervised representation learning, and 2. Unsupervised representation learning. Supervised representation learning approaches are generally applied to get the *task-specific representations* of the linguistic units. These approaches assume that text data containing labels are available for training. Let us suppose n-data samples, $\mathscr{D} = \{(x_i, y_i)\}_{i=1}^{n}$ are given, where x_i is the linguistic object and y_i the corresponding label. Let $\mathscr{X}$ be the generic set of these linguistic objects such that $x_i \in \mathscr{X}$ as well as $\mathscr{Y}$ be the set of possible labels, $y_i \in \mathscr{Y}$. Then the supervised *task-specific representation* learning algorithm learns a parameterized function which maps each linguistic object to corresponding vector representation while encoding the label-related information as:

$$f_{Y,\theta} : \mathscr{X} \rightarrow \mathbb{R}^d \tag{2.19}$$

where θ are parameters to be learned. Most of the neural network based approaches used to solve a specific task fall into this category such as the recently proposed approach for temporal relation classification (Han et al., 2019a,b) or bridging resolution (Hou, 2020a; Yu and Poesio, 2020).

On the other hand, unsupervised representation learning approaches obtain generic representations with unlabeled texts. These representations are not task-specific so can be used as a base representations for other tasks. The commonly used word embeddings such as Word2vec (Mikolov et al., 2013a), Glove (Pennington et al., 2014) can be considered as unsupervised representation approaches. Formally, these approaches learn parameters

θ only from an unlabeled data $\mathscr{D} = \{(x_i)\}_{i=1}^{n}$ as:

$$f_\theta : \mathscr{X} \rightarrow \mathbb{R}^d \tag{2.20}$$

Representation learning shares resemblance with *metric learning* (Bellet et al., 2013) in the sense that metric learning projects similar data samples on similar vectors [4]. This is governed by learning distance metric between two data samples, $d : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}$. The whole idea in the metric learning algorithms is to learn appropriate distance measure d so that it correctly produces small distances between similar objects and bigger distances for dissimilar objects. One of the examples of this distance measure is Mahalanobis distance (Mahalanobis, 1936), which calculates the distance between two objects x, x' as:

$$d_M(x, x') = \sqrt{(x - x')^T M (x - x')} \tag{2.21}$$

Following this, various methods (Bellet et al., 2013) are proposed that learn matrix M to get the distance between data-points based on above-mentioned similarity constraint (i.e. similar object pairs should have smaller distance and dissimilar pairs bigger distance). After learning this distance metric, it is applied to the unseen data to accurately predict the output. In other words, metric learning can be seen as weakly supervised representation learning with the additional condition of learning metric which measures the distance between data points. Consequently, metric learning can be used to improve the performance of classification (Meyer et al., 2018; Weinberger and Saul, 2009) for ranking in information retrieval (Cakir et al., 2019; McFee and Lanckriet, 2010), for recommending relevant items to users (Hsieh et al., 2017), etc.

Dimensionality reduction (Xie et al., 2018) is another sub-field that shares similarity with representation learning. But, the fundamental goal in the two tasks is different where on one hand representation learning approaches concentrate on finding the meaningful representations, on the other hand, dimensionality reduction approaches compress the representation while preserving as much original information as possible. The necessity of reducing the dimensions of the representation rises due to the high-dimensional input representations. Because having a higher number of features to represent the data can be detrimental to the generalization of machine learning models. Additionally, dimensionality reduction provides numerous advantages such as a reduction in the computational cost (both in space and time) of the algorithms used over the data, or the removal of the possible noise introduced when picking up the data. Due to these benefits, usually, it is a good idea to reduce the feature space (dimensions of the input representation)

[4] It generally holds true, but more specifically depends on properties of matrix M (Eq. 2.21).

while preserving the relevant information. Dimensionality reduction approaches obtain functions that project higher dimension data into lower dimensional space $f_d : \mathbb{R}^k \rightarrow \mathbb{R}^d$ where $k \gg d$. Broadly there are two approaches to achieve this: *feature selection* (Chandrashekar and Sahin, 2014) where certain important features are selected from the original set of features that are useful for the further task and other is *feature extraction* (Dara and Tumma, 2018; Khalid et al., 2014) which combines given features into smaller features. Many methods have been proposed to reduce dimension with *feature extraction*, such as matrix factorization approaches: Principle Component Analysis (PCA) (Jolliffe, 2011), Singular Value Decomposition (Golub and Reinsch, 2007), recently proposed deep learning methods: autoencoders (Baldi, 2011), etc.

2.4 Word representations

In any text, words are considered as core constituents and treated as the lowest meaningful units of a language[5]. It is also assumed that meanings of the bigger units of language such as phrases, sentences, or documents can be derived from the constituent words. Besides, often some form of text (i.e. a sequence of words) is an input for several NLP tasks. Therefore, it is essential to obtain a meaningful representations of words to solve NLP tasks.

The ideal word representation algorithm should map all the words in a language to its vector representation. However, obtaining all the words in the language is difficult as language is evolving and new words are added constantly. This is addressed by creating a huge vocabulary containing millions or billions of words and getting a vector representation for each word in the vocabulary. A word representation learning algorithm finds a map from each word in vocabulary to their corresponding d-dimensional vector. Let us assume that the vocabulary of words be $\mathcal{V}$, then the algorithm finds following map f :

$$f : \mathcal{V} \rightarrow \mathbb{R}^d \tag{2.22}$$

One of the simplest ways of word representations is *one-hot vector representation* which is quite intuitive. The algorithm assigns one-hot vector to each word from the vocabulary $\mathcal{V}$ which contains 1 only at the position of the word otherwise 0. Formally, for a word w which occurs at l^{th} position in $\mathcal{V}$, the corresponding one-hot vector $\mathbf{w}$ is given as $\mathbf{w} = \{0, 1\}^{|\mathcal{V}|}$, and vector element $\mathbf{w}_l = 1$.

[5]It is not true in the stricter sense as words can be further broken into *morphemes*, but for the scope of this discussion, we consider words as the lowest units.

Though it is a simple approach to obtain word representation, it has multiple disadvantages. The main drawback of this method is the failure at encoding any semantic or syntactic information of the word. For example, in this way of representation, “dog” and “cat” are equally unrelated as “dog” and “machine”. This is evident from the dot product of vectors corresponding to these words, as for all the pairs of different words the similarity will be 0. This method also suffers from producing high-dimensional sparse vectors, because each vector will be of the size of the vocabulary. This sparse representation is not so useful for the downstream tasks.

2.4.1 Distributed representations

The drawbacks of one-hot vector representations are solved with the *distributed representations* of words. On the contrary to high-dimensional one-hot vector representations, distributed representations use continuous low-dimensional vectors as word representations and encode semantic information related to the word in the corresponding vector. These approaches produce a *dense* representation which means multiple dimensions may capture one concept and each dimension in the vector may capture multiple concepts.

These *dense* distributed representations of words are commonly derived from the words’ context and are based on the distributional hypothesis of linguistic objects (Firth, 1957; Harris, 1954): Linguistic units possessing similar text distribution have similar meanings. It implies, the more similar two linguistic objects are the more distributionally similar they will be. In turn suggesting that semantically similar linguistic objects occur in similar linguistic contexts. By applying this hypothesis specifically to words, it can be stated that words that occur in a similar context tend to possess a similar meaning.

Though the words distributed (representations) and distributional (hypothesis) sound similar, they are not strictly related. The only relation they possess is that generally the distributional hypothesis is used to obtain a distributed representation. The embeddings which are obtained with the use of distributional hypothesis are a specific type of distributed embeddings which are also called *distributional embeddings* (Ferrone and Zanzotto, 2020). However, it is possible to obtain distributed representations without the use of distributional hypothesis. For instance, obtaining word representations based on the semantic networks is distributed but not distributional (Baroni and Lenci, 2010). Semantic network contains concepts as nodes, and edges as semantic relations between them, for instance, WordNet (Fellbaum, 1998) is a specific example of semantic network [6]. Thus, the word representations obtained only with the use of WordNet are called *dis-*

[6] We will use embeddings learned over WordNet as well in this work which will be introduced later.

tributed but not *distributional*. In this section, we focus on the distributed embeddings which are obtained based on the *distributional* hypothesis as those are widely used for word representations.

Several models have been proposed based on this hypothesis to produce continuous valued vectors (Elman, 1990; Hinton et al., 1986; Rumelhart et al., 1986a). Before the popularity of the neural models to obtain word representations, dimensionality reduction techniques such as PCA, SVD are used over the co-occurrence matrix to get the low dimensional vector representations (Dhillon et al., 2015; Lebret and Collobert, 2014). A promising approach based on neural network (Bengio et al., 2003) learned language model and continuous vector representation words simultaneously.

Most of these word representation algorithms make use of language modeling objective to produce the embeddings. Let us brief about language modeling task before diving into these embedding algorithms. Language modeling (LM) finds probability distribution over a sequence of words. It gives a likelihood of a sequence of words appearing in a language. Formally, for a sequence of words $w_1, w_2, \cdots, w_N$, LM produces joint probability by considering the tokens that appeared before the current token as:

$$p(w_1, w_2, \cdots, w_N) = \Pi_{i=1}^{N} p(w_i | w_1, w_2, \cdots, w_{i-1}) \tag{2.23}$$

Calculating exact joint probability for all the sequences is computationally infeasible, so Markov assumption is applied. The assumption simplifies the calculation as it curtails the dependence of the current word to only n prior words. The approximate joint probability is given as:

$$p(w_1, w_2, \cdots, w_N) \approx \Pi_{i=1}^{N} p(w_i | w_{i-n}, w_{i-n+1}, \cdots, w_{i-1}) \tag{2.24}$$

Word embedding algorithms learn parameterized joint probabilities while learning the word representations to optimize the LM objective. With this brief understanding of LM, we discuss different popular word embeddings algorithms in the coming sections.

2.4.1.1 Word2vec

The basic idea in Word2vec (Mikolov et al., 2013a,b,c) is to produce vectors depending on the context of words (distributional hypothesis). Their approach uses simple feed-forward neural networks with a single hidden layer to reconstruct either a word from the given context (*Continuous bag-of-words (CBOW)*), or the context from a given word (*skip-gram*) and the output from the hidden layer is considered as a Word2vec representation for words.

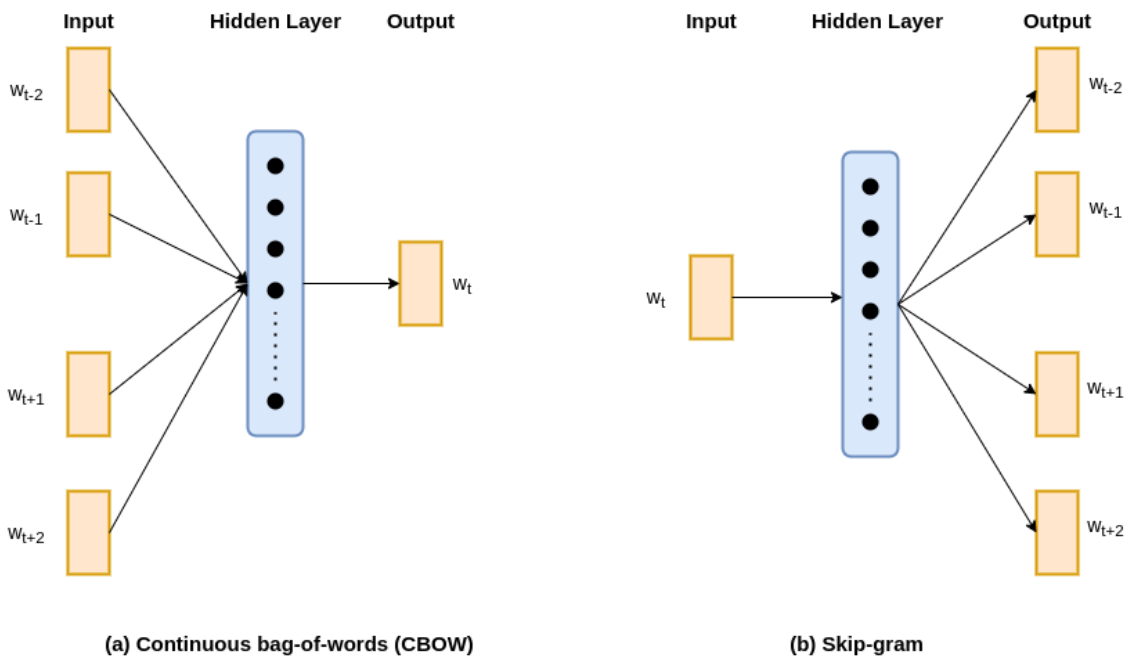


Fig. 2.7 Two neural models - (a) continous bag-of-words (CBOW) which takes input as a context of words and predicts the word, on othe hand (b) skip-gram predicts context of words from the given of word.

Continuous Bag-of-Words (CBOW) based neural model predicts a word from its context. The architecture is shown in Fig. 2.7(a). The input to the model is all the words in the window of some randomly chosen number. In the figure, a window of 2 is used, therefore, two words prior to the word and two words after the word are given as an input to the feed-forward model. Then each word is projected onto the same space with the use of a single layer perceptron and then all these vectors are added. This sum of vectors is multiplied with weight matrix and then passed through a softmax to get the probability score.

Let $w_{j-l}, w_{j-l+1}, \cdots, w_j, \cdots, w_{j+l-1}, w_{j+l}$ be the context of word w_j in the window of l-words. CBOW model produces conditional probability of w_j given the context as:

$$P(w_j | w_{t(|t-j|\leq l, t\neq j)}; \Theta) = \frac{e^{\mathbf{s}_j}}{\sum_{j'=1}^{|\mathcal{V}|} e^{\mathbf{s}_{j'}}} \tag{2.25}$$

where $\mathbf{s}_j$ is a jth element of vector $\mathbf{s} \in \mathbb{R}^{|\mathcal{V}|}$ which denotes confidence score for word w_j being the context of $w_{t(|t-j|\leq l, t\neq j)}$. The confidence score $\mathbf{s}$ for each word in vocabulary is calculated as:

$$\mathbf{s} = M^T \sum_{|t-j|\leq l, t\neq j} H^T \mathbf{w_t} \tag{2.26}$$

where $M \in \mathbb{R}^{m \times |\mathcal{V}|}$ and $H \in \mathbb{R}^{|\mathcal{V}| \times m}$ are hidden layer projection matrices learned by neural network, and $\mathbf{w_t} \in \mathbb{R}^{|\mathcal{V}|}$ be the $\mathcal{V}$-dimensional one-hot vector of word w_t (where $\mathcal{V}$ is the vocabulary of words).

The parameters Θ are learned to minimize negative log probabilities :

$$\mathscr{L}(\Theta) = -\sum_j P(w_j | w_{t(|t-j| \leq l, t \neq j)}; \Theta) \tag{2.27}$$

Skip-gram is opposite in the functionality to CBOW. It produces probability for context words given a target word. It is depicted in the section (b) of Fig. 2.7. Consider the same context as mentioned in CBOW, $w_{j-l}, w_{j-l+1}, \cdots, w_j, \cdots, w_{j+l-1}, w_{j+l}$, for which the skip-gram model produces probabilities for all the words w_t where $|t-j| \leq l, t \neq j$ in the context of a given word w_j as:

$$P(w_t | w_j; \Theta) = \frac{e^{\mathbf{s}_t}}{\sum_{t'=1}^{|\mathcal{V}|} e^{\mathbf{s}_{t'}}} \tag{2.28}$$

Here, $\mathbf{s}_t$ denotes confidence score of context word w_t given the target word w_j which subtly differs from CBOW. The score $\mathbf{s} \in \mathbb{R}^{|\mathcal{V}|}$ for each word in vocabulary denoting the compatibility with word w_j is given as:

$$\mathbf{s} = M^T H^T \mathbf{w_j} \tag{2.29}$$

where similar to CBOW, $M \in \mathbb{R}^{m \times |\mathcal{V}|}$ and $H \in \mathbb{R}^{|\mathcal{V}| \times m}$ are hidden layer projection matrices, and $\mathbf{w_j} \in \mathbb{R}^{|\mathcal{V}|}$ be the $\mathcal{V}$-dimensional one-hot vector of word w_j.

Similar to CBOW, the parameters Θ are learned by reducing sum of negative log probabilities:

$$\mathscr{L}(\Theta) = -\sum_j \sum_{|t-j| \leq l, t \neq j} P(w_t | w_j; \Theta) \tag{2.30}$$

Negative sampling and Hierarchical softmax The above approach of finding probabilities suffers from huge time complexity because of softmax calculation (Eq. 2.25 and 2.28), because for probability calculation of a single word, all the words have to be considered. Word2vec proposed two approaches to solve them, *Negative sampling* and *Hierarchical softmax*.

In *negative sampling*, instead of considering all the words to calculate the softmax probability only a few words (n) are considered as negative samples. These are selected based on the word co-occurrence frequency, with which top-n words having the smallest

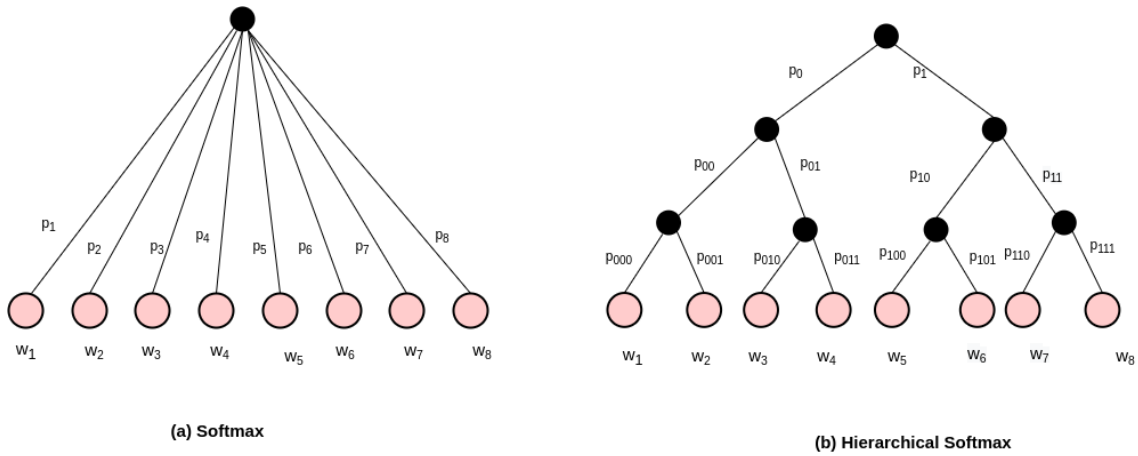


Fig. 2.8 Hierarchical softmax.

frequency are chosen. This simple approximation reduces the calculation from $|\mathcal{V}|$ words to only $n+1$ words.

Hierarchical softmax approximation approach is inspired from the binary trees proposed by Morin and Bengio (2005). The actual softmax calculation can be considered as a tree of depth 1 where all the words are leaves in this tree. Then probability estimation requires $|\mathcal{V}|$ calculations because it has to go over all the nodes. But, in hierarchical softmax the balanced binary tree is created which has $log_2(|\mathcal{V}|)$ depth. Consider the example in Fig. 2.8, the softmax calculation is similar to the one-depth tree shown in (a) part of the figure, and the hierarchical softmax approximation (b) shows words arranged in the balanced tree. This formulation enables the decomposition of probability calculation of one word to a sequence of probability calculation of words in the path of the word. Specifically, the probability for each word is calculated by multiplying all probabilities on the path from root to the word, so for instance, the probability for word w_3 is given as $p_0 \times p_{01} \times p_{010}$. So the overall, calculation reduces from $|\mathcal{V}|$ to $log_2(|\mathcal{V}|)$.

Once the models are trained with these approximations, the embeddings for a given word are obtained from the hidden layer of the network. Precisely, the weight matrix H of the hidden layer produces m-dimensional Word2vec vector representation as: $H^T\mathbf{w_j}$.

2.4.1.2 Global vector (Glove)

Word2vec embeddings are capable of capturing the semantics of words but they only use local context to learn these embeddings. Because CBOW predicts a word given its context, whereas the skip-gram objective predicts a word's context given the word itself. As a result, global statistical information is ignored which can be crucial for deriving word representations. Global Vectors (Glove)(Pennington et al., 2014) solve this problem by

obtaining global co-occurrence matrix X where each X_{ij} indicates the frequency of word w_i co-occurring with w_j.

They optimize following loss function which reduces the difference between actual and predicted co-occurrence frequency as:

$$J(\theta) = \sum_{i,j=1}^{\mathcal{V}} f(X_{ij})(\mathbf{w_i^T} + \mathbf{w_j'} + b_k + b_j' - \log(X_{ij}))^2 \tag{2.31}$$

where $\mathbf{w_i} \in \mathbb{R}^d$ is a d-dimensional word vector for w_i, $\mathbf{w_j'} \in \mathbb{R}^d$ is a d-dimensional context word embeddings of w_j, b_k and b_j' are bias terms, and $f(x)$ is weighting function. The weighting function $f(x)$ in the paper is defined as:

$$f(x) = \begin{cases} (\frac{x}{\beta})^\alpha & \text{if } x < \beta \\ 1 & \text{otherwise} \end{cases}$$

where α, β are pre-defined scalars which are set to $\alpha = 1$ and $\beta = 100$.

2.4.1.3 FastText

Word representation algorithms like Word2vec and Glove capture the general semantics of words using their co-occurrence context. However, these methods neglect the internal structure of the word. Hence, they lack in finding representations for words which occur rarely but are morphologically similar (those words which possess a similar sequence of characters) because there is no parameter sharing between words which have overlapping character patterns. For example, vectors for words “eat” and “eaten” are distinct even though they have overlapping internal structures. These problems are especially severe for morphologically rich languages. Moreover, these methods fail at producing vectors for out-of-vocabulary (OOV) words.

FastText (Bojanowski et al., 2017) remedies both these issues as it generates embeddings for character n-grams instead of directly producing the word representation. The word representation is obtained by summing all the vector representations of character n-grams present in the word. Thus, retaining morphological information in the representation as well as solving the OOV problem.

They achieve this by extending the continuous skip-gram (Mikolov et al., 2013b) method with subword information (Section 2.4.1.1), where each word is considered as a bag of character n-grams. Before creating these character n-grams for a word, markers “<” and “>” are added as prefix and suffix, respectively. Plus, in addition to all the character n-grams, embeddings for actual word is also added to the list of these n-grams. Let us see

this with an example, for word *learn* with n=3, all character n-grams are:

$$< le, lea, ear, arn, arn, rn >, < learn >$$

Suppose, for a word w, $\mathscr{M}_w$ is the corresponding set of character n-grams, then in this model, a scoring function $s(w,c)$ measures the confidence of word c being in the context of w as:

$$s(w,c) = \sum_{m \in \mathscr{M}_w} \mathbf{u_m}^T \mathbf{v_c} \tag{2.32}$$

where $\mathbf{u_m}$ is vector representation of characters m and $\mathbf{v_c}$ is vector representation of word c. Based on this confidence score, the objective function is optimized which is similar to skip-gram negative sampling objective mentioned in Eq.2.30.

2.4.2 Contextual word representations

A word can have multiple meanings, *polysemy*. Therefore, there should be different representations of the same word depending on the meaning in which it is present. However, the previous distributed representations produce one vector per word irrespective of the meaning. For instance, in these algorithms, a word "Bank" will have a single vector independent of its meaning: *financial institute* or *river-side*. The contextual word representation methods remedy this as they learn context-dependent representations where they produce distinct word representations.

In the recent years, ELMo and BERT have been two popular approaches which produce contextual embeddings, let us look at them here.

2.4.2.1 ELMo

Embeddings from Language Models (ELMo) (Peters et al., 2018) produces representations with the use of forward and backward language model: bidirectional Language Model (biLM). The forward language model (FLM) is similar to the language model mentioned in Eq.2.23 where for sequence of words $w_1, w_2, \cdots, w_N$ produces joint probability by considering the tokens appeared before the current token as:

$$p(w_1, w_2, \cdots, w_N) = \Pi_{i=1}^{N} p(w_i | w_1, w_2, \cdots, w_{i-1}) \tag{2.33}$$

Conversely, the backward language model (BLM) gives joint probability by considering the tokens appearing after the current token, which is given as:

$$p(w_1, w_2, \cdots, w_N) = \Pi_{i=1}^{N} p(w_i | w_{i+1}, w_{i+2}, \cdots, w_N) \tag{2.34}$$

ELMo combines these probabilities to jointly maximize the log-likelihood of the forward and backward language models as:

$$\mathscr{L}(\Theta) = \sum_{i=1}^{N} \log p(w_i | w_1, w_2, \cdots, w_{i-1}; \Theta_c, \Theta_f) + \log p(w_i | w_{i+1}, w_{i+2}, \cdots, w_N; \Theta_c, \Theta_b) \tag{2.35}$$

where Θ_c are common parameters between forward and backward LMs whereas Θ_f are specific to FLM, and Θ_b correspond to BLM.

Separate LSTMs are trained for FLM and BLM. Typically, learning L-layers of LSTMs produces L+1 representations for each word w_k as :

$$H_k = \{h_{k,j} | j = 0, 1, \cdots, L\}$$

where $h_{k,j}$ at $j = 0$ is token input representation and otherwise concatenation of vectors from the two LSTMs at j^{th} layer, can be given as:

$$h_{k,j} = \begin{cases} h_{k,0} & \text{if } j = 0 \\ h_{k,j}^{f} \oplus h_{k,j}^{b} & \text{otherwise} \end{cases}$$

where $h_{k,j}^{f}$, $h_{k,j}^{b}$ are j^{th}-layer output from forward and backward LSTM, respectively and $\oplus$ denotes concatenation. Finally, to get the representation of the word w_k all the representations from the set H_k are weighted as :

$$\mathbf{w}_k^{task} = \gamma^{task} \sum_{j=0}^{L} a_j \, h_{k,j} \tag{2.36}$$

where a_j are softmax normalized weights for layer j which are learned depending on the task and γ^{task} is task-dependent scaling factor.

2.4.2.2 BERT

Bidirectional Encoder Representations from Transformer (BERT) (Devlin et al., 2019) learns parameters jointly conditioned on the bidirectional language model (biLM) objective. The subtle difference between ELMo and BERT is that ELMo learns separate

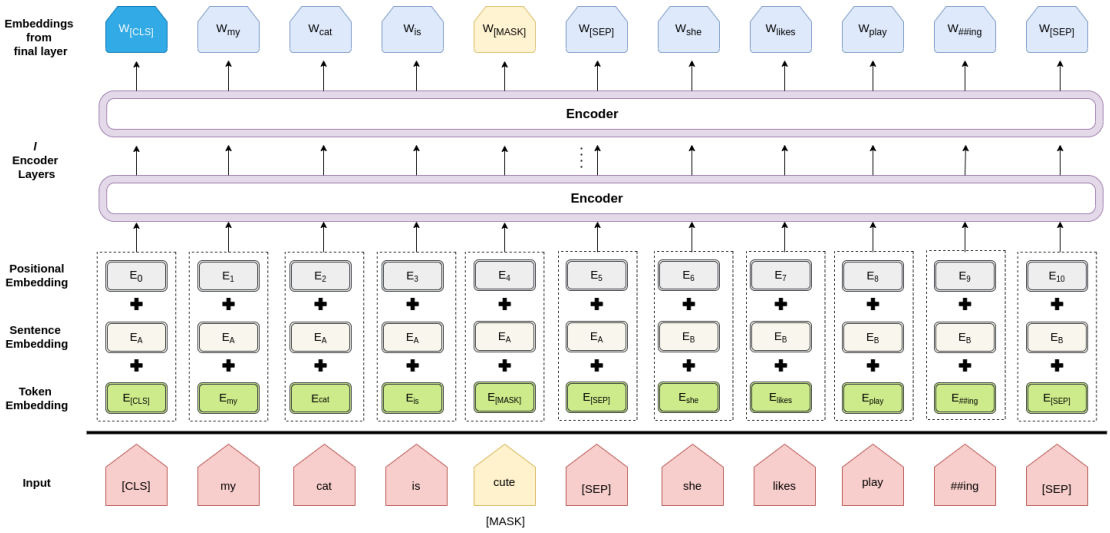


Fig. 2.9 BERT architecture (Devlin et al., 2019).

parameters for forward and backward language models as separate LSTMs are learned, on the other hand, BERT learns only a single set of parameters for biLM.

BERT achieves this with *masked language modeling* (MLM) objective. The task is similar to Cloze task (Taylor, 1953) i.e. fill-in-the-blanks formulation where the model predicts masked word appropriately depending on its context. For this, the model randomly masks some tokens from the given sequence of words and attempts to predict them accurately. Further, the authors think that the MLM does not capture relevant sentence level relations which are useful for NLP tasks such as Question Answering, Natural Language Inference (NLI), etc. For that, they use *next sentence prediction* (NSP) objective where for given two sentences the model predicts whether the second sentence can truly be the next sentence after the first one.

The input to BERT can be either single sentence or pair of sentences. The input sentence is tokenized with WordPiece tokenizer (Wu et al., 2016) and input tokens can only be from pre-defined dictionary of 30,000 tokens. Further, input to BERT always starts with special token "[CLS]" and in case of two sentences, the sentence boundary is indicated by token "[SEP]". "[SEP]" token can also be used to indicate the end of input. This is depicted in Fig. 2.9 with an example of pair of input sentences. Two sentences, "my cat is cute" and actual next sentences "she likes playing", are tokenized and tokens are provided as an input with special tokens "[CLS],[SEP]". Note from the figure that all the words except "playing" of the given sentences are present in the dictionary because of which they are not further tokenized but "playing" is divided into two tokens, "play" and "ing".

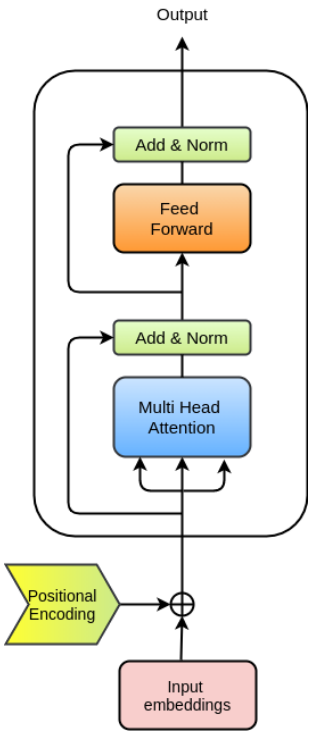


Fig. 2.10 Internal components of encoder (Vaswani et al., 2017).

Once the tokenization is done, the m-dimensional vector representation for each input *token* is obtained by summing their *token embeddings*, *sentence embeddings*, and *positional embeddings* (as shown in Fig. 2.9). The *token embeddings* are randomly initialized for each token in the dictionary whereas *sentence embeddings* for each token are determined based whether the token belongs to first or second sentence (denoted as A and B in the figure). In addition to that, BERT considers the position of the token in the sentence by learning positional embeddings. All these embeddings are of m-dimension so that they can be summed to produce vector $\mathbf{x_i} \in \mathbb{R}^m$ for i^{th} token. Let the m-dimensional vector representation of n tokens be arranged as row of the matrix $X \in \mathbb{R}^{n \times m}$ as $X = [\mathbf{x_1}, \mathbf{x_2}, \cdots, \mathbf{x_{n-1}}, \mathbf{x_n}]^T$. This matrix X is passed through l-layers of encoders to obtain the final representation. BERT is trained with two different values of l: BERT-base with $l = 12$ encoder layers and bigger BERT-large model with $l = 24$ encoders.

An encoder layer contains multiple attention heads as well as feed forward network as shown in Fig. 2.10. Let us look at these parts one by one.

- **Multi Head Attention**: An encoder consists of multiple attention heads, i.e., number of separate single attention heads. An attention head captures different interaction between all the tokens. Here, the number of attention heads is pre-decided, let that number be denoted as h. Let us look at the mathematical operations happening in a

single attention head to understand it better. Initially, the input matrix representation $X \in \mathbb{R}^{n \times m}$ is projected with three different matrices: $W^K \in \mathbb{R}^{m \times d_k}, W^V \in \mathbb{R}^{m \times d_v}, W^Q \in \mathbb{R}^{m \times d_k}$ to get *key*, *value*, and *query*. The dimensions are set to $d_k = d_v = m/h$ where m is input dimension. At each layer, each attention head in multi-head attention, learns different set of matrices, in turn yielding different key, query, and value. For instance, for i^{th} attention head, key, query, and value matrices are obtained as:

$$K_i = XW_i^K \tag{2.37}$$

$$Q_i = XW_i^Q \tag{2.38}$$

$$V_i = XW_i^V \tag{2.39}$$

where $K_i \in \mathbb{R}^{n \times d_k}, V_i \in \mathbb{R}^{n \times d_v}, Q_i \in \mathbb{R}^{n \times d_k}$.
With the use of key and query matrices, $n \times n$ attention weight matrix between every token is calculated as:

$$A_i = \sigma(\frac{Q_i K_i^T}{\sqrt{d_k}}) \tag{2.40}$$

where row-wise softmax function σ normalizes scores. This is the crucial part of the encoder architecture where different attention heads capture various interaction between input tokens. This attention matrix $A_i \in \mathbb{R}^{n \times n}$ is used to weight the embeddings captured by the value matrix as:

$$H_i = A_i V_i \tag{2.41}$$

Then these weighted embeddings output of each attention head is concatenated to produce the H as:

$$H = [H_1, H_2, \cdots, H_h] \in \mathbb{R}^{n \times (h.d_v)} \tag{2.42}$$

Finally, projection matrix $W_o \in \mathbb{R}^{(h.d_v) \times m}$ is learned to get the output $M \in \mathbb{R}^{n \times m}$ dimension from multi-head attention same as input dimension with the following operation:

$$M = HW_o \tag{2.43}$$

- **Feed-forward network**: This matrix M is passed through two layers as:

$$F = max(0, MW_1 + b_1)W_2 + b_2 \tag{2.44}$$

where $W_1 \in \mathbb{R}^{m \times d_f}, W_2 \in \mathbb{R}^{d_f \times m}$ are weights, $b_1 \in \mathbb{R}^{n \times d_f}, b_2 \in \mathbb{R}^{n \times m}$ are biases, and $F \in \mathbb{R}^{n \times m}$.

- **Add & norm**: The output from the multi-head attention or the feed-forward network is passed through this layer (green rectangle in Fig. 2.10). The relation between input I and output O obtained from this layer is given as:

$$O = \psi(I + \varphi(I)) \tag{2.45}$$

  where ψ is layer normalization function, and φ is either feed-forward or multi-head attention output.

As shown in Fig. 2.9, these multiple encoders are stacked upon each other and the output of the underneath layer is passed to the above encoder. Finally, the output of the lth layer encoder is used for predicting the masked tokens as well as next sentence. The output corresponding to the index of the masked token is used to predict the token whereas the output of "[CLS]" token is used to predict if B is the next sentence of A. The whole BERT model is trained by minimizing the sum of loss on MLM and NSP tasks.

$$\mathscr{L} = \mathscr{L}_{MLM} + \mathscr{L}_{NSP} \tag{2.46}$$

Loss for masked language modeling, $\mathscr{L}_{MLM}$, is calculated by considering the probabilities over the masked token prediction. Let us assume that the ith position in the sentence is masked and $\mathbf{w}_i$ be the m-dimensional vector representation obtained from the last layer. Then the predicted probability over all the tokens in the dictionary is given as:

$$q = \sigma(W_{MLM}\mathbf{w}_i) \tag{2.47}$$

where $W_{MLM} \in \mathbb{R}^{|V|\times m}$ is a learned projection matrix and σ denotes softmax function. Then the loss is calculated as

$$\mathscr{L}_{MLM} = -\sum_{j=1}^{|V|} p_j \log q_j \tag{2.48}$$

Next sentence prediction loss, $\mathscr{L}_{NSP}$, is calculated as a cross entropy between predicted, $\hat{y}$ and true label $y \in 0, 1$ where 1 denotes next sentence and 0 otherwise.

$$\mathscr{L}_{NSP} = y \log(p(\hat{y}|x;\Theta)) + (1-y)\log(1 - p(\hat{y}|x;\Theta)) \tag{2.49}$$

where predicted probability is calculated as $p(\hat{y}|x;\Theta) = \sigma(h_{nsp}.\mathbf{w}_{[CLS]})$, $h_{nsp} \in \mathbb{R}^m$ is learned weight vector, $\mathbf{w}_{[CLS]}$ is the vector representation corresponding to [CLS] token, and σ is sigmoid function.

The word representation is obtained after pre-training BERT model on large unlabeled text. Sentences containing words for which we want representations are given as an input to BERT and then the output from the last layer of encoders is considered as a vector representation for each word. In some of the cases, the last l-layers output is also combined either by summing or concatenating to get the representation for each word.

2.5 Composing word representations

In most of the NLP tasks, we are interested in obtaining representations of word sequences, in other words, for bigger linguistic units such as phrases, sentences, paragraphs, or documents rather than words. In these cases word representations are of little use directly, for example, consider the task of sentence classification where we want to assign a certain class to a sentence then it is beneficial to get the sentence representation, or consider the task of assigning topics such as Sports, Finance, Medicine, etc. to documents which will also require document representations.

It is usually assumed that linguistic structures are compositional i.e. simpler elements are combined to form more complex ones. For example, morphemes are combined into words, words into phrases, phrases into sentences, and so on. Therefore, it is reasonable to assume that the meanings of bigger linguistic chunks such as phrases, sentences, paragraphs, and documents are composed of the meaning of constituent words (*Frege's principle*). This compositional principle is used to obtain the representation of these bigger chunks by composing the representations of constituent words[7].

Suppose u is any bigger linguistic unit (phrase, sentence or document) containing sequence of words as $w_1, w_2, \cdots, w_l$ and $\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_l$ is their corresponding representation. Then representation $\mathbf{u}$ for linguistic unit u is obtained as :

$$\mathbf{u} = f(\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_l) \tag{2.50}$$

One of the important things while acquiring function f is that the syntax of the unit u should be considered. Because the meaning of word sequence is derived not only from the meaning of its constituent words but also from the syntax in which they are combined (Partee, 1995). For example, if the syntax of the sentence is not considered then the meaningful sentence "I ate pizza" will get a similar representation as "ate I pizza".

[7]The representations of bigger linguistic units can be obtained without explicitly composing representations of constituent units, we omitted that, as it is not relevant to the present discussion.

Hence, the composition function f should consider the syntactic information S in Eq. 2.50.

In addition to the syntactic information, the meaning of the word sequence also depends on the additional knowledge which is outside of the linguistic structure. This additional information includes both knowledge about the language itself and also knowledge about the real world. For example, the sentence "Let's dig deeper." can mean either *digging the soil further* or *making the extra efforts*[8]. So, the composition function f needs to be changed again to incorporate this additional knowledge K. The modified composition function which includes syntactic information S and knowledge K is given as:

$$\mathbf{u} = f(\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_l, S, K) \tag{2.51}$$

This composition function f can be either designed (fixed composition functions) or can be learned (learned composition functions). We look at them separately in the following paragraphs.

2.5.1 Fixed composition functions

These functions generally ignore the information K (Eq. 2.51) while obtaining the representation. Also, it is assumed that vector representations of word sequences lie in the same vector space of the constituent words. Because of these assumptions, simple addition, average, or multiplicative functions can be used to get the composite representation (Foltz et al., 1998; Landauer and Dumais, 1997; Mitchell and Lapata, 2010; Zanzotto et al., 2010)[9].

$$\mathbf{u}_{sum} = \sum_{i=1}^{i=l} \mathbf{w}_i \tag{2.52}$$

$$\mathbf{u}_{av} = \frac{1}{l} \sum_{i=1}^{i=l} \mathbf{w}_i \tag{2.53}$$

$$\mathbf{u}_{wav} = \sum_{i=1}^{i=l} \alpha_i \mathbf{w}_i \tag{2.54}$$

$$\mathbf{u}_{mul} = \mathbf{w}_1 \odot \mathbf{w}_2 \odot \cdots \odot \mathbf{w}_l \tag{2.55}$$

Equation 2.52 is an additive function that produces representation for the linguistic unit u with summation of the representations of all the constituent words. This is slightly

[8]These are the most common meanings of this phrase. There are other multiple meanings, again depending on the context.

[9]Mitchell and Lapata (2010) focused only on the composition of two constituent vectors but these composition functions can be extended over more than two constituent words.

changed in equations 2.53 and 2.54 where unweighted and weighted averages are taken to get the final representation. Hadamard product of the constituent words is taken in Eq. 2.55 to produce the composite representation.

2.5.2 Learned composition functions

The previous approach of combining the constituent word representations puts a lot of constraints while designing the function, for instance these approaches assume that a vector of word sequences also lies in the same space as word vectors, which may not hold in reality. Also, often the functions designed are not effective because of their simplistic way of combination. Because of this, instead of manually designing these functions, functions are parameterized and the parameters governing the function are learned. The general definition of these functions is slightly different from Eq. 2.51 which is given as:

$$\mathbf{u} = f(\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_l; \Theta) \tag{2.56}$$

Here, parameters Θ are learned with machine learning models. It is important to learn Θ in such a way that they can capture the syntactic information present in the unit u. Generally, these parameters also capture a small amount of additional knowledge because of the context but these methods also largely ignore the external knowledge while acquiring the composite representation. Commonly, the parameters Θ are learned either in the *task-agnostic* or *task-specific* fashion.

In the *task-agnostic* methods, the parameters are usually trained by unsupervised or semi-supervised learning and can be served as features for many other NLP tasks such as text classification and semantic textual similarity. This includes recursive auto-encoders (Socher et al., 2011), ParagraphVector (Le and Mikolov, 2014), SkipThought vectors (Kiros et al., 2015), FastSent (Hill et al., 2016), Sent2Vec (Pagliardini et al., 2018), GRAN (Wieting and Gimpel, 2017), transformer based models like BERT (Devlin et al., 2019).

On the other hand, in *task-specific* approach, the representation learning is combined with downstream applications and trained by supervised learning. Different deep learning models are trained to solve certain NLP tasks, FFNNs (Huang et al., 2013), (Chung et al., 2014; Hochreiter and Schmidhuber, 1997), CNNs (Kalchbrenner et al., 2014; Kim, 2014; Shen et al., 2014), and recursive neural networks (Socher et al., 2013).

Overall, the approaches based on the deep learning techniques have shown promising performance for learning these parameters. Socher et al. (2012) show the efficiency of deep learning approaches by comparing them with the simple average of word vectors,

elementwise multiplication, and concatenation. Further, similar results were observed in (Socher et al., 2013).

2.6 Knowledge graphs and representations

In previous sections, we looked at various approaches of obtaining word embeddings and several composition methods to get word sequences representations from them. However, these word embedding algorithms use *only* text data to learn representations, as a result, they fail to adequately acquire *commonsense* knowledge like semantic and world knowledge. To address that limitation, various methods have been proposed to enrich word embeddings with commonsense knowledge (Faruqui et al., 2015; Osborne et al., 2016; Peters et al., 2019; Sun et al., 2020; Yu and Dredze, 2014).

As we also make use of such external knowledge in our work, in this section, we describe one of the popular sources of commonsense knowledge: *Knowledge Graph*, and approaches of representing knowledge held by them. Specifically, in Section 2.6.1, we describe knowledge graph and look at the popular lexical knowledge source: WordNet (Fellbaum, 1998), which is used in this work. We also describe another knowledge source, TEMPROB (Ning et al., 2018a), which is specifically constructed to store probabilistic temporal relations information, and used for temporal relation classification in this work. Next, in Section 2.6.2, we explain the problem of graph representations which is a challenging task, as the information present in the whole topology of the graph should be captured in the representation. Node embeddings learned over graphs proved to be effective at capturing such knowledge (Hamilton et al., 2017) so we describe their general framework and two prominent families of approaches in the subsequent subsections. This background of node embeddings framework will be beneficial for understanding specific node embedding algorithms used over WordNet and TEMPROB in Chapter 6.

2.6.1 Knowledge graphs

Commonsense knowledge is generally stored in a graph-structure format, commonly called as *Knowledge Graphs*. In knowledge graphs, nodes denote real-world entities or abstract concepts, and edges show relations between them. Because of this broad definition, knowledge graphs can be found with a variety of data. Broadly speaking, they can be categorized as *open-domain* or *domain-specific* knowledge graphs. For example, popular knowledge graphs such as YAGO (Hoffart et al., 2011), DBpedia (Lehmann et al., 2015) contain open-domain information as the nodes can be people, organizations, or

places, and multiple relations between them are denoted with edges. On the other hand, some knowledge graphs are designed for specific domains: language, specifically lexical resources, WordNet (Fellbaum, 1998), FrameNet (Ruppenhofer et al., 2006), ConceptNet (Speer et al., 2018), geography (Stadler et al., 2012), media (Raimond et al., 2014), and many more.

Formally, let $G = (V, E, R)$ be any knowledge graph where V, E denote nodes and edges of the graph and R is a set of possible relations between nodes. Then, graphs can possess different information depending on the types of edges. An unlabeled knowledge graph contains edges that only have tuples of nodes: $E = \{(u, v) : u, v \in V\}$. Next, the edges of a knowledge graph with labels are set of triples: $E = \{(u, r, v) : u, v \in V, r \in R\}$. On the other hand, for a probabilistic graph, in addition to relations there is a scalar value denoting strength of the edge: $E = \{(u, r, v, s) : u, v \in V, r \in R, s \in \mathbb{R}\}$.

In this work, we used two knowledge graphs: WordNet (Fellbaum, 1998) and TEMPROB (Ning et al., 2018a). Let us look at them in the following sections.

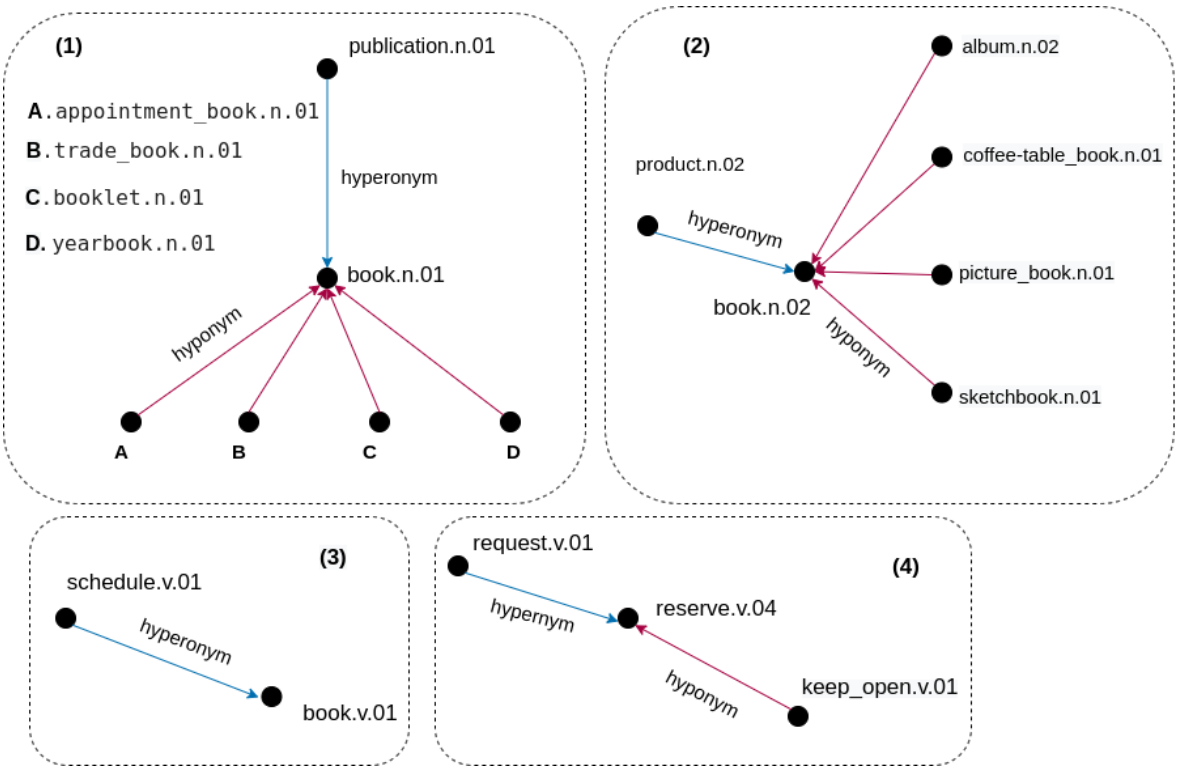


Fig. 2.11 A subset of WordNet related to the four senses of *book*. Figures (1) book.n.01 and (2) book.n.02 show two noun senses of book and their hyperonyms and hyponyms. Similarly, figures (3) book.v.01 (4) reserve.v.04 show two verb senses and their related synsets.

2.6.1.1 WordNet

WordNet (Fellbaum, 1998) is a large lexical database that stores possible senses of words and semantic relations between them [10]. The senses of words that have similar meanings are grouped and referred to as *synset* (synonym set). Each *synset* stores a simple definition explaining the meaning of the *synset* as well as examples depicting the use of the word in sentences. Further, each sense of the word is assigned its POS tag and a unique number to differentiate between multiple senses of the same word. For instance, Fig. 2.11 depicts multiple senses of word *book*: book.n(oun).01, book.v(erb).01, etc. Formally, WordNet graph $G_W = (V_W, E_W, R_W)$ contains nodes, V_W, which are synsets, R_W, the set of semantic relations, and E_W, the set of edges consisting of triples having two synsets and semantic relation between them: $E_W = \{(u, r, v) : u, v \in V_W, r \in R_W\}$.

The set R_W contains lexical semantic relations such as synonymy, antonymy, hyperonymy, hyponymy, meronymy, holonymy, etc. Where synonymy, antonymy indicates similarity or dissimilarity between senses. Hyperonymy and hyponymy indicate "ISA" relation between synsets. If X is a generic term for Y, then X is a hyperonym of Y. At the same time, Y is a hyponym of X, as Y is a specific type of X. For example, *animal* is hyperonym of *dog* and *dog* is hyponym of *animal*. Whereas, meronymy and holonymy indicate *part-whole* relation. If X is a part of Y, then X is a meronym of Y, conversely, Y is a holonym of X. For instance, *wheel* is a meronym of *car* and *car* is a holonym of *wheel*.

In total, WordNet (English) contains 117,000 synsets where a synset can have POS tag as *noun, verb, adjective* or *adverb*. However, the major portion of synsets is either nouns or verbs. We show a small subset of WordNet concerning the word *book* in Fig. 2.11. For the word *book*, WordNet contains 11 different senses, out of which 7 are nouns and 4 are verbs (only two of each are shown in the figure). A *book* (noun) can mean a written or published work: *book.n.01*, a physical object consisting of a number of pages: *book.n.02*, a written version of play: *script.n.01*, a commercial record: *ledger.n.01*, or seven other senses such as Bible, Quoran, etc. Also, book as verb has multiple meanings, engage someone (artist) for performance: *book.v.01*, reserve a seat or ticket: *reserve.v.04*, etc. We show a subset of these senses as well as their semantic relations (hyperonymy or hyponymy) with other synsets in Fig. 2.11.

2.6.1.2 TEMPROB

Temporal relation probabilistic knowledge base (TEMPROB) (Ning et al., 2018a) is specially constructed to hold prior temporal relation probabilities (frequencies) between semantic

[10] In the stricter sense, WordNet is not a graph but many graphs are constructed over it for the use.

Verb1	Verb2	Temporal Relation	Frequency
chop.01	taste.01	after	9
chop.01	taste.01	before	285
chop.01	taste.01	undef	44
conspire.01	kill.01	after	6
conspire.01	kill.01	before	117
conspire.01	kill.01	equal	3
conspire.01	kill.01	included	3
conspire.01	kill.01	undef	30
dedicate.01	promote.02	after	6
dedicate.01	promote.02	before	71
dedicate.01	promote.02	equal	1
dedicate.01	promote.02	included	3
dedicate.01	promote.02	undef	9

Table 2.7 A portion of TEMPROB where each row is a quadraple in the graph. Frequency indicates likelihood of temporal relation, in case of chop and taste high frequency is for before relation, indicating *chopping* of food comes before *taste*. Similarly, in most of the cases *conspire* occurs before *killing*, and *dedicated* efforts are before *promotion*.

verb frames. Suppose $G_T = (V_T, E_T, R_T)$ denotes TEMPROB, then V_T are the set of semantic verb frames, R_T is the set of temporal relations, and the edges store quadruples: $E_T = \{(u, v, r, f_{u,v,r}) : u, v \in V_T, r \in R_T, f_{u,v,r} \in \mathbb{R}\}$.

Now, let us look at different parts of graph G_T to understand TEMPROB. Nodes V_T, are a set of semantic verb frames where each verb frame denotes the meaning of the verb in a specific environment (*frame*). This notion is based on frame semantics (Fillmore, 1976) that derives lexical meaning from prototypical situations captured by *frames*. For instance, verb *sew* means stitching *clothes* in the frame corresponding to textile, cotton, fabrics, whereas it also can mean stitching *wounds* in the medical frame containing doctors, nurses, syringe, etc. Next, R_T is a set of temporal relations which consists of *after, before, includes, included,* or *undef (vague)*. At last, the frequency $f_{u,v,r}$ denotes the number of times relation r existed between semantic verb frames (u, v). Specifically, the frequency measures the number of predictions of certain relations only over the pairs that appeared in the corpus (1 million NYT times articles) considered while constructing TEMPROB. The assumption is that these statistics can be generalized over other datasets, as a result, in general, a higher frequency of certain temporal relation for the pair can be considered as a higher likelihood of that relation. Overall, TEMPROB contains such 51 thousand nodes, 80 million temporal relations between them, and corresponding frequencies. The small portion of TEMPROB is shown in Fig. 2.7.

Now, we detail the procedure of TEMPROB construction which can be beneficial for gaining further insights. To construct TEMPROB, first, temporal relation classification system is trained which is used over NYT articles to predict temporal relations between detected event pairs. The aggregated frequency of the prediction of temporal relations for each event-pair over all the documents is stored to form the knowledge base. Let us look at these steps of the construction of TEMPROB separately:

1. *Temporal relation classification system*: Pairwise classification models to predict temporal relations are trained. Specifically, two averaged perceptrons (Freund and Schapire, 1998) each for event-pairs occurring in the same sentence, and adjacent sentences are trained (rest of the event-pairs are not considered). TBDense (Cassidy et al., 2014) dataset containing 36 documents is used in the experiment with Train (22 docs), Dev (5 docs), and Test (9 docs) split. Further, simple hand-crafted features such as POS tags of verbs and three surrounding words, number of tokens between verbs, presence of modal verbs (e.g. would, might, may) and temporal indicators (e.g. before, since), etc. are used in the model.

2. *Event detection*: After training the temporal relation classification system, the next step is to apply it over the NYT articles. But, these documents do not contain annotations for events. For this reason, they used an off-the-shelf Semantic Role Labeling (SRL) system to detect events. Then, events that are nominals are deleted from the list and only verbs (semantic verb frames) are kept.

3. *Inference*: Next, each article is considered separately where event pairs appearing in the same sentences, and adjacent sentences are separated. First temporal relations for verb pairs appearing in the same sentences are predicted and then verb pairs from the adjacent sentences. Greedy strategy is used for inference where after the addition of new temporal relation temporal graph closure is performed over the document. The preference is given to the relation obtained from the graph closure over the prediction such that relation is not at all predicted if it is already deduced.

4. *Graph construction*: Temporal graphs over each article are obtained, and the frequencies for the verb pairs are aggregated to form the final knowledge base.

Out of these two knowledge graphs, we used WordNet for bridging anaphora resolution, since it contains semantic relations which are beneficial for bridging inference such as meronymy relations are especially useful (Hou, 2018b; Hou et al., 2013b). Next, we also used it in temporal relation classification because semantic relations like hyperonymy

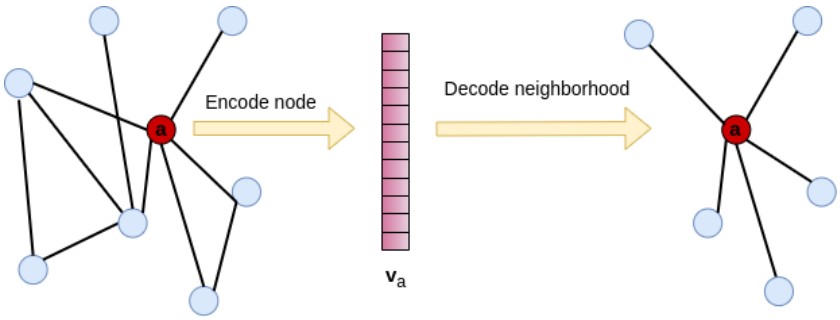


Fig. 2.12 Overview of graph node embeddings: A conceptual encoder-decoder framework (Hamilton et al., 2017). Given the graph, encoder encodes the node a to low-dimensional vector $\mathbf{v}_a$. Encoder takes into consideration node's structure in the graph while projecting it into vector space. Then the decoder retrieves the original graph structure of the node given its vector representation. The node embeddings are learned in this encoder-decoder framework where they are optimized simultaneously.

can indicate event-subevent relations which can be beneficial for the task. In addition to WordNet, for temporal relation classification, we separately used TEMPROB to exploit the prior knowledge about events. We further detail about this in Section 6.2.

2.6.2 Graph node embeddings

Until now, we discussed knowledge graphs which are a special type of graphs that contain useful commonsense information. But, in this section, we are going to consider generic graph as a point of discussion (without narrowing down to only knowledge graph). The reason being, the complexity because of graph-structure is prevalent in all graphs and not specific to only *knowledge* graphs. Similarly, the proposed approaches are more general and can be applied to any graph.

Incorporating knowledge possessed by graphs into machine learning models is a challenging task, due to the difficulty of encoding high-dimensional non-Euclidean information of the graph-structure. Because of this complexity, earlier approaches of feature designing or use of summary statistics of graphs (e.g degree or clustering coefficients) are rendered inefficient. Moreover, these approaches become computationally expensive because of huge sizes of the graphs. Therefore, it is beneficial to learn low-dimensional representations over graphs instead of relying on hand-crafted heuristics to utilize the information held by graphs.

Graph embeddings achieve exactly that where they may encode the whole graph, subgraphs, or nodes into low-dimensional vector spaces. Fundamentally, graph embeddings must preserve the structural information of the graph, i.e. in the case of graph node

embeddings, nodes which are in a neighborhood in the actual graph should have closer representations in the latent space. This is the main constraint while designing the embeddings algorithm. In our work as well we resorted to graph node embeddings learned over knowledge graphs for enriching event and mention representations. Because low-dimensional node embeddings can encode node-specific information as well as global structure which is advantageous for the downstream tasks.

Now, we provide an overview of graph node embedding algorithms. First, we describe a unifying conceptual framework where the process of obtaining graph node embeddings can be viewed as training of encoder-decoder pair (Hamilton et al., 2017). Further, we discuss two broad categories of node embeddings approaches: 1. Matrix factorization based approaches, and 2. Random walk based approaches. This background is useful to understand the graph node embeddings algorithms presented in Section 6.3.1 over WordNet and TEMPROB.

2.6.2.1 Unified framework

As stated earlier, node embeddings capture the global position of the node in the topology as well as local neighborhood information. Let us suppose $G = (V, E)$ be the graph where V and E respectively denote vertices, and edges of the graph. Here, we do not make any assumptions about the type of graph G where it can be directional, unidirectional, labeled, etc. Then, node embedding encodes structural information by transforming node into d-dimensional vector space $\mathbb{R}^d$ where $d \ll |V|$.

The node embeddings learning can be thought as a pair of encoder-decoder functions (Hamilton et al., 2017). Let $\mathscr{F}_{E,\theta}$ be the encoder function which converts graph nodes to vectors:

$$\mathscr{F}_{E,\Theta} : V \rightarrow \mathbb{R}^d \tag{2.57}$$

where Θ denote set of parameters to be learned associated with encoder. Then the decoder function reconstructs graph properties from the encoded vectors. The embedding algorithm decides which graph properties to reconstruct and designs a specific decoder function. Suppose a decoder function $\mathscr{F}_{D,\Psi}$ measures pairwise similarity between the nodes in the actual graph through their embeddings as:

$$\mathscr{F}_{D,\Psi} : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R} \tag{2.58}$$

where Ψ are decoder specific set of parameters.

Next, the parameters Θ, Ψ are learned to minimize the reconstruction loss. Suppose $a, b \in G$ and $\mathbf{v}_a := \mathscr{F}_{E,\Theta}(a)$, $\mathbf{v}_b := \mathscr{F}_{E,\Theta}(b)$ be their node embeddings. Let $s(a, b)$ be a

similarity score between nodes a, b obtained from the graph G with user-defined measure. Then embeddings learning procedure minimizes the following reconstruction loss:

$$\mathscr{L}(\Theta, \Psi) = \sum_{(a,b)\in V} \ell(\mathscr{F}_{D,\Psi}(\mathbf{v}_a, \mathbf{v}_b), s(a,b)) \tag{2.59}$$

where $\ell : \mathbb{R} \times \mathbb{R} \to \mathbb{R}$ is a loss function. The learning algorithms are usually agnostic about the downstream tasks, as they depend solely on the design of the loss function ℓ and similarity measure s. Once the parameters Θ, Ψ are learned, the *encoder* output is considered as node embeddings of the provided graph node.

Following the discussion from the work (Hamilton et al., 2017), we note that most of the node embedding algorithms differ in the way the encoder function, decoder function, pairwise similarity function, or loss functions are designed. Broadly, two kinds of general settings are prominently used to obtain node embeddings, we look at them separately in the following sections.

2.6.2.2 Matrix factorization based approaches

These approaches learn node embeddings such that inner product of vector representations of nodes is closer to the deterministic similarity measure defined by the algorithm. Hence, roughly they reduce the loss of the following form:

$$\mathscr{L} = ||\mathbf{V}^T\mathbf{V} - \mathbf{S}||^2 \tag{2.60}$$

where $\mathbf{V}$ is the matrix of node embeddings and $\mathbf{S}$ is a pairwise node similarity matrix.

Concretely, the popular embedding algorithms based on this approach, Graph Factorization (Ahmed et al., 2013), GraRep (Cao et al., 2015), and HOPE (Ou et al., 2016) design their decoder function and loss function as follows:

$$\mathscr{F}_D(\mathbf{v}_a, \mathbf{v}_b) = \mathbf{v}_a^T \mathbf{v}_b \tag{2.61}$$

$$\mathscr{L}(\Theta) = \sum_{(a,b)\in V} ||\mathscr{F}_D(\mathbf{v}_a, \mathbf{v}_b) - s(a,b)||^2 \tag{2.62}$$

where $\mathbf{v}_a, \mathbf{v}_b$ are the learned vector representations for nodes a, b and $s(a,b)$ is the graph similarity between them. However, these three algorithms differ in the way similarity between nodes is measured. The Graph Factorization uses adjacency matrix as to get the similarity – $s(a,b) = A_{a,b}$, whereas GraRep uses higher power of adjacency matrix so as to obtain more general similarity – $s(a,b) = A^2_{a,b}$, and HOPE measures general similarity with Jaccard neighborhood overlap. The matrix factorization based approach (Saedi et al.,

2018), and Path2vec (Kutuzov et al., 2019) used for obtaining WordNet embeddings in Section 6.3.1 can be considered to be matrix factorization approaches.

2.6.2.3 Random walk based approaches

In comparison to matrix factorization approaches, random walk based approaches differ in the way the similarity between nodes is measured. The factorization based approaches produce deterministic similarity scores between nodes, for instance with the use of the adjacency matrix. On the contrary, the random walk based approaches use a stochastic approach to obtain the pairwise similarity between nodes. More precisely, the similarity between two nodes, a, b, is the probability of encountering node b if the random walk started from node a.

Deepwalk (Perozzi et al., 2014) and Node2vec (Grover and Leskovec, 2016) are the two popular algorithms based on random walk. In addition to them, a random walk based graph node embeddings (Goikoetxea et al., 2015) algorithms used over WordNet employ the similar strategy which is detailed in Section 6.3.1. In these approaches the decoder function gives the approximate probability of the nodes being in the neighborhood. Hence, the decoder function in these methods is given as:

$$\mathscr{F}_D(\mathbf{v}_a, \mathbf{v}_b) = \frac{e^{\mathbf{v}_a^T \mathbf{v}_b}}{\sum_{c \in V} e^{\mathbf{v}_a^T \mathbf{v}_c}} \tag{2.63}$$

The decoder score is approximately equals to the probability of nodes being in the neighborhood i.e. $\mathscr{F}_D(\mathbf{v}_a, \mathbf{v}_b) \approx p(b|a)$ where $p(b|a)$ is the probability of encountering b if random walk started from a.

These approaches generate a sequence of nodes by sampling the random walks from each node. This generated sequence is used as the training data for learning the embeddings. The core of these algorithms is Word2vec (Mikolov et al., 2013b) as once the sequence of nodes is obtained with repeated random walks they can be treated as corpus and then the algorithm is trained. Similar to the Word2vec objective, the following negative log of probability loss is optimized:

$$\mathscr{L}(\Theta) = -\sum_{(a,b) \in \mathscr{D}} \log\left(\mathscr{F}_D(\mathbf{v}_a, \mathbf{v}_b)\right) \tag{2.64}$$

where $\mathscr{D}$ is the data generated with random walks and Θ be the learning parameters to be optimized. Notice that, Eq. 2.63 is similar to the probability calculation equations for Word2vec (Section 2.4.1.1, Eq. 2.25 and 2.28). Therefore, similar to Word2vec, directly optimizing Eq. 2.64 is computationally expensive because of the denominator term in

Eq. 2.63. To solve this problem, deepwalk uses hierarchical softmax approach whereas node2vec uses negative sampling approach, both of these approaches were introduced in Section 2.4.1.1.

2.7 Summary

This chapter presented background information needed to understand the rest of the thesis. First, we described task definitions and three main components of supervised learning approaches: event and mention representations, local or global models, and inference. We also described corpora used in the work and evaluation schemes for both temporal relation classification and bridging anaphora resolution. Next, we briefly introduced artificial neural networks and few popular types which are used in this work. Further, we discussed representation learning and related fields. Then, we summarized different distributional and contextual approaches of obtaining word representations. The word embeddings algorithms such as Word2vec, and FastText are used in Chapters 4 for event representations whereas Chapter 5 probes BERT model. Many distributional embeddings and BERT embeddings are again used for representations in Chapter 6. Afterward, we briefly discussed different composition approaches of obtaining word sequences representations from words which is similar to what we are doing but in task-specific learning setting. Finally, we explained knowledge graphs and graph node embeddings. We first discussed different types of knowledge graphs and detailed WordNet and TEMPROB which are used in the work. Then we described a unified framework view and two families of graph node embedding approaches. This context will be beneficial at understanding graph node embeddings used in this work which are presented in Section 6.3.1.

In the next chapter, we detail the previously proposed approaches for event and mention representations, and point out their drawbacks which is beneficial to gain perspective about our proposed approaches. We also briefly describe some of the prominent models and inference strategies in the same chapter.

Chapter 3

Related Work

In the previous chapter, we discussed different methods to obtain word representations, followed by composition methods to obtain word sequences representations. These representations learned in a *task-agnostic* way are insufficient to solve specific tasks. Contrarily, a *task-specific* representation can associate with a desired output of the task, as a result producing more accurate solutions. In this chapter, we review different approaches designed to obtain event representations for temporal relation classification and mention representations for bridging anaphora resolution. In addition, for both tasks, we also briefly discuss other systems that did not specifically concentrate on improving representations but focused more on modeling and inference.

3.1 Temporal relation classification

Earlier research in computational linguistics extensively studied temporal ordering between discourse units (Lascarides and Asher, 1993; Lascarides and Oberlander, 1993; Passonneau, 1988; Webber, 1988). These works explored various temporal order defining linguistic structures and features such as tense, aspect, temporal adverbials, rhetorical relations, and pragmatic constraints. Then, the construction of annotated corpora, such as TimeBank (Pustejovsky et al., 2003a) sparked the use of machine learning approaches for temporal analysis (Boguraev and Ando, 2005; Bramsen et al., 2006; Lapata and Lascarides, 2004; Mani et al., 2003, 2006) and has further accelerated (Bethard, 2013; Bethard et al., 2007; Chambers; Chambers et al., 2007; Laokulrat et al., 2013; Verhagen and Pustejovsky, 2008) by multiple TempEval campaigns (UzZaman et al., 2013; Verhagen et al., 2007, 2010). The majority of these approaches employed supervised learning models, barring few exceptions such as (Mirroshandel and Ghassem-Sani, 2014) which explored unsupervised

learning methods. In our work too, we focus on supervised machine learning approaches employed to solve temporal relation classification.

Recall from the previous chapter that supervised learning based temporal relation classification systems have three main components: representation of events, model, and inference. Most of the proposed systems generally differ in the way of obtaining representation, in modeling (*local, global models*), or inference (e.g. greedy or ILP). In the following sections, first, we present details about the methods that focus on event representations, later we briefly discuss the approaches that concentrate on modeling and inference.

3.1.1 Work on event representations

As a general trend in NLP, initial approaches obtained event representations by manually designing features and later features were learned automatically with extensive neural network use. We follow the same chronological order, first summarize manually hand-engineered works followed by automatic representation learning approaches.

3.1.1.1 Manually designed representations

The initial studies on temporal ordering explored various ordering units: a clause, a sentence, or an event (Boguraev and Ando, 2005; Lapata and Lascarides, 2004; Mani et al., 2003). Despite these different discourse units, they resorted to similar lexical, grammatical, and semantic features to obtain representations. Mani et al. (2003) found reference time of the clause, and then established temporal order between them. They called reference time of the clause as Temporal Value (*tval*) which can be an explicit time such as *year 2001* or some implicit time inferred from the text, and it is obtained by employing different rules, for instance, a number of temporal expressions present in the clause. This *tval* is used as one of the features for establishing temporal order between events in addition to temporal adverbials, sentence number, paragraph number, aspect, and tense. Further, Lapata and Lascarides (2004) designed features to capture verb tense and aspect as well as temporal indicators surrounding the verbs. Similar to these approaches, Boguraev and Ando (2005) also used lexical features such as tokens, capitalization of tokens, headwords, grammatical features such as POS of the tokens as well as of the words chunk, etc. to obtain the event representation.

Later on, the prominent approaches (Bethard et al., 2007; D'Souza and Ng, 2013) used TimeBank (Pustejovsky et al., 2003a) corpus for the analysis, hence, consistently used event as one of the ordering units and improved the representation by proposing an

additional set of features. Bethard et al. (2007) concentrated only on the event-pairs which are present in the verb-clause syntax. They considered the verb from the clause as the first event and then the head of the clause as another event. Features were designed based on the words which connect the event words as these connecting words like *because, since, as, while* indicate temporal relations, specifically, *because, since* indicate *after* relation and *as, while* indicate *overlap* relation. In addition to that, syntactic features were also extracted such as dependency paths between events to include in their feature-set. Further, they used all the words in-between events and derived features from them and empirically showed that among these different features, the syntactic features have helped the most.

Next, D'Souza and Ng (2013) proposed rich linguistic features to further improve the representation. Their main contribution is the proposal of various pairwise relations between events. So for instance, to establish temporal relations between two events e_1 and e_2, the baseline features mostly concentrate on features related to either e_1 or e_2 but not both. They filled this gap by extracting various relations like *dependency, lexical, semantic,* and *discourse* relations between both events to improve pairwise representations. For the events that are present in the same sentence, they argue *dependency* relation between events implies *simultaneous, before* or *after* temporal relations. In addition to that, they claim *lexical* relations such as antonymy, hyponymy, etc., are useful in capturing temporal relations. To extract these lexical relations they used Webster dictionary and WordNet graph. Further, they used *semantic* relations, particularly predicate-argument relations such as *cause* as well as *discourse* relations: causation, elaboration and enablement. All these features were evaluated empirically to show that the event-pair relations are crucial for temporal relation classification.

3.1.1.2 Automatic representation learning

In the previous section, we have discussed the approaches that employed hand-crafted features to represent events and event-pairs for temporal relation classification. The process of acquiring representations by manually designing features is laborious and requires expertise in the task. To mitigate these issues, automatically learned dense vectors are used to represent events. Then interaction between these vectors is obtained to get the event-pair representations. The assumption here is that the learned representation adequately captures relevant features for temporal relation classification.

One of the first works (Mirza and Tonelli, 2016), assessed the effectiveness of the use of *word vectors* for event representations that are learned over huge unannotated texts. Also, they experimented on multiple simple ways of combining them to get the event-pair representations. In their approach, events were represented with a pre-trained

Word2vec (Mikolov et al., 2013b) vector of events' headwords. Suppose e_i and e_j are the two events having headwords w_i and w_j, respectively and $\mathbf{w_i}, \mathbf{w_j}$ are the d-dimensional Word2vec representations corresponding to them, and $\mathbf{e}_i, \mathbf{e}_j$ is the representation of events. Then, event representations of each event is nothing but its headword embeddings: $\mathbf{e}_i := \mathbf{w_i}$ and $\mathbf{e}_j := \mathbf{w_j}$. This was much more efficient than designing multiple features to represent an event. Because obtaining Word2vec vectors corresponding to events is fairly simple as most of the events are either verbs or nouns.

Next, they conducted experiments over different approaches of combining these event representations. In those experiments, they applied multiple simple ways to obtain interaction between event-pairs such as concatenation, addition, or subtraction over event representations. Let $f_e : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}^{d'}$ be the function which models interactions between event-pairs. They used different function forms to capture this interaction:

$$f_e^a(\mathbf{e}_i, \mathbf{e}_j) = \mathbf{e}_i + \mathbf{e}_j \tag{3.1}$$

$$f_e^s(\mathbf{e}_i, \mathbf{e}_j) = \mathbf{e}_i - \mathbf{e}_j \tag{3.2}$$

$$f_e^c(\mathbf{e}_i, \mathbf{e}_j) = \mathbf{e}_i \oplus \mathbf{e}_j \tag{3.3}$$

where $\oplus$ indicates concatenation of vectors, and observed that concatenation (Eq. 3.3) is more effective in most of the cases.

The event representations obtained by considering the headword of the event was efficient but still failed at capturing the context of events. The context of the event can easily indicate the tense and aspect of the event as well as it can also show the presence of any temporal markers such as *before, after* etc. As we have seen in the manually designed features, this information is crucial for temporal relation classification. This issue is partially handled by (Cheng and Miyao, 2017; Choubey and Huang, 2017; Meng et al., 2017) who use *dependency paths* between events to obtain event-pair representations. In these approaches, first dependency parsed trees are generated with the use of previously proposed methods (e.g. Stanford Parser), and then these parsed trees of the sentences containing both events are considered to get the context. For that, the common ancestor between events is found and all the words from both the events up to this common ancestor are considered as a context. Next, all these words are represented with Word2vec vectors and provided to an LSTM (Hochreiter and Schmidhuber, 1997). Finally, the output of the LSTM is considered as event-pair representations. They observe that event-pair representations with such approach is more beneficial than single headword representation approach of Mirza and Tonelli (2016).

One of the disadvantages of using dependency trees is that it can not be directly used for events that are present in *different sentences*. To circumvent the issue, for both the events dependency paths from them to roots of the respective sentences in which they are present is considered and context is derived from these paths. This approach is exclusively taken for those events which are present in different sentences, in addition to the previous common ancestor approach for events in the same sentence. This leads to the overhead of training another LSTM separately for event-pairs that are in the different sentences. Also, in this approach, instead of all the words in the context, only those words which are on the dependency tree path are considered. We solve this issue by considering all the words in the context-window and use RNN to get the representation (Pandit et al., 2019) which is detailed in the coming chapter.

The work of Han et al. (2019a,b) further improved the representation by including the whole sentence as the context of the event. It inputs the whole sentence to a BiLSTM (forward and backward LSTMs) where each word is represented by concatenating the word vectors obtained with BERT (Devlin et al., 2019) model as well as POS vectors of each word. Let e_i be any event present in a sentence containing n words. Here, each kth word is represented by vector

$$\mathbf{w}_k = b_k \oplus p_k \tag{3.4}$$

where b_k is BERT based representation, p_k is POS embeddings of kth word, and $\oplus$ indicates concatenation of vectors. Then all the words' representations: $\mathbf{w}_1, \cdots, \mathbf{w}_k, \cdots, \mathbf{w}_n$ are passed through BiLSTM. The output from the forward LSTM and backward LSTM corresponding to event word is concatenated to get the contextualized event representation. So, the vector representation corresponding to event e_i is obtained as, $\mathbf{e}_i = f_i \oplus b_i$ where f_i, b_i are hidden vectors from forward and backward LSTMs corresponding to event e_i. Similarly, for event e_j vector representation $\mathbf{e}_j$ can be obtained. Finally, to get the event pair representation both these embeddings are concatenated:

$$\mathbf{e}_{ij} = \mathbf{e}_i \oplus \mathbf{e}_j \tag{3.5}$$

Also, these systems learned representations in a *global* fashion. As we will mention in the *models and inference* section, these systems are trained with a deep *structured learning* approach where Structured SVM (SSVM) is used to model the global loss. This leads to more effective representation learning as underline neural networks capture the relations between other event-pairs as well while training.

Using a different approach, Ning et al. (2018a) developed TEMPROB knowledge resource to improve event representations. As discussed in Section 2.6.1.2, TEMPROB

contains prior probabilities for relations between different verbs, for instance, *marry – divorce* have higher probability score for *before* relation than any other temporal relation. These prior probability scores between the event-pairs for each temporal relation are used as one of the features to represent event-pairs. Their approach is conceptually similar to ours where we also inject commonsense information in addition to text-based embeddings, but they relied only on the specific prior information, even in that they just used pairwise probability scores as a feature instead of getting overall information from the general structure of TEMPROB. This naive method of injecting commonsense knowledge is further improved in Ning et al. (2019) where they trained auxiliary Siamese network (Bromley et al., 1993) over TEMPROB and a portion of ConceptNet (Speer et al., 2018) and included features from this network into their main system.

Further, Wang et al. (2020) combined the previously mentioned BiLSTM based approach (Han et al., 2019a) and trained a MLP auxiliary network as proposed by Ning et al. (2019) to include TEMPROB and ConceptNet information to improve the representations. They used RoBERTa (Liu et al., 2019b) embeddings and external features obtained from the trained auxiliary network to get event-pair representations. Their approach can also be described with Eq. 3.4 with the only difference is that instead of b_k BERT-based representations, r_k RoBERTa-based embeddings are used. Also, the pairwise representation obtained in Eq. 3.5 is further concatenated by the knowledge graph based information, elementwise multiplication, and subtraction of outputs of BiLSTMs. With this event-pair representations they solved the broader event-event relation problem instead of just focusing on temporal relations by addressing event coreference as well as event parent-child relation in their approach. This joint formulation seems to improve the performance further.

In addition, some recent works (Han et al., 2020; Lin et al., 2020) have used similar techniques to get the event-pair representations, where they extended these representations to the biomedical domain temporal relation extraction.

3.1.2 Work on models and inference

So far, we discussed approaches that differed in the way of obtaining event representations. Now, we review the approaches that focus on the model or inference, the other component of the supervised temporal relation classification systems. *Local* temporal classification models learn temporal relations between temporal entities (event–event, event–TimEx, TimEx–TimEx) independent of temporal relations between other pairs. The general framework in these models is to obtain representations of event-pairs, then employ the machine learning classification models, such as SVM, CRF, or neural networks, to

assign probability scores for each possible temporal relation. Followed by *local inference* strategy to select the highest scoring relation as the predicted temporal relation for that pair. It is crucial to note that the relations are inferred without considering predictions between other pairs. The approaches (Bethard, 2013; Bethard et al., 2007; Chambers; Chambers et al., 2007; Laokulrat et al., 2013; Mani et al., 2006; Verhagen and Pustejovsky, 2008) fall into this category. Despite the simplicity and wide use of these approaches, they suffer from two major drawbacks. First, the temporal relations between pairs are learned independent of each other, thus missing out on the available global information. Second, due to *local inference* strategies, systems can produce inconsistent temporal relations between event-pairs. For instance, these systems can predict *A before B*, *B before C*, and *A after C*, which violates temporal constraints.

To solve the problem of inconsistent temporal relation predictions caused by local inference, different strategies to impose global constraints were designed. Initially, the approaches (Mani et al.; Verhagen and Pustejovsky, 2008) proposed greedy inference strategies to solve the global inference problem. Further improvements in inference are achieved by formulating inference as integer linear programming (ILP)(Bramsen et al., 2006; Chambers and Jurafsky, 2008; Denis and Muller, 2011; Do et al., 2012). On similar lines but a slightly different approach is developed by (Chambers et al., 2014; McDowell et al., 2017): They employ many hand-crafted rules and machine learned classifiers called sieves, to form a stack, and predicted temporal relations are passed from one sieve to another where the consistency is enforced by inferring all possible relations before passing by using greedy inference strategy similar to (Mani et al.; Verhagen and Pustejovsky, 2008).

Though these approaches solve the problem of inconsistent predictions, they still learn parameters *locally* i.e. independent of temporal relations between other pairs. This issue of *local parameter learning* is addressed by the *global models* which apply *structured learning* approach to learn temporal relations globally and employ global inference strategies (Han et al., 2019a,b; Ning et al., 2017; Yoshikawa et al., 2009). Ning et al. (2017) applied semi-supervised constraint driven learning (Chang et al., 2012) to learn consistent temporal relations, as they leveraged unlabeled data in their approach to improve the performance of the system. The approaches (Han et al., 2019a,b) further improved the performance with the application of deep structured learning. Both works use the same neural model which consists of a BiLSTM network to learn scoring functions for pairwise relations, and a SSVM to predict temporal relations that comply with global constraints. The only difference is that the latter approach (Han et al., 2019b) predicts events and temporal relations jointly, instead of taking a common approach of relying on the gold event annotations.

3.1.3 Summary

We observed that the earlier approaches predominantly employed hand-engineered features for event representations. The hand-engineered approaches concentrated on tense, aspect, modality, and certain grammatical features of the event. These approaches relied mostly on event specific information, barring works such as (D'Souza and Ng, 2013), which focused on the broader context to capture semantic and discourse relations between events. The earlier approaches also attempted to exploit contextual information by looking for temporal clues like temporal markers such as an explicit mention of *year*, *day*, etc. as well as clause connectors such as *because, as*, etc. Though these manually designed representations attempt to leverage contextual information, they still remain inefficient because of the inherent hand-picky approach taken, because the methods capture only those features that experts deem important while neglecting broader contextual information. This trend has changed with automatic representation learning due to neural networks. The earliest work (Mirza and Tonelli, 2016) based on automatically learned word vectors just used headword vectors by ignoring crucial contextual information. The more recent approaches tried to solve the contextual information problem by using dependency parse based context (Cheng and Miyao, 2017; Choubey and Huang, 2017; Meng et al., 2017) as well as with window based context (Dligach et al., 2017). We argue that the former study is difficult to be applied effectively if the events are not present in the same sentence and latter study is not done on the standard dataset used for temporal relation classification.

The pairwise representations of events is another necessary part of these approaches because we are trying to capture the temporal relation between pair of events and not the events separately. This is a less investigated area in the literature as most of the works simply concatenated event representations of both events to get the pairwise representations barring (D'Souza and Ng, 2013; Mirza and Tonelli, 2016). D'Souza and Ng (2013) designed pairwise features such as pairwise grammatical features, features based on the different lexical, semantic, and discourse relations, whereas (Mirza and Tonelli, 2016) resorted to linear operations such as summation, multiplication, etc. over event representations to get the interaction between events.

Further, use of the external knowledge resources for capturing lexical relations is explored in (D'Souza and Ng, 2013) and in (Ning et al., 2018a) developed external knowledge source with TEMPROB to capture prior temporal information of the events. However, both these approaches resorted to hand-picked features for the event representations, (D'Souza and Ng, 2013) used specific lexical relations where as (Ning et al., 2018a) used prior temporal relation probability as a feature. The approaches (Ning et al., 2019; Wang

et al., 2020) attempted to remedy this by training auxilary network instead of relying on hand-picked features, but it still captured only shallow features. As a result, these approaches fail to acquire broader commonsense information available in the knowledge sources encoded by the topology of the graph.

All in all, the representation learning approaches produced superior results in comparison to the feature engineering based approaches and seem to be a promising way of obtaining representations. This was first shown by Mirza and Tonelli (2016) when they experimented with Word2vec representations and observed absolute performance gain of around 2 points in F1 score against strong sieve-based CAEVO (Chambers et al., 2014) on TimeBank-Dense dataset. Further recent approaches (Han et al., 2019a,b; Ning et al., 2019; Wang et al., 2020) also benefited from the improved representations and shown gains in performances, albeit the systems were evaluated on different dataset (MATRES) so direct comparison between earlier hand-crafted feature based approaches and these approaches is difficult. Though there are improvements in event representations, they still lack at acquiring some crucial information as discussed above.

In our work, we try to remedy all these shortcomings. We capture the contextual information for the event representation with the window of n-words context to RNN and then capture non-linear interaction with CNN between these representations to get event-pair representation which is detailed in the next chapter (Chapter 4). Next, in the final chapter (Chapter 6), we explain the work where we combine embeddings learned over knowledge graphs such as TEMPROB, WordNet with text-based representations to acquire both contextual and commonsense information.

3.2 Bridging anaphora resolution

Bridging anaphora resolution is a subtask of bridging resolution. Recall from the previous chapter that bridging resolution involves identifying bridging anaphors which is referred to as bridging anaphora recognition and linking these bridging anaphors to appropriate antecedents is called bridging anaphora resolution. We are focusing on the latter task.

In the literature, Cahill and Riester (2012); Hou (2016, 2019); Hou et al. (2013a); Markert et al. (2012); Rahman and Ng (2012) focused on bridging anaphora *recognition*, on the other hand, Hou (2018a,b); Hou et al. (2013b); Lassalle and Denis (2011); Poesio et al. (2004); Poesio and Vieira (1998); Poesio et al. (1997) studied bridging anaphora *resolution*, whereas, Hou et al. (2014, 2018); Roesiger et al. (2018); Yu and Poesio (2020) solved both problems. We focus on the work which solves the bridging anaphora resolution as that is the main point of investigation in our study.

All these works employed a supervised learning approach to solve bridging anaphora resolution, then similar to temporal relation classification, we can divide them as well into two broad categories: bridging anaphor and antecedent representations based work, and task modeling and inference based work. First, we detail the approaches that focused on the representations, later, we briefly note approaches that focused on models and inference.

3.2.1 Work on mention representation

In all the models, we have to obtain representations for bridging anaphors, antecedents as well as antecedent candidates. Recall from the previous chapter that all of these linguistic objects are a subtype of *mentions*. Therefore, almost similar features are used to represent them. In the earlier approaches, similar to all NLP tasks including temporal relation classification, hand-engineered features were designed to get representations whereas the latest work has exploited neural networks to learn them. So, first, we summarize the mention representations obtained with hand-engineered features and then examine the latest automatic representation learning approaches.

3.2.1.1 Manually designed representation

Most of the earlier approaches (Lassalle and Denis, 2011; Poesio et al., 2004; Poesio and Vieira, 1998; Poesio et al., 1997) made a strong assumptions on bridging relations either by considering only definite Noun Phrases (NPs) as bridging anaphors or limiting types of relations can be held between bridging anaphor and antecedent (e.g. mostly considering meronymic relations). But recent approaches have got rid of these restrictions and tackled *unrestricted* bridging anaphora resolution (Hou, 2018a,b; Hou et al., 2013b).

Poesio et al. (2004) applied a pairwise model combining lexical semantic features as well as salience features to perform mereological bridging resolution in the GNOME corpus. They addressed only mereological bridging relations which is one type of bridging reference. Lexical distance is used as one feature in their approach and WordNet is used to acquire that distance, but sometimes relation between particular pair is not found in WordNet, therefore, as an alternative, Google API is used to get the distance between anaphor-antecedent. Given noun head h_a of anaphor a and h_m of potential antecedent m, the query of the form "the h_a of the h_m" is provided to API to get the number of hits and from that lexical distance is calculated. After obtaining these features, a multi-layer perceptron is used for the classification. Their training dataset is constructed by keeping a window size of 5, i.e., all the NPs occurring before an anaphor in the window of 5

sentences are considered as negative samples except antecedent. They also apply a data undersampling strategy for data balancing.

Based on this method of Poesio et al. (2004), Lassalle and Denis (2011) developed a system that resolved mereological bridging anaphors in French. They argued that the linguistic resources are scarcer in languages other than English, thus the use of resources like WordNet was difficult in other languages (e.g. French). To mitigate these challenges, raw texts were used, specifically, the system was enriched with meronymic information extracted from raw texts where they iteratively collected meronymic pairs and the corresponding syntactic patterns in a bootstrapping fashion. Finally, they evaluated their system on mereological bridging anaphors annotated in the DEDE (Gardent and Manuélian, 2005) corpus.

Deviating from all the previous studies, Hou et al. (2013b) proposed the first work on unrestricted bridging anaphora resolution. Also, they take a global approach to resolve bridging anaphora. For that, they designed various new global and local features to get mention representations. We detail their approach in Section 3.2.2, but for now, note down the prominent features used by them for the mention representations.

We compile some of the generally used features for mention representations from the previously proposed approaches (Hou et al., 2013b; Lassalle and Denis, 2011; Poesio et al., 2004) as follows:

Semantic features

- Semantic class: Mentions are assigned one of the semantic classes (Markert et al., 2012) e.g. location, organization, GPE (Geo-political Entity), product, language, and so on, because certain semantic class pairs indicate bridging relation between the mentions. For instance, suppose a semantic class of anaphor is a professional role and that of candidate antecedent is organization. Then, they may exhibit employee-employer relation, indicating bridging.

- Meronym relation: It captures *part-of* relation between mention pairs. Two approaches are broadly used to get this information. First, use of external resources like WordNet which holds information about meronymy relation between nodes (Poesio et al., 2004). This is done by measuring the shortest path length between an anaphor and an antecedent candidate among all synset combinations. The inverse value of this distance produces confidence about the relation between anaphor and candidate antecedent. On the other hand, the second approach exploits preposition patterns like **X of Y** or possessive structure **Y's X** (Hou et al., 2013b). The query like "*anaphor preposition antecedent*" which is a generalization of "*anaphor of an-*

tecedent" is created and passed to Google API to get the number of hits. This gives probability of *part-of* relation between anaphor and candidate antecedent.

- Verb pattern: The compatibility of the anaphor and candidate antecedent is captured with the verb on which anaphor depends (Hou et al., 2013b). Suppose anaphor depends on verb v then queries with all candidate antecedents of the *subject-verb* and *verb-object* are searched over a corpus. The hits are transferred into the normalized scores for each anaphor-candidate antecedent pair which indicates likeliness of them being bridging pair.

Syntactic and lexical features

- Same head: Head of the anaphor and antecedent are rarely same, so it is good to exclude those pairs (Hou et al., 2013b).
- Word overlap: Check if the anaphor is pronominally modified by the head of candidate antecedent (Hou et al., 2013b). For example *the mine* - **mine security**, the headword *mine* modifies **security** in anaphor.
- Co-argument: The subject can not be the antecedent of the object anaphor in the same clause (Hou et al., 2013b). This feature checks if it is the case.

Salience feature

Salient entities are preferred as antecedents. These features are captured by considering the position of the antecedent candidate in the document.

- Global first mention: It is assumed that global salient entities are presented at the beginning of the document (Poesio et al., 2004), based on that a binary feature is designed to indicate if the mention is the first mention in the whole document.
- Local first mention: Binary feature denoting if the mention is the first in the last five sentences is used (Poesio et al., 2004).
- Utterance distance: It calculates the number of sentences between anaphor and candidate antecedent (Poesio et al., 2004).
- Document span: This captures the local context of the candidate antecedent, i.e., the sentences which contain antecedent (Hou et al., 2013b).

3.2.1.2 Automatic representation learning

Until now, we discussed hand-crafted features and approaches that proposed them. We now move to approaches that automatically learn mention representations. There has been little work (Hou, 2018a,b, 2020a; Yu and Poesio, 2020) on this front because of the inherent difficulty of the task and more importantly small size of the annotated corpora.

Hou (2018b) learned embeddings_PP, a customized embeddings specifically for bridging resolution and extended them in (Hou, 2018a). In the first approach, she argues distributional word embeddings learned in a task-agnostic way (e.g. Word2vec, Glove) capture both genuine similarity and relatedness between words which is not quite suitable for resolving bridging relation, as it requires more knowledge of lexical association. Therefore, she resorts to the prepositional structure of NP, **X of Y** and possessive pattern **Y'X** (as mentioned previously in 3.2.1.1) to acquire non-identical associative relation between two nouns. On these noun-pairs having *part-of* relations, she learned embeddings_PP while completely avoiding the hand-crafted ways of obtaining features. She empirically showed that embeddings_PP significantly improved the accuracy of bridging resolution in comparison to the task-agnostic word embeddings (Glove). In the following work (Hou, 2018a), she extended this approach and designed embeddings_bridging that combines embeddings_PP and Glove (Pennington et al., 2014) embeddings, as embeddings_PP contained representations only for nouns. This enhanced representation further improved the accuracy of bridging anaphora resolution.

In the latest approaches (Hou, 2020a; Yu and Poesio, 2020), BERT embeddings are used to get the contextualized representation of bridging anaphor and antecedent candidates. However, both approaches differ in the way BERT is used. In the former approach, BERT is fine-tuned for bridging whereas the latter approach uses pre-trained BERT embeddings in their neural learning model.

BARQA system proposed by Hou (2020a) differs from commonly proposed approaches in two ways: First, instead of relying on already extracted *gold* mentions to form the set of antecedent candidates for bridging anaphors, the system extracts these candidates itself, followed by selecting the appropriate antecedent from the set. Second, bridging anaphora resolution is formulated as a question-answering problem where every anaphor is rephrased as a question, and the answer generated by the system is considered as a predicted antecedent. Specifically, for a bridging anaphor a, a question of the form "a of what" is generated and context c_a is provided to BERT. The context c_a contains the first sentence of the document, the previous two sentences from anaphor a and the sentence containing a. Then the system predicts an answer for the question from the context c_a which is treated as predicted antecedent for a. This formulation produced

effective representations as BARQA system achieved state-of-the-art performance over ISNotes (Markert et al., 2012) as well as BASHI (Roesiger, 2018a) datasets.

The system proposed by Yu and Poesio (2020) also differs in the way the problem is formulated. This system solved the more general and harder *full bridging resolution* task where both bridging anaphor as well as antecedent candidates are detected and resolved. Also, they formulated the task differently where they learn bridging and coreference resolution in multi-task fashion as both are similar tasks (reference resolution tasks). The primary reason behind such a formulation is the lack of training data for bridging resolution. Specifically, their system extends state-of-the-art coreference resolution system (Kantor and Globerson, 2019; Lee et al., 2018) with the addition of a feedforward network at the end and two different classifiers each for bridging and coreference resolution. They mainly used part of ARRAU dataset (Uryupina et al., 2019) for training as it contains both bridging as well as coreference annotations. Further, they evaluated their system on ARRAU, ISNotes (Markert et al., 2012), BASHI (Roesiger, 2018a), and SciCorp (Roesiger, 2016). Their system achieved substantial improvements over previous best results for full bridging resolution for all corpora.

3.2.2 Work on models and inference

Supervised learning approaches for the task have considered bridging anaphora resolution as a classification problem and have commonly used two types of models: *local* and *global*. Similar to the models for temporal relation classification, *local* models predict the antecedent for anaphor, independent of other anaphor linkings. In a nutshell, the local models construct a set of antecedent candidates for the anaphor, then formulate anaphor linking as a classification problem and assign a compatibility score for each antecedent candidate of the anaphor. At inference, the highest scoring candidate antecedent is predicted as an antecedent for the anaphor. On the contrary, the learning in the *global* models consider other bridging anaphor-antecedent pairs as well, though the dependency on the other anaphor links is not so complex as temporal relations. The main constraints in the bridging anaphor resolution are the low probability of bridging anaphor being the antecedent for another anaphor, high probability of the entity being the antecedent for another anaphor once it is an antecedent, and certain anaphor being more likely to share the same antecedents. Because of these simple linguistic constraints to be enforced for the bridging anaphora resolution, most of the works resorted to local models and simple greedy inference strategy. Majority of the works (Hou, 2018a,b; Lassalle and Denis, 2011; Poesio et al., 2004; Poesio and Vieira, 1998; Poesio et al., 1997) employed local models, whereas (Hou et al., 2013b) used global model to resolve bridging anaphors.

The model (Hou et al., 2013b) integrates global as well as local features in the Markov Logic Networks (MLN) (Domingos and Lowd, 2009), thus, differs from previous approaches where only local features were used to infer antecedent for an anaphor. They argued that if antecedent candidates for linking anaphors are selected from a particular window of sentences, it can result in either too many wrong candidates in case of bigger window size or lose out correct antecedent in case of smaller window size. They solved this by taking a global approach where candidate antecedents are not restricted to any window size but all the NPs are considered as candidates. Specifically, in a local approach, for anaphor a antecedents are selected from set E_a of NPs but in this approach the antecedent is selected at discourse level from $E = \cup_{a \in \mathscr{A}} E_a$ where $\mathscr{A}$ denotes set of anaphors in the document. Next, in their MLN system, three types of formulas were defined: hard constraints, discourse level formulas, and local formulas. The hard constraints specified rules like an anaphor can have only one antecedent, the antecedent of an anaphor should occur before it, and some other rules. In discourse level formulas, they preferred globally salient antecedents based on the assumption that similar or related anaphors in one document are likely to have the same antecedent. The local formulas are based on previously proposed local features (Poesio et al., 2004) and few new features proposed by them as noted in the previous sections.

3.2.3 Summary

Similar to temporal relation classification approaches, the earlier mention representation approaches for the bridging anaphora resolution paid less attention to context. The feature-engineered approaches mainly concentrated on semantic, lexical, syntactical, and salient features, ignoring much of the contextual information. The learning based approach Hou (2018a,b) that designed custom-tailored embeddings, emb_pp for bridging anaphors also neglected the broader context of the anaphors. This is changing in recent approaches based on transformer language models as they leveraged the inherent context capturing capabilities of these models. These approaches (Hou, 2020a; Yu and Poesio, 2020) built on the bridging related information captured by pre-trained models. They trained their models with different objectives, Hou (2020a) formulated bridging as a question-answering task, on the other hand, Yu and Poesio (2020) jointly resolved bridging and coreference tasks. However, there is no study done to assess the capability of pre-trained transformer models at capturing bridging information, which could help at designing better models for bridging. We think that this kind of study is necessary to get an effective fine-tuning objective and in turn for an effective proposal of bridging resolution systems based on transformer models.

Though these models excelled at capturing contextual information, less attention has been paid to capture commonsense information. The initial approaches based on manually designed features have tried to extract some information from WordNet, raw texts or web(Hou et al., 2013b; Lassalle and Denis, 2011; Poesio et al., 2004). Specifically, they designed features to capture certain semantic relations such as meronymy, hypernymy, etc. Also, emb_pp (Hou, 2018a,b) leveraged the *part-of* relation by training these embeddings over large unannotated corpora. However, these approaches still fail to capture broader commonsense information encoded in the knowledge graphs which can be beneficial for bridging anaphora resolution.

Overall, we observe that automatic mention representations produce better results than manually designed approaches. On ISNotes dataset, the manually designed representations with MLN (Hou et al., 2013b) produce accuracy of 41.3%, whereas mention representation with emb_pp (Hou, 2018a) improves this performance and achieves an accuracy of 46.5%. The gain is further enhanced by BARQA (Hou, 2020a) system which achieves 50.7% accuracy on ISNotes. Unfortunately for recently proposed datasets: BASHI and ARRAU, results with feature engineered approaches are not readily available for bridging anaphora resolution, so it is not straightforward to do a similar comparison for them. However, results of *full bridging resolution* obtained over these datasets by Roesiger et al. (2018) and performance gain achieved by Yu and Poesio (2020) over their system indicate the similar trend observed in the case of ISNotes. Yet all these approaches fall short in some aspects as pointed in the preceding paragraphs.

We fill these gaps in our work. In chapter 5, we investigate the pre-trained transformer language models for bridging information. We carry out two complementary approaches where we first probe internal parts of the transformer model individually and in the second approach, we take a more general view by looking at the model as a whole. In chapter 6, we present a detailed study on the inclusion of external knowledge for improved bridging representation. We note challenges in adding such information, followed by proposed solutions and empirical results.

Chapter 4

Learning Rich Event Representations and Interactions

In the last chapter, we detailed the shortcomings of previously proposed approaches. We observed that most existing systems for identifying temporal relations between events heavily rely on hand-crafted features derived from the event words and explicit temporal markers. On the other hand, the word embeddings based approach (Mirza and Tonelli, 2016) failed at capturing contextual information. Besides, less attention has been given to automatically learning contextualized event representations or to finding complex interactions between events. The work presented in this chapter fills this gap in showing that a combination of rich event representations and interaction learning is essential to more accurate temporal relation classification[1]. Specifically, we propose a neural architecture, in which i) a Recurrent Neural Network (RNN) is used to extract contextual information for pairs of events, ii) character embeddings capture morpho-semantic features (e.g. tense, aspect), and iii) a deep Convolutional Neural Network (CNN) architecture is used to find out intricate interactions between events. We show that the proposed approach outperforms most existing systems on commonly used datasets while replacing gold features of TimeBank with fully automatic feature extraction and simple local inference.

4.1 Introduction

Recall from our task description from Section 2.1.1 that temporal relation extraction is divided into two main tasks, i) the identification of events and time expressions (TimEx's), and ii) the classification of temporal relations (or `TLINK`s) among and across events and

[1]This work is an extension of our work (Pandit et al., 2019).

time expressions. Possible temporal relations for this latter task include temporal precedence (i.e., *before* or *after*), *inclusion* (i.e., *includes* or *is_included*), and others inspired from Allen's algebra (Allen, 1983). Here, we concentrate on temporal relation classification, specifically event-event relations, the most frequent type of `TLINK`s and arguably the most challenging task.

Previously we have seen that tense, aspect, temporal connectives such as *before*, *during*, and temporal markers such as *today, last day* are crucial for determining temporal ordering between events. We hypothesize that the context and morphology of the event capture this useful temporal information. Consequently, it is important to encode the contextual and morphological information into the event representations. Next, temporal relations are determined between pairs of events (binary relations), thus, it is necessary to acquire pairwise features that can capture the interaction between them. Section 4.2 talks in more detail about the significance of context, morphology and interaction for effective event-pair representations.

Based on the hypothesis, in section 4.3 we propose an approach that learns task-specific event representations from event's context and morphology. These representations include information both from the event words *and* its surrounding context, thus giving access to the events' arguments and modifiers. Furthermore, the character-based model adds another type of information captured by morphology such as tense and aspect of the event. Plus, we also attempt to learn the potentially rich interactions between events. Concretely, our learning framework is based on a neural network architecture, wherein: i) Recurrent Neural Network (RNN) is used to learn contextualized event representations, ii) character embeddings is used to capture morphological information, hence encoding tense, mood and aspect information, and iii) a deep Convolutional Neural Network (CNN) architecture is then used to acquire complex, non-linear interactions between these representations (Fig. 4.1).

Next, we empirically show the potency of our system. We first detail the experimental setup in section 4.4 and present results in section 4.5. We also perform ablation studies to see the effectiveness of each component of the system in section 4.6. Finally our findings and observations are summarized in section 4.7.

4.2 Effective event-pair representations

Importance of context and morphology The fundamental requirement for event representations in temporal relation classification is the presence of the event related temporal information in the representations so that the further algorithms can use that information

to establish temporal relations accurately. The following are a few prominent factors that are crucial for temporal analysis of events:

- **Tense**: The tense of the event provides the most useful temporal signal. It indicates if the event has occurred in the past, present, or will occur in the future with reference to the time of writing the text.
- **Grammatical aspect**[2] The grammatical aspect adds granular details to the information provided by the tense. It tells if the event is still going on (progressive), finished (perfect) or event is started in the past but has a varying end (perfect progressive) in the given tense. The presence of auxiliary verbs like *will, was, is, etc.* provides this information.
- **Temporal indicators**: The words like *before, after* which are used to connect different clauses are also instant give-aways of the temporal relations. Similarly, connecting words such as *because, since, as, while* indicate temporal relations – *because, since* indicate *after* relation and *as, while* indicate *overlap* relation.
- **Temporal markers**: The temporal markers like "February", "Thursday" are definite indicators of exact time and are crucial for the analysis. In addition to that, the presence of the words like "yesterday", "today" as well as the markers like "last", "next", "since" also offer certain reference time.

The earlier approaches (Bethard et al., 2007; Boguraev and Ando, 2005; Lapata and Lascarides, 2004; Mani et al., 2003, 2006) acquired these features from TimeBank annotations. In general, they detected the presence of certain words such as auxiliary verbs (e.g. is, was, will, etc.), temporal markers (dates, days, etc.), temporal indicators (e.g. before, after,etc.) from the context to acquire these features. Similarly, the event representation *learning* approach should also capture these features from the context. However, recently proposed event representation learning approaches either completely ignored them (Mirza and Tonelli, 2016) or added extra pre-processing steps in the form of syntactic parsing (Cheng and Miyao, 2017; Meng et al., 2017).

[2] *Grammatical aspect* (Comrie, 1976) is different from *lexical aspect* (Vendler, 1957). The *lexical aspect* divides verbs into four categories: states, processes, accomplishment, and achievements. These distinctions are mainly based on the temporal properties such as whether the event is ongoing or ended, whether it occurs at a specified time or over a period. For instance, "running", "writing" are processes whereas "knowing" is a state. Generally, these distinctions are independent of the tense in which verbs are used as they depend on the verb's inherent meaning. Though, *lexical aspect* is a fantastic temporal indicator (Costa and Branco, 2012) it is not readily marked in the corpora. On the other hand, TimeML (Pustejovsky et al., 2003b) is annotated with different grammatical aspects as *progressive, perfect, perfect progressive, none*. Hence, the latter being popularly used as a feature for temporal analysis.

We argue that in addition to the context, the inflectional suffixes of event headword can indicate the tense of the event. For instance, tense information can be captured from context with auxiliary verbs (*will*, *is*), and in the absence of these words or in combination with them, tense and aspect information of the event is expressed with inflectional suffixes such as *-ed*, *-ing*, *-en* which respectively indicate paste tense, progressive, and paste participle.

Importance of interaction learning The final goal of the temporal relation classification task is to determine the temporal ordering between *event-pairs*, which makes their representation indispensable. The first important step in that is to get the effective event representations which we obtain with the contextual and morphological information. Then the next equally important step is to acquire meaningful interactions between these representations, which has been a less studied area in the literature. Mirza and Tonelli (2016) experimented with simple operations like summation, multiplication, subtraction, etc. over event representations to get the interactions, but these functions are inadequate as they are inflexible at dynamically weighting the event representations.

Overall, we argue that though contextual, morphological information, and complex interaction learning are essential for temporal relation classification, less attention has been paid to acquiring them[3]. Recently proposed LSTM-based neural network architectures (Cheng and Miyao, 2017; Dligach et al., 2017; Meng et al., 2017) learn event representations with the use of the event headwords as well as context. Also, the newly proposed method (Meng and Rumshisky, 2018) has shown the efficacy of context with the use of a gated RNN-attention based neural architecture. However, by using only word embeddings they fail to capture inflectional morphology of event headword, which includes crucial linguistic information such as tense, aspect, and mood. Also, they lacked in finding complicated interaction between events and relied only on the concatenation of event features. Moreover, they (Cheng and Miyao, 2017; Meng et al., 2017) used syntactically parsed trees as inputs to the LSTM which adds the burden of pre-processing. We remedy that by proposing the neural model as described in the following sections.

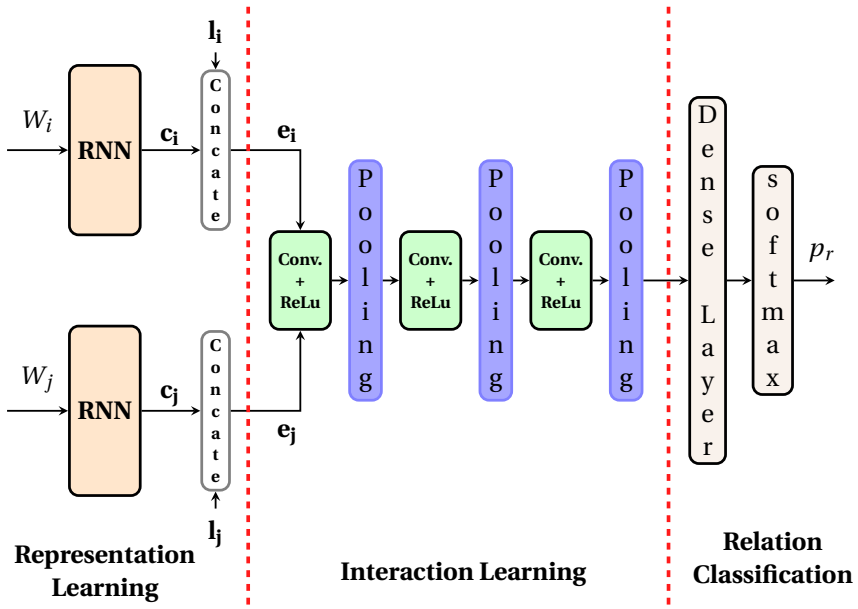


Fig. 4.1 Architecture of our proposed model.

4.3 Method

Our proposed neural architecture (Fig. 4.1), consists of two main components: Representation Learning and Interaction Learning. In the Representation Learning part, a bag-of-words based on a fixed size window centered on each event word is fetched and fed into a RNN to get a more expressive and compact representation of events, as RNNs have proven to be better at modeling sequential data. Output of the RNN is concatenated with the character embedding of the event headword to get the final vector for each event. This vector representation is then used at the Interaction Learning stage: the vector representation of each event is fed to a convolution layer and the final pooling layer outputs an interaction vector between the events. A dense layer is used to combine the interaction vector before obtaining a probability score for each temporal relation. All these components are learned end-to-end with respect to the output of the model i.e. based on the prediction of temporal relation.

4.3.1 Representation Learning

Context-aware Representation Each word is encoded in the event headword window with word embeddings, as a result, each word is assigned a fixed d-dimensional vector rep-

[3]We are referring to systems which were proposed before this work, there has been significant improvement at capturing contextual information since then.

resentation. Suppose w_i is the event headword for an event e_i, n is the window size such that n surrounding words from the left and right of w_i are considered, then the input given to RNN is: $W_i = [\mathbf{w_{i-n}} \cdots \mathbf{w_i} \cdots \mathbf{w_{i+n}}] \in \mathscr{R}^{(2n+1)\times d}$, where $\mathbf{w_k}$ is word embeddings of word w_k (illustrated as W_i and W_j for events e_i, e_j in Fig. 4.1). Also, note that while considering event contexts we stop at sentence boundaries, and pad special symbols if the context is less than n words. Further, recall from Section 2.2 that RNN is sequential in nature and produces outputs corresponding to each input word (Eq. 2.18). We consider the output vector of the last word of the event context (i+n) as the context-aware representation of the event, as it captures the complete information about the whole sequence. Then for events e_i, e_j, we denote respective context-aware representations as $\mathbf{c_i}, \mathbf{c_j}$.

Morphological Representation Semantics and arguments of events are captured with context-aware representations but they do not capture morphological information. The event headword's internal construction contains this information, and to acquire this information we employed a character-based representations of event headwords, which is obtained with FastText (Bojanowski et al., 2017) embeddings. As discussed in Section 2.4.1.3, FastText obtains representations of character *n-grams* contained by each word and sums those representations to get the final word representations. Let $\mathbf{l_i}$ and $\mathbf{l_j}$ be the morphological representations obtained with this approach corresponding to events e_i, e_j, respectively.

Next, the context-aware representation $\mathbf{c_i}$ and the morphological representation $\mathbf{l_i}$ are concatenated to obtain the final event representation $\mathbf{e_i}$ for event e_i as: $\mathbf{e_i} = \mathbf{c_i} \oplus \mathbf{l_i}$. Similarly, event representation $\mathbf{e_j} = \mathbf{c_j} \oplus \mathbf{l_j}$ is also obtained for event e_j.

4.3.2 Interaction Learning

Next, a Deep Convolution Neural Network (DCNN) is employed to learn nonlinear interactions over event representations $\mathbf{e_i}$ and $\mathbf{e_j}$. Our DCNN contains three CNN layers stacked on each other where a CNN layer consists of several filters, non-linear projection layer and max-pooling layer (recall the discussion about CNN from Section 2.2). To get the interaction between events, we concatenate vectors of event representations to get $\mathbf{x_{ij}}$: $\mathbf{x_{ij}} = \mathbf{e_i} \oplus \mathbf{e_j}$. This vector representation $\mathbf{x_{ij}}$ is given to the first layer of DCNN and the output from the last layer of the DCNN is considered as the interaction between event representations, given as:

$$\mathbf{e_{ij}} = DCNN(\mathbf{x_{ij}}, \theta) \tag{4.1}$$

where θ are DCNN parameters.

The output $\mathbf{e_{ij}}$ captures the interaction between event-pairs and is further fed to a fully connected dense layer, followed by a softmax function to get a probability score for each temporal relation class. Next, we use simple local inference strategy and select most probable temporal relation for any given event-pair.

4.4 Experiments

4.4.1 Datasets and Evaluation

Temporal Relations Following recent work (Ning et al., 2017), a reduced set of temporal relations: AFTER , BEFORE , INCLUDES , IS_INCLUDED , EQUAL, and VAGUE are considered for classification.

Evaluation Complying with common practice, a system's performance is measured over gold event pairs (pairs for which relation is known). Our main evaluation measure is the Temporal Awareness metric (UzZaman and Allen, 2011), adopted in recent TempEval campaigns. We also used standard precision, recall, and F1-score to allow direct comparison with (Mirza and Tonelli, 2016). Further details on the exact calculations of the scores with these evaluation schemes were presented in Section 2.1.1.4.

Datasets Following the data splits from previous work (Ning et al., 2017) for the direct comparison of results, we used TimeBank (Pustejovsky et al., 2003a) and AQUAINT (Graff, 2002) datasets for training, TimeBank-Dense (Cassidy et al., 2014) for development and TE-Platinum (UzZaman et al., 2013) datasets for test. We provided more details about these datasets in Section 2.1.1.3.

4.4.2 Training details

We used pre-trained Word2vec vectors from Google[4], and represented each word in the context winow with this 300-dimensional vectors. Next, hyperparameters were tuned on the development set using a simple grid search, where we considered different set of values for each hyperparameter: window size (n): 3,4,5, number of neurons at RNN (#RNN): 64,128,256,512, number of filters for CNN (#filters): 32,64,128,256, and dropout rates: 0.1,0.2,0.3,0.4. We also explored several optimization algorithms such as AdaDelta (Zeiler, 2012), Adam (Kingma and Ba, 2017), RMSProp (Tieleman and Hinton, 2012) and Stochastic

[4]https://code.google.com/archive/p/word2vec/

Gradient Descent (SGD). From our experiments on the validation datasets, we found out the optimal hyperparameter values: n = 4,#RNN =256, #filters = 64, dropout = 0.4 and Adam optimizer.[5] Then we re-trained multiple models with 50 random seed values on the combined training and development data and reported the averaged test performances.

4.4.3 Baseline systems

In addition to our main system we implemented a number of baselines for comparison.

Different representations In these baseline systems, we varied the approaches of getting representations of events as follows:

- **(i) Only headwords**: First, we re-implemented the system of Mirza and Tonelli (2016). Recall from the previous sections that event representations in their model is obtained by considering word embeddings of event headwords. Specifically, word embeddings $\mathbf{w_i}$ and $\mathbf{w_j}$ for events e_i and e_j are obtained with Word2vec of corresponding headwords. These embeddings were simply concatenated ($\mathbf{w_i} \oplus \mathbf{w_j}$) as this combination produced the best results in their experiments. Finally, we used scikit-learn logistic regression module, using l_2 regularization for learning.

- **(ii) Addition of context**: This is the variation of our system where we consider event headwords as well as the n-word context to obtain event representations. To achieve that, from our proposed system, we use only RNN model while removing character embeddings and DCNN used for interaction learning. For instance, for events e_i and e_j, the event-pair representation in this baseline is obtained as: $\mathbf{c_i} \oplus \mathbf{c_j}$, only by concatenating the context-aware representations $\mathbf{c_i}, \mathbf{c_j}$.

- **(iii) Addition of morphology**: We add morphological information in the previous setup while still removing the interaction learning part obtained with DCNN. So, in this setup also we use simple concatenation but this time over rich representations that combine context-aware and morphological representations, to produce even-pair representations $\mathbf{e_i} \oplus \mathbf{e_j}$ for events e_i and e_j.

Different interactions In this set of baseline systems, we keep the event representations obtained with RNN and character representations of events in place and just vary the interaction learning part of the system.

[5] We tried different unidirectional and bidirectional variations of RNN: LSTM, and GRU, but RNN gave the best development results.

- **(iv) mlp**: First, we used simple multi-layer perceptron (MLP) over rich event representations, $\mathbf{e_i}$,$\mathbf{e_j}$, and noted as *mlp*.
- **(iv) cnn**: Then, we went a step further to understand the gains produced by *cnn* over *mlp*. Here, we employed simple CNN, noted as *cnn*.

4.4.4 Ablation setup

In addition to these baseline implementations, we systematically removed some components of our system to assess the contributions made by individual components.

- **Without morphological information:** We remove the morphological information from the system. To achieve that, we build our system without the character embeddings (FastText) but keep other components like contextual and interaction learning in place.
- **Without rich representation:** This system is implemented without contextual as well as morphological information. Here, we remove the major part of the system, we get rid of RNNs and character embeddings and only use event headwords to represent events. The rest of the interaction learning is used to produce event-pair representations only with headword information.

4.5 Results

4.5.1 Comparison to baseline Systems

We first compare our RNN-Deep CNN approach to various baseline systems to assess the effectiveness of the learned event representations. Sections (a) and (b) of Table 4.1 summarize the performance of these different systems in terms of pairwise classification accuracy and temporal awareness scores.

Section (a) of the table presents results with different representation learning strategies. The first row notes the result obtained with Mirza and Tonelli (2016) system which uses only event headword for representations (Baseline (i)). Next baseline is a variation of our system where contextual information is added on top of the event headwords (Baseline (ii)) and results are presented in the second row (noted as +Context). We further add morphological information on top of the contextual information in this baseline (Baseline (iii)), results are shown in the third row of Table 4.1 (noted as +Morphology). Looking at the first two rows of the table, we see that, as hypothesized, contextually rich features outperform pre-trained event headword embeddings even when combined with simple

Systems	Pair Classification			Temporal Awareness		
	P	R	F1	P	R	F1
(a) Different representations						
Event head	39.3	34.2	35.5	27.1	45.8	34.1
+ Context	35.7	38.9	37.2	36.5	35.9	36.2
+ Morphology	37.6	44.5	40.8	41.2	45.9	43.4
(b) Different interactions						
mlp	40.2	46.3	43.0	51.8	42.5	46.7
cnn	38.2	53.7	44.6	41.7	60.1	49.2
dcnn	39.4	58.9	47.2	43.2	70.1	53.4
(c) Comparison with state-of-the-art						
ClearTK (Bethard, 2013)	-	-	-	33.1	35.0	34.1
LSTM (Meng et al., 2017)	38.7	43.1	40.5	34.6	51.7	41.4
SP (Ning et al., 2017)	-	-	-	69.1	65.5	67.2
Our model	39.4	58.9	47.2	43.2	70.1	53.4

Table 4.1 Results of baseline and state-of-the-art systems

concatenation. We see improvement from 35.5 points to 37.2 in pairwise classification evaluation and 34.1 to 36.2 in temporal awareness. A further gain in the performance is seen with the addition of morphological information. Results from this section establish the effectiveness of our rich representation learning.

Next, section (b) of the table compares different interaction learning strategies. Firstly, we observe that the system with *mlp* (Baseline (iv)) interaction learning outperforms simple *concatenation* (noted in the final row of section (a)). There is an improvement from 40.8 to 43.0 in the pairwise classification evaluation and 43.4 to 46.7 in the case of temporal awareness. This itself establishes the importance of interaction learning over simple concatenation. Further improvement in the results with the use of *cnn* (Baseline (v)) and *dcnn* strengthens our claims. There, the Deep CNN outperforms the single-layer CNN, with F1 scores of 53.4 and 49.2, respectively in temporal awareness evaluation, showing similar gains with pairwise classification evaluations. This further confirms the importance of non-linear interaction learning in the task.

4.5.2 Comparison with state-of-the-art

Finally, we compare the performance of our best system with recently proposed systems in section (c) of Table 4.1. We compare with two *local models*, ClearTK (Bethard, 2013), and LSTM based system (Meng et al., 2017), and a *global model* based on structured

prediction (SP) approach (Ning et al., 2017). The *local model* ClearTK used *gold* features to obtain the representation and was the winner of the TempEval 2013 campaign. For fair comparison, we also compare with a representation learning system which employs LSTM and syntactic parsed trees to get the context. Additionally, we compared with SP system as it is the best system to date[6]. We observe, our system (Table 4.1) delivers substantial improvements over ClearTK, proving effectiveness of our approach over hand-crafted approach. In comparison with the LSTM-based system, we also see gains in performance. However, our system lags in comparison with SP. The reason might be the difference between learning and inference strategies. SP takes a global learning approach which learns model parameters while considering relations between all the event-pairs simultaneously. Further, they also used unlabeled data in their semi-supervised learning setup.

4.6 Ablation study

Now, we assess the contributions of different components of our system.

Rich event representation: To assess the importance of rich event representations, we remove both contextual (RNN) and morphological information (character embeddings) from our system and rely only on the interaction learning part obtained with DCNN. We compare result of this system (Table 4.2: row 2), with our system (Table 4.2: row 1). We observe a significant drop in the results compared to our system with the reduction of 9.1 F1 points in the pairwise score and 14.9 points in the temporal awareness score. This drop indicates the importance of our rich event representations which includes contextual as well as morphological information.

Interaction learning: Next, we determine the role of interaction learning obtained with the use of DCNN. For that, we simply concatenate the rich representation of events and observe the results. The results in the third row of Table 4.2 show the drop of 6.4 F1 points in pairwise evaluation whereas 10 points drop in temporal awareness. This is a slightly lesser reduction in the results in comparison to the drop produced because of absence of rich event representations (the second row of the table). This suggests, even though the interaction learning is important, it adds less value in-comparison to the rich event representations.

[6]This was true at the time we conducted experiments.

Systems	Pair Classification				Temporal Awareness			
	P	R	F1	**ΔF1**	P	R	F1	**ΔF1**
Our model	39.4	58.9	47.2	-	43.2	70.1	53.4	-
– Rich representation	39.3	36.8	38.1	-9.1	42.6	35.2	38.5	-14.9
– Interaction learning	37.6	44.5	40.8	-6.4	41.2	45.9	43.4	-10.0
– Morphology	42.4	41.3	41.8	-5.4	46.9	41.5	44.1	-9.3

Table 4.2 Ablation study.

Morphology: Finally, we remove morphology information obtained with character embeddings. The final row in Table 4.2 shows the result. The pairwise evaluation F1 score drops by 5.4 points and temporal awareness score drops by 9.3 points. This is the least of the reductions in the results in comparison to the previous two ablations. This shows that character representations play a relatively small role at producing effective representations. This again highlights the importance of the other two components of the representations: contextual information and complex interaction learning.

4.7 Conclusions

We proposed a system to learn rich event representations and complex interactions between them to produce effective event-pair representations. To achieve that, we used RNN to capture event-related contextual information from the window of n-words around the event as well as added morphological information with character-based embeddings. We used DCNN to further obtain the complex interaction between the rich representations.

Our experimental results prove that the system successfully captures the beneficial features required to predict temporal relations more accurately. The system outperforms previously proposed local models either based on hand-crafted representations or automatically learned features, confirming its efficacy. Further, our analysis shows that the rich event representation plays the biggest role in the system's success in comparison to the other components of the system: morphological information with character representations and interaction learning. This solidifies our claim that context is required for obtaining effective event representations. We also found that complex interaction learning obtained with DCNN always outperformed simple interactions acquired with concatenation, MLP, or CNN. This signifies the role of complex interaction learning required to accurately determine the temporal ordering between events.

Although the proposed system produces improvement over other local models, it still misses at including other useful information such as semantic relations between events, or world knowledge about event pairs. We think, in addition to the event-related information captured with context and morphology, this information is also crucial for the task. Also, here, we used a simple inference strategy to obtain final temporal relations between events, and as pointed in Chapter 2 this may lead to inconsistent temporal graphs. We work on both these limitations in the work detailed in Chapter 6.

Chapter 5

Probing for Bridging Inference in Transformer Language Models

In the previous chapter, we developed an effective approach for capturing contextual information to improve event representation for temporal relation classification. We intend to design a similar approach to acquire contextual information for bridging resolution as well. The recently proposed transformer language models have shown to be effective at capturing contextual information (Devlin et al., 2019; Liu et al., 2019b). Also, these transformer language models have been successfully applied for various NLP tasks (Joshi et al., 2020; Lee et al., 2020; Song et al., 2019; Sun et al., 2019) including bridging resolution (Hou, 2020a; Yu and Poesio, 2020). In the future, it will be natural to employ these models to further improve mention representations for bridging resolution. The first step in this direction is to understand the overall capability of these pre-trained models at capturing bridging information to design effective architecture and develop better fine-tuning strategies. Next, if these models are potent at bridging inference then, it will be interesting to understand what kind of input is required to get these results. We answer these questions in this chapter [1]. We probe pre-trained transformer language models for bridging inference. We first investigate individual attention heads in BERT and observe that attention heads at higher layers prominently focus on bridging relations compared to the lower and middle layers. More importantly, we consider language models as a whole in our second approach where bridging anaphora resolution is formulated as a masked token prediction task (*Of-Cloze test*). Our formulation produces optimistic results without any fine-tuning, which indicates that pre-trained language models substantially capture bridging inference. Next, we experiment with different context constructions to understand the role of context. Our investigation shows that the context provided to

[1] This chapter is based on our work (Pandit and Hou, 2021).

language models and the distance between anaphor-antecedent play an important role in the inference.

5.1 Introduction

Recall from section 2.1.2 that bridging inference involves connecting conceptually related discourse entities: anaphors and antecedents (Clark, 1975). A bridging anaphor shares *non-identical* relation with its antecedent and depends on it for complete interpretation. Consider the following example:

"*In Poland's rapid shift from socialism to an undefined alternative, environmental issues have become a cutting edge of broader movements to restructure* ***the economy****, cut cumbersome bureaucracies, and democratize local politics.*"

Bridging inference connects the anaphor "***the economy***" and its antecedent "*Poland*" and deduces that "the economy" specifically refers to "the economy of Poland".

We want to investigate if the pre-trained transformer language models that are known to be proficient at acquiring contextual information capture any bridging inference information. We chose transformer models for the investigation, as they are superior to RNNs (Lakew et al., 2018) that were used to capture the context in the previous chapter. Because transformers are better at handling long distance dependencies of the given sequence and can be easily parallelized to take full advantage of modern fast computing devices such as TPUs and GPUs, as they avoid recursions. Due to these advantages of transformers over RNNs, we also intend to use them to capture contextual information. Though transformer based models are better, they are quite complex because of multiple attention heads and several layers of encoders, resulting in unclarity of exact reasons behind their success and little understanding of the information held by them. For that reason, recently there has been an increasing interest in analyzing pre-trained transformer based language models' ability at capturing syntactic information (Clark et al., 2019), semantic information (Kovaleva et al., 2019), as well as commonsense knowledge (Talmor et al., 2020). There are also a few studies focusing on probing coreference information in pre-tained language models (Clark et al., 2019; Sorodoc et al., 2020). So far, there has been no work on analyzing bridging, which is conceptually similar to coreference. We try to fill this gap in our work. Section 5.2 details previously proposed probing approaches for this relevant linguistic information as well as few employed probing methods.

Next, section 5.3 clearly states the research questions we are addressing in this chapter. The section also briefs the dataset used for the investigation as well as specifies the transformer models used for the experiments.

We employ two different but complementary approaches for the investigation of pre-trained transformer language models for bridging inference. Section 5.4 details the first approach where we investigate the core internal part of transformer models, self-attention heads, in vanilla BERT (Devlin et al., 2019). We believe understanding which attention head or group of attention heads at particular layer capture bridging information will be beneficial for designing better representation learning strategies. We look at the attention heads of each layer separately and measure the proportion of attention paid from anaphor to antecedent and vice versa. This captures the magnitude of bridging signal corresponding to each attention head. We observed that attention heads of higher layers are more active at attending to bridging relations as well as some of the individual attention heads prominently look at the bridging inference information.

In the second approach (Section 5.5), we treat pre-trained transformer language models as a black box and form bridging inference as a masked token prediction task. This formulation takes into consideration the whole architecture and weights of the model rather than concentrating on individual layers or attention heads, thus complementing our first approach where we looked at the individual parts of the transformer model. For each bridging anaphor, we provide input as "*context anaphor of [MASK]*" to language models and get the scores of different antecedent candidates for mask token. We then select the highest scoring candidate as the predicted antecedent. Surprisingly, the best variation of this approach produces a high accuracy score of 28.05% for bridging anaphora resolution on ISNotes (Markert et al., 2012) data without any task-specific fine-tuning of the model. On the same corpus, the current state-of-the-art bridging anaphora resolution model *BARQA* (Hou, 2020a) achieves an accuracy of 50.08%, while a solid mention-entity pairwise model with carefully crafted semantic features (Hou et al., 2013b) produces an accuracy score of 36.35%. This shows that substantial bridging information is captured in the pre-trained transformer language models.

Thus far, our experiments show the decent capability of the transformer models at acquiring bridging information but could not identify the exact role of the context in achieving that. The fill-in-the-gap formulation for the antecedent selection task is flexible enough to easily explore the role of context in their bridging inference ability. We provide differently constructed contexts to the transformer language models to measure the impact of the context on the accuracy of *Of-Cloze test* in section 5.6. Our analysis shows that, although pre-trained language models capture bridging inference substantially, the overall performance depends on the context provided to the model.

In the next section, Section 5.7, we analyze the errors incurred by the *Of-Cloze test*. The error analysis shows the limitation of the transformer models as well as the inherent

shortcomings of the *Of-Cloze test*. The analysis unearths interesting findings about the capability of transformer models, especially BERT, at acquiring commonsense information. It reveals that BERT can capture basic commonsense information but fails at capturing sophisticated commonsense information. With these findings, finally, we conclude in Section 5.8.

5.2 Probing transformer models

The development of language models based on Transformers (Vaswani et al., 2017) has been a significant breakthrough for the research in NLP. Specifically, BERT (Devlin et al., 2019) pushed the state of the art for many NLP tasks (Hou, 2020a; Joshi et al., 2020; Lee et al., 2020; Song et al., 2019; Sun et al., 2019). Evidently, these models are remarkably good at capturing long-range dependencies from the given context. As a consequence, the contextual embeddings produced by these models seem to be more effective than the static embeddings (e.g. Word2vec, Glove) that fail to accommodate context-specific information. Besides these *prima facie* arguments, the specific reasons behind their success are still unknown. This lack of understanding hampers the further efficient improvement of the architecture. The huge number of parameters trained in these models makes this investigation further challenging as it restricts the ability to experiment with pre-trained models and perform ablation studies. Because of the *non-interpretability* of these models, a lot of work has been done to probe these models. These probing approaches differ in their objectives. Some approaches probe the capability of transformer models at capturing certain information such as syntactic (Htut et al., 2019; Jawahar et al., 2019; Lin et al., 2019; Liu et al., 2019a), semantic (Broscheit, 2019; Ettinger, 2020; Tenney et al., 2019) or world knowledge (Da and Kasai, 2019; Ettinger, 2020; Talmor et al., 2020). Another set of approaches researched different training objectives and architectures (Joshi et al., 2020; K et al., 2020; Liu et al., 2019a,b) whereas few others have focused on overparameterization issue, and approaches to compression (Gordon et al., 2020; Michel et al., 2019; Voita et al., 2019).

Out of all these approaches, we discuss a few that are relevant to our study. First, we look at the approaches that investigate different entity reference information, as bridging resolution also falls into this category. Next, we look for similar studies done on the ability of BERT at capturing commonsense information as it is crucial for bridging inference. Afterward, we briefly discuss different probing approaches used for the investigation. Attention head analysis is the most commonly used approach because attention heads are

the core elements of the transformer models. Further, because of the masked modeling objective used to train these models, fill-in-the-gap probing also has been used extensively.

5.2.1 Probing for relevant information

Entity Referential Probing Previous studies on entity referential probing mainly focus on coreference. Clark et al. (2019) showed that certain attention heads in pre-trained BERT correspond well to the linguistic knowledge of coreference. Particularly, the authors found that one of BERT 's attention heads achieves reasonable coreference resolution performance compared to a string-matching baseline and performs close to a simple rule-based system. Sorodoc et al. (2020) investigated the factors affecting pronoun resolution in transformer architectures. They found that transformer-based language models capture both grammatical properties and semantico-referential information for pronoun resolution. Recently, Hou (2020b) analyzed the attention patterns of a fine-tuned BERT model for information status (IS) classification and found that the model pays more attention to signals that correspond well to the linguistic features of each IS class. For instance, the model learns to focus on a few premodifiers (e.g., "more", "other", and "higher") that indicate the comparison between two entities.

Commonsense Knowledge Probing. A lot of work has been carried out to analyze various types of commonsense knowledge encoded in transformer language models. Talmor et al. (2020) constructed a set of probing datasets and test whether specific reasoning skills are captured by pre-trained language models, such as age comparison and antonym negation. Da and Kasai (2019) found that pre-trained BERT failed to encode some abstract attributes of objects, as well as visual and perceptual properties that are likely to be assumed rather than mentioned.

5.2.2 Probing approaches

Attention Analysis. Recently there has been an increasing interest in analyzing attention heads in transformer language models. Although some researchers argue that attention does not explain model predictions (Jain and Wallace, 2019), analyzing attention weights still can help us to understand information learned by the models (Clark et al., 2019). Researchers have found that some BERT heads specialize in certain types of syntactic relations (Htut et al., 2019). Kovaleva et al. (2019) reported that pre-trained BERT 's heads encode information correlated to FrameNet's relations between frame-evoking lexical units (predicates, such as "*address*") and core frame elements (such as "*issues*"). In our

work, we try to analyze whether certain attention heads in a pre-trained BERT model capture bridging relations between entities in an input text.

Fill-in-the-gap Probing. One of the popular approaches to probe pre-trained language models is fill-in-the-gap probing, in which the researchers have constructed various probing datasets to test a model's ability on different aspects. Goldberg (2019) found that BERT considers subject-verb agreement when performing the cloze task. Petroni et al. (2019) reported that factual knowledge can be recovered from pre-trained language models. For instance, "JDK is developed by [Oracle]". Similarly, we apply fill-in-the-gap to probe bridging by formulating bridging anaphora resolution as a *Of-Cloze test*.

5.3 Methodology

We mainly investigate the following research questions:

- How important are the self-attention patterns of different heads for bridging anaphora resolution?
- Do pre-trained transformer language models capture information beneficial for resolving bridging anaphora in English?
- How do the context and the distance between anaphor-antecedent influence pre-trained language models for bridging inference?

We designed a series of experiments to answer these questions which will be detailed in the coming sections. In these experiments, we used the PyTorch (Wolf et al., 2020) implementation of BERT-base-cased, BERT-large-cased, RoBERTa-base and RoBERTa-large pre-trained transformer language models with the standard number of layers, attention heads, and parameters. In the attention head-based experiments, we have limited our investigation only to the BERT-base-cased model as it is relatively smaller compared to other models and findings of this model can be generalized to other models as well.

Probing Dataset We used ISNotes (Markert et al., 2012) dataset for all experiments. We choose this corpus because it contains "unrestricted anaphoric referential bridging" annotations among all available English bridging corpora (Roesiger et al., 2018) which covers a wide range of different relations. Recall from Section 2.1.2 that ISNotes contains 663 bridging anaphors but only 622 anaphors have noun phrase antecedents, as a small number of bridging antecedents in ISNotes are represented by verbs or clauses. In our experiments,

we only consider these 622 anaphors for investigation. For any anaphor, the predicted antecedent is selected from the set of antecedent candidates. This set is formed by considering all the mentions which occur before the anaphor. We obtained the candidate set for each anaphor by considering "gold mentions" annotated in ISNotes. Further, we observed that only 531 anaphors have antecedents in either previous 2 sentences from the anaphor or the first sentence of the document. Therefore, in the experiments when antecedent candidates are considered from the window of previous two sentences plus the document's first sentence, only 531 anaphors are considered. In all the experiments, accuracy is measured as the ratio between correctly linked anaphors to the total anaphors used in that particular experiment (not total 663 anaphors).

5.4 Probing individual attention heads

Attention heads are an important part of transformer based language models. Each layer consists of a certain number of attention heads depending on the model design and each attention head assigns different attention weight from every token of the input sentence to all the tokens. In our approach, we measure the attention flow between anaphors and antecedents for each attention head separately. In this experiment we investigate all the attention heads of every layer one-by-one. Specifically, the BERT-base-cased model used for probing contains 12 layers and 12 attention heads at each layer. Therefore, we investigate 144 attention heads for their ability to capture bridging signals.

5.4.1 Bridging signal

We look for two distinct bridging signals – one from anaphor to antecedent and other from antecedent to anaphor. The bridging signal from anaphor to antecedent is calculated as the ratio of the attention weight assigned to antecedent and the total cumulative attention paid to all the words in the input. Similarly, the bridging signal from antecedent to anaphor is found in a reverse way.

There are two difficulties while getting the attention weights corresponding to anaphor or antecedent. First, the anaphor or antecedent can be a phrase with multiple words. So, we need to decide how to aggregate words' weights. For this, we decide to consider the semantic heads of both anaphor and antecedent, and get the attention weight between them. For instance, the semantic head for "*the political value of imposing sanction against South Africa*" is "*value*". Most of the time, a semantic head of an NP is its syntactic head word as in the above example. However, for coordinated NPs such as "*the courts and*

the justice department", the syntactic head will be "*and*" which does not reflect this NP's semantic meaning. In such cases, we use the head word of the first element as its semantic head (i.e., *courts*).

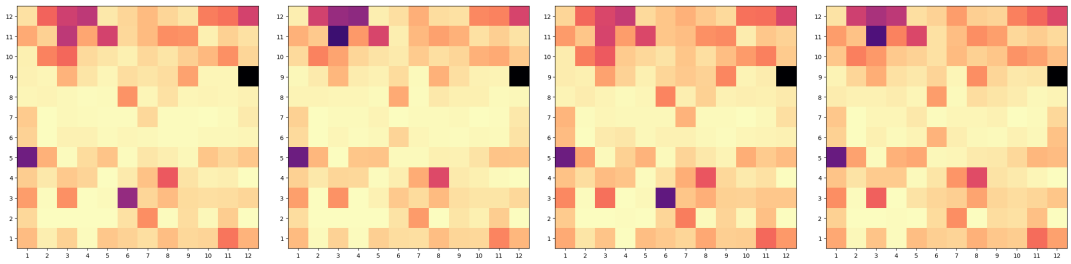
Secondly, transformer language models use the wordpiece tokenizer to break words further. This produces multiple tokens from a single word if this word is absent from the language model's dictionary. Here, for a bridging anaphor a and its head word a_h, we first calculate the average weight of all word piece tokens of the head word a_h to other words. From these weights, we consider the weight from the anaphor a to its antecedent (w_1). Subsequently, we add weights from a_h to all other tokens present in the sentence and normalize the weight using sentence length (w_2). Note that we neglected weights assigned to special tokens (i.e. [CLS], [SEP], [PAD], etc.,) while calculating both weights as previous work suggest that these special tokens are heavily attended in deep heads and might be used as a no-op for attention heads (Clark et al., 2019). Finally, bridging signal is measured as the ratio between w_1 and w_2 as mentioned earlier.

5.4.2 Experimental setup

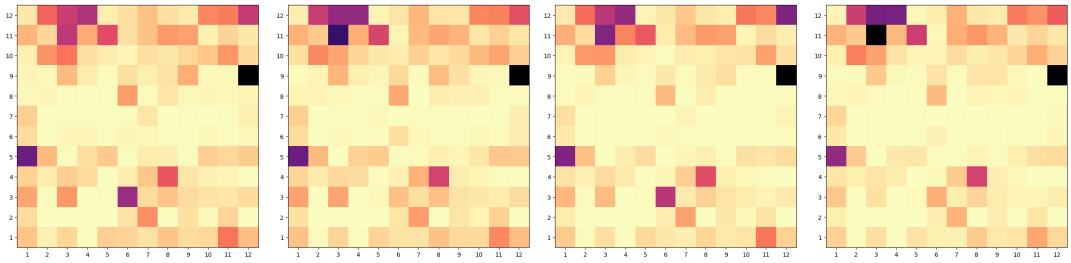
We provide sentences containing a bridging anaphor (Ana) and its antecedent ($Ante$) to the pre-trained BERT model as a single sentence without the "[SEP]" token in-between. However, an anaphor and its antecedent do not always lie in the same or adjacent sentence(s). Therefore, we design two different experiments. In the first setup, we provide the model with only those sentences which contain Ana and $Ante$ while ignoring all the other sentences in-between. This setting is a bit unnatural as we are not following the original discourse narration. In the second setup, we provide the model with sentences which contain Ana and $Ante$ as well as all the other sentences between Ana and $Ante$. Note that in both experiments we add markers to denote the anaphor and its antecedent in order to get exact corresponding attention weights.

5.4.3 Results with only Ana-Ante sentences

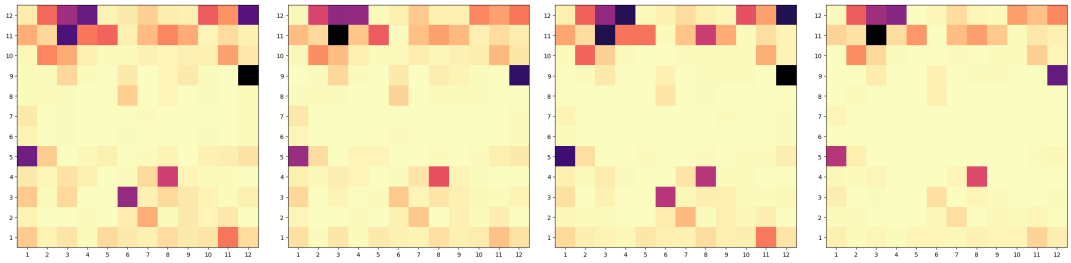
For the input of only sentences containing anaphors and antecedents, we plot the bridging signals corresponding to each attention head separately (see the heatmaps in Fig. 5.1a). The left heatmap shows the signals from anaphors to antecedents and the right one shows the signals from antecedents to anaphors. Both heatmaps are based on the pre-trained BERT-base-cased model. The x-axis represents the number of attention heads from 1-12 and the y-axis represents the number of layers from 1-12. The darker shade of the color indicates stronger bridging signals and brighter color indicates a weak signal.



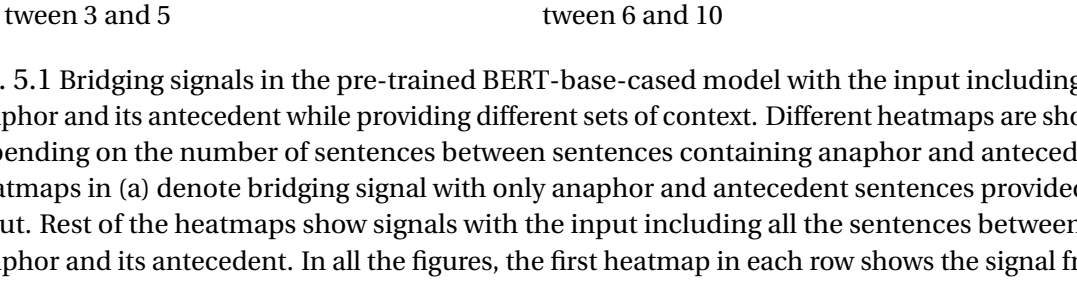
(a) Without any in-between sentences.



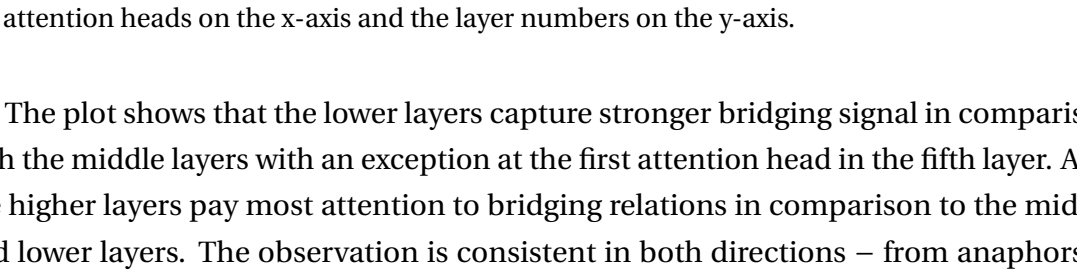
(b) Anaphor-antecedent sent. distance 0



(c) Anaphor-antecedent sent. distance 1



(d) Anaphor-antecedent sent. distance 2



(e) Anaphor-antecedent sent. distance between 3 and 5

(f) Anaphor-antecedent sent. distance between 6 and 10

Fig. 5.1 Bridging signals in the pre-trained BERT-base-cased model with the input including an anaphor and its antecedent while providing different sets of context. Different heatmaps are shown depending on the number of sentences between sentences containing anaphor and antecedent. Heatmaps in (a) denote bridging signal with only anaphor and antecedent sentences provided as input. Rest of the heatmaps show signals with the input including all the sentences between an anaphor and its antecedent. In all the figures, the first heatmap in each row shows the signal from anaphor to antecedent and the second one from antecedent to anaphor. All the heatmaps present the attention heads on the x-axis and the layer numbers on the y-axis.

The plot shows that the lower layers capture stronger bridging signal in comparison with the middle layers with an exception at the first attention head in the fifth layer. Also, the higher layers pay most attention to bridging relations in comparison to the middle and lower layers. The observation is consistent in both directions – from anaphors to antecedents and from antecedents to anaphors.

5.4.4 Results with all sentences

As stated earlier, for an anaphor, the antecedent can lie in the same sentence or any previous sentence. This demands a separate investigation of bridging signals depending on the distance (measured in terms of sentences) between anaphors and antecedents. Therefore, we plot bridging signals captured by all attention heads depending on the distance between anaphors and antecedents in Fig. 5.1b-5.1f.

The second plot in the first row (Fig. 5.1b) shows the signals between anaphors and antecedents where the distance between them is 0 (i.e., they occur in the same sentence). The plots in row 2 (Fig. 5.1c and Fig. 5.1d) show the bridging signals between anaphors and antecedents in which the anaphor-antecedent sentence distance is 1 and 2, respectively.

In ISNotes, 77% of anaphors have antecedents occurring in the same or up to two sentences prior to the anaphor. The remaining anaphors have distant antecedents and each distance group only contains a small number of anaphor-antecedent pairs. Therefore, we divide the remaining anaphors into two coarse groups. The plots in Fig. 5.1e and Fig. 5.1f are plotted by combining anaphor-antecedent pairs which are apart by 3 to 5 sentences and 6 to 10 sentences, respectively. Note that we could not plot attention signals for bridging pairs with sentence distance longer than 10 sentences because of the limitation of the input size in BERT.

We observe that the patterns which are visible with only anaphor-antecedent sentences as the input (Section 5.4.3) are consistent even with considering all the sentences between anaphors and antecedents. It is clear that higher layers attend more to bridging relations in comparison with lower and middle layers. Also, the lower layers fail to capture bridging signal as the distance between anaphors and antecedents increases. Attention weights assigned by certain attention heads (5:1, 9:12, 11:3 and 12:2-4) are fairly consistent. One more important thing to observe is that as the distance between anaphors and antecedents increases the overall bridging signal decreases. This can be observed by looking at all the heatmaps in Fig. 5.1 as the heatmaps with lower distances are on the darker side.

5.4.5 Discussion

Based on the results from the previous two experiments, we observed that in the pre-trained BERT model, the higher layers pay more attention to bridging relations in comparison with the middle and the lower layers. This observation is in-line with other studies in which the authors found that simple surface features were captured in the lower layers and complex phenomenons like coreference were captured in the higher layers (Jawahar

Easy Bridging Relations
The move will make the drug available free of charge for a time to children with the disease and symptoms of advanced **infection**.
Last year, when the rising Orange River threatened to swamp the course, the same engineers rushed to build a wall to hold back **the flood**.
At age eight, Josephine Baker was sent by her mother to a white woman's house to do chores in exchange for meals and a place to sleep – a place in **the basement** with the coal.
Difficult Bridging Relations
In addition, Delmed, which makes and sells a dialysis solution used in treating kidney diseases, said negotiations about pricing had collapsed between it and a major distributor, National Medical Care Inc. Delmed said Robert S. Ehrlich resigned as chairman, president and chief executive. Mr. Ehrlich will continue as a director and **a consultant**.
The night the Germans occupied all of France, Baker performed in Casablanca. The Free French wore black arm bands, and when she sang "J'ai deux amours" they wept. Ms.Rose is best on **the early years** and World War II.
In Geneva, however, they supported Iran's proposal because it would have left the Saudi percentage of the OPEC total intact, and increased actual Saudi volume to nearly 5.3M barrels daily from 5M. Some of the proposed modifications since, however, call on Saudi Arabia to "give back" to the production-sharing **pool** a token 23,000 barrels.

Table 5.1 Examples of easy and difficult bridging relations for the prominent heads to recognize. Bridging anaphors are typed in boldface, antecedents in underscore.

et al., 2019). Also, the overall attention decreases with the increase in the distance between anaphors and antecedents.

We also observed that there are some prominent attention heads which consistently capture bridging relations (5:1, 9:12, 11:3 and 12:2-4). In order to check which bridging relations are easier or harder for these prominent attention heads to capture, we further investigated qualitatively to identify bridging pairs that get higher or lower attentions in these attention heads. Specifically, we consider pairs which have the bridging signal ratio (defined in Section 5.4.1) more than 70% as easier bridging relations for BERT heads to recognize. If the bridging signal ratio is less than 10%, then the corresponding bridging relation is considered as difficult for BERT heads to identify. We list a few easy and difficult examples in Table 5.1. In general, we observe that semantically closer pairs are easy for prominent heads to identify (e.g., house-basement, disease-infection). On the other hand,

pairs that are distant and require more context-dependent as well as common-sense knowledge inference are difficult for the prominent heads to recognize.

5.5 Fill-in-the-gap probing: LMs as Bridging anaphora resolvers

The transformer-based language models are trained with an objective to predict the masked tokens given the surrounding context. Thus, they can also produce a score for a word which can be placed at the masked token in a given sentence. We make use of this property of the language models and propose a novel formulation to understand the bridging anaphora resolution capacity of the pre-trained language models.

5.5.1 *Of-Cloze test*

The syntactic prepositional structure (*X of Y*, such as "the door of house" or "the chairman of company") encodes a variety of bridging relations. Previous work has used this property to design features and develop embedding resources for bridging (Hou, 2018a,b; Hou et al., 2013b).

Inspired by this observation, we formulate bridging anaphora resolution as a cloze task. Specifically, given a bridging anaphor and its context, we insert "of [MASK]" after the head word of the anaphor (see Example 7). We then calculate the probability of each candidate to be filled as the mask token. The highest scoring candidate is selected as the predicted antecedent for the anaphor. One of the advantages of our formulation is that we can easily control the scope of the context for each bridging anaphor (e.g., *no-context*, *local context* or *global context*). This allows us to test the effect of different types of context for bridging inference.

(7) *Original context*: The survey found that over a three-year period 22% of <u>the firms</u> said employees or owners had been robbed on their way to or from work or while on the job. **Seventeen percent** reported their customers being robbed.

Cloze test context: The survey found that over a three-year period 22% of <u>the firms</u> said employees or owners had been robbed on their way to or from work or while on the job. **Seventeen percent of [MASK]** reported their customers being robbed.

5.5.2 Experimental setup

Recall that in our *Of-Cloze test*, antecedent candidates are provided and the highest scoring candidate is selected as the predicted antecedent. These candidates are formed by considering mentions which are occuring prior to the anaphor. We design two different experiment sets based on the scope of antecedent candidates.

Candidates Scope We consider two different sets of antecedent candidates for an anaphor a. The first set contains *salient and nearby mentions* as antecedent candidates. Here, mentions only from the first sentence of the document, previous two sentences preceding a and the sentence containing a are considered as candidates. This setup follows previous work on selecting antecedent candidates (Hou, 2020a). The second set contains *all mentions* occurring before the anaphor a from the whole document. The second setup of forming antecedent candidates is more challenging than the first one because the number of candidates increases which makes selecting the correct antecedent difficult.

Next, we provide the same context for anaphors in both of the experiments described above. We construct the context c for the bridging anaphor a. Precisely, c contains the first sentence of the document, the previous two sentences occurring before a, as well as the sentence containing a. We replace the head of a as "a of [MASK]".

We also compare this fill-in-the-gap probing approach with the attention heads-based approach for resolving bridging anaphors. Specifically, we use the prominent heads in BERT for identifying bridging relations from Section 5.4. Here, we obtained attention weights from an anaphor head to all antecedent candidate heads by adding attentions from prominent heads 5:1, 9:12, 11:3, and 12:2-4. Then the highest scoring candidate is predicted as the antecedent for the anaphor.

5.5.3 Results and Discussion

5.5.3.1 Results on candidates scope

Table 5.2 shows the accuracy of using only the *prominent heads* and our *Of-Cloze test* approach for bridging anaphora resolution. All experiments are based on the same context (i.e., the sentence containing an anaphor, the previous two sentences preceding the anaphor as well as the first sentence from the document).

We find that the *Of-Cloze* probing approach achieves higher result in comparison to the prominent attention head approach (31.64% vs. 20.15%) under the same conditions. One reason might be that although other attention heads do not significantly attend to bridging relations but cumulatively they are effective.

Antecedent Candidate Scope	**No. Anaphors**	**BERT-Base**	**BERT-Large**	**RoBERTa-Base**	**RoBERTa-Large**
Prominent attention heads					
(1) Salient/nearby mentions	531	20.15	-	-	-
Of-Cloze test					
(2) Salient/nearby mentions	531	31.64	33.71	34.08	**34.65**
(3) All previous mentions	622	26.36	28.78	27.49	**29.90**
Of-Cloze Test: Anaphors with antecedents in the provided contexts					
(4) All previous mentions	531	29.00	30.88	30.32	**32.39**
Of-Cloze Test: Anaphors with antecedents outside of the provided contexts					
(5) All previous mentions	91	10.98	**16.48**	10.98	15.38

Table 5.2 Result of selecting antecedents for anaphors with two different probing approaches (*Prominent attention heads* and *Of-Cloze test*) based on the same context. Accuracy is calculated over a different number of anaphors.

We also observe that in the *Of-Cloze test*, the results of using salient/nearby mentions as antecedent candidates are better than choosing antecedents from all previous mentions (Row (2) vs. Row (3), and Row (2) vs. Row (4)). This is because the model has to choose from a smaller number of candidates in the first case as the average number of antecedent candidates are only 22 per anaphor as opposed to 148 in the later case.

We further divide 622 anaphors in Row (3) into two groups (Row (4) and Row (5) in Table 5.2) depending on whether the corresponding antecedents occur in the provided contexts. It can be seen that the performance is significantly better when antecedents occur in the contexts.

Finally, when comparing the results of each language model in each row separately, it seems that the bigger models are always better at capturing bridging information. In general, the RoBERTa-large model performs better than other models except when antecedents do not occur in the provided contexts (Row (5)).

Note that the results in Table 5.2 are not calculated over all 663 anaphors in ISNotes. Therefore, if the results are normalized over all anaphors then we get the best result with the RoBERTa-large model (28.05%), which is reasonably fine in comparison with the state-of-the-art result of 50.08% (Hou, 2020a) given that the model is not fine-tuned for the bridging task.

5.5.3.2 Results on Ana-Ante distance

We further analyze the results of choosing antecedents obtained using the BERT-base-cased model with all previous mentions as the antecedent candidate scope in our *Of-Cloze*

Distance	Accuracy
salient*	38.65
0	26.92
1	20.58
2	17.30
>2	10.98

Table 5.3 Anaphor-antecedent distance-wise accuracy with the BERT-base-cased model. * indicates that the antecedent is in the first sentence of the document.

test probing experiment (Row (3) in Table 5.2) to understand the effect of distance between anaphors and antecedents. The results are shown in Table 5.3.

In general, it seems that the accuracy decreases as the distance between anaphors and antecedents increases except when antecedents are from the first sentences of the documents. This is related to the position bias in news articles from ISNotes. Normally globally salient entities are often introduced in the beginning of a new article and these entities are preferred as antecedents. The other reason for the lower results in case of antecedents being away for more than two sentences might be that these antecedents are absent from the provided context.

5.6 Importance of context: *Of-Cloze test*

Until now, we provided pre-designed context for the *Of-Cloze test*, i.e. first sentence of the document, the previous two sentences occurring before anaphor, as well as the sentence containing anaphor. This yielded competitive results. Now, we provide a different set of contexts to measure its impact on accuracy.

5.6.1 Experimental setup

Our goal is to probe the behavior of language models at capturing bridging relations with different contexts. To achieve that, we experiment with the following four settings:

- a. Only anaphor: in this setup, only the anaphor phrase (with "of [MASK]" being inserted after the anaphor's head word) is given as the input to the model.
- b. Anaphor sentence: the sentence containing the anaphor is provided. The phrase "of [MASK]" is inserted after the head word of the anaphor.

Context Scope	with "of"	without "of"	perturb
only anaphor	17.20	5.62	-
ana sent.	22.82	7.71	10.28
ana+ante sent.	27.81	9.61	10.93
more context	26.36	12.21	11.41

Table 5.4 Accuracy of selecting antecedents with different types of context using BERT-of-Cloze Test.

- c. Ante+Ana sentence: on top of b, the sentence containing the antecedent is also included in the context.
- d. More context: on top of b, the first sentence from the document as well as the previous two sentences preceding the anaphor are included.

Without "of" Context To test the effect of the strong bridging indicating signal "*of*", we further execute another set of experiments. Specifically, We remove "of" from "anaphor$_{head}$ of [MASK]" and instead, provide "anaphor$_{head}$ [MASK]" for each type of the context described above.

Perturbed Context In this setting, we perturb the context by randomly shuffling the words in the context except for the anaphor and antecedent phrases for each type of the context mentioned above. Note that we still have the "*of*" indicator in this setup.

5.6.2 Results on different contexts

The results of experiments with different types of contexts are shown in Table 5.4. All experiments are based on the BERT-base-cased model with all previous mentions as the antecedent candidate scope. We refer to this model as *BERT-Of-Cloze* in the following discussion.

In the first column of the table, *BERT-Of-Cloze* achieves an accuracy score of 17.20% with only the anaphor information plus "*of [mask]*". We can see that the results improve incrementally with the addition of context. More specifically, the accuracy score improves from 17.20% to 22.82% by adding sentences containing anaphors. Adding sentences which contain antecedents (*ana + ante sent.*) further improves the accuracy score to 27.81%. Finally, adding more local context and the first sentence leads to an accuracy score of 26.36%. Note that compared to "*ana + ante sent.*", "*more context*" represents a more

realistic scenario in which we do not assume that the antecedent position information is known beforehand. In general, the results in the first column of Table 5.4 indicate that the model can leverage context information when predicting antecedents for bridging anaphors.

Results reduce drastically when *"of"* is removed from the "anaphor of [MASK]" phrase (Table 5.4, column:2) from all context scopes. Without this indicator, the language model cannot make sense of two adjacent tokens such as "*consultant company*".

It is interesting to see that the results reduced drastically as well when we perturb the context between the anaphor and antecedent (Table 5.4, last column). This establishes the importance of meaningful context for performing bridging inference effectively in transformer language models.

5.7 Error analysis: *Of-Cloze test*

We analyzed anaphor-antecedent pairs that are linked wrongly by the *Of-Cloze* formulation and observed some common errors.

Failure at capturing sophisticated common-sense knowledge: We found that the pre-trained transformer language model such as BERT acquires simple common-sense knowledge, therefore it can link anaphor-antecedent pairs such as "*sand–dunes*" and "*principal–school*". But it fails at capturing sophisticated knowledge, such as "*consultant–Delmed (a company)*" and "*pool–OPEC (Organization of petroleum countries)*". This might be happening because of the rare co-occurrences of these pairs in the original text on which BERT is pre-trained. Also, BERT has inherent limitations at acquiring such structured knowledge (Park et al., 2020).

Language modeling bias: In our *Of-Cloze test* probing, we use pre-trained transformer language models without fine-tuning. As a result, the model fills masked tokens that are fit according to the language modeling objective, not for bridging resolution. Thus, sometimes, the selected token perfectly makes sense in the single sentence but the choice is incorrect in the broader context. Consider the example, "Only 22% of [MASK] supported private security patrols [...]". BERT predicts "*police*" as a suitable antecedent that produces a meaningful local sentence. However, the correct antecedent is "*correspondents*" according to the surrounding context of this sentence.

Unsuitable formulation for set-relations: Our *Of-Cloze* formulation produces awkward phrases for some bridging pairs that possess set-relations. Considering a bridging pair – "*One man - employees*", in this case the model should assign high score for the phrase – "One man *of* employees". But, as this phrase is quite clumsy, BERT naturally being a language model assigns low scores for these pairs.

5.8 Conclusions

We investigated the effectiveness of pre-trained transformer language models in capturing bridging relation inference by employing two distinct but complementary approaches.

In the first approach, we probed individual attention heads in BERT and observed that attention heads from higher layers prominently captured bridging compared to the middle and lower layers and some specific attention heads consistently looked for bridging relation. In our second approach, we considered using language models for bridging anaphora resolution by formulating the task as a *Of-Cloze test*. We carefully designed experiments to test the influence of different types of context for language models to resolve bridging anaphors. Our results indicate that pre-trained transformer language models encode substantial information about bridging.

We go one step further to analyze the role of context in achieving this bridging information. We separately provided a different set of contexts such as no context other than anaphor phrase, removing "Of" from our fill-in-the-blank formulation, and shuffled words context. We saw a substantial drop in the accuracy in comparison to the case where provided context was appropriate. This shows BERT's capability of bridging inference depends on the input context, the more the appropriate context better the result.

Finally, our error analysis highlighted the crucial limitation of BERT at capturing commonsense information which is required in bridging inference. We observed BERT fails to accurately select antecedents for anaphors that required sophisticated commonsense knowledge. It could easily resolve easy pairs such as "*sand–dunes*" and "*principal–school*" but failed at "*consultant–Delmed (a company)*" and "*pool–OPEC (Organization of petroleum countries)*". For this reason, we need to design approaches that can fill this missing commonsense information from BERT. We will look at that in the next chapter.

Chapter 6

Integrating knowledge graph embeddings to improve representation

Until now we have explored the use of *contextual information* for both temporal relation classification and bridging anaphora resolution. We developed an effective neural network based approach for temporal relation classification in Chapter 4, followed by the investigation of transformer language models for bridging inference in Chapter 5. Now, we explore the use of *commonsense information* for both tasks and extend our work (Pandit et al., 2020). To the best of our knowledge, this is the first work where a principled approach is taken to represent knowledge graphs for bridging and temporal relation identification. We discuss the significance of world knowledge for these tasks as well as challenges in extracting them from knowledge graphs and injecting them into bridging resolution and temporal relation classification systems. To address these challenges, we design a generic approach that can be applied to both tasks. As a knowledge source, we explore the use of WordNet (Fellbaum, 1998) for both the tasks and the specially designed TEMPROB (Ning et al., 2018a) for temporal relation classification. More specifically, we employ *low-dimensional* graph node embeddings learned on these knowledge graphs to capture crucial features of the graph topology and rich commonsense information. Thereafter, we propose simple methods to map mentions and events to knowledge graph nodes and disambiguate senses to obtain embeddings corresponding to them. We also tackle the case of the absence of knowledge from the graph. Once properly identified from the mention and event text spans, these low dimensional graph node embeddings are combined with contextual representations to provide enhanced mention and event representations. We illustrate the effectiveness of our approach by evaluating it on commonly used datasets for both tasks where significant accuracy improvements are achieved compared to standalone text-based representations

6.1 Introduction

Recall from the task definitions given in Section 2.1 that bridging anaphora resolution links bridging anaphors to corresponding antecedents and temporal relation classification determines temporal ordering between event pairs. To successfully solve these tasks, effective mention and event representation is essential, and commonsense information is critical to obtain such an effective representation.

Section 6.2 demonstrates the significance of commonsense information for effective representation and discusses challenges in integrating such knowledge in the bridging resolution and temporal relation classification systems. We first describe the importance of this information and motivate it by providing examples. We also review previously proposed approaches to acquire that information for both tasks. Next, we discuss challenges of incorporating such knowledge in the systems. The knowledge graphs used as an external knowledge source contain information over abstract concepts and entities, whereas mentions and events are linguistic units. This fundamental difference leads to challenges such as mapping mentions and events to graph nodes, disambiguating distinct senses due to mapping to multiple nodes, and tackling the instances of non-availability of knowledge.

Consequently, we propose solutions to these challenges in Section 6.3. We propose simple heuristics to map mentions and events to the graph nodes. Specifically, we remove modifiers or use the semantic head of the mention, and lemmatize events to *normalize* them. If this normalized form maps to multiple nodes in the graph then we use Lesk (Lesk, 1986) sense disambiguation algorithm or simple average over them, whereas in the case of mapping to no nodes i.e. absence of knowledge, we use the zero vector. This proposed approach is generic and can be applied to any knowledge graph. In this work, we specifically evaluate our approach over two knowledge graphs: WordNet and TEMPROB. We use WordNet to get lexical semantics such as hypernymy, hyponymy, meronymy, etc., and general relatedness between nodes, and TEMPROB to capture prior probabilities of temporal relations between verbs, specifically for temporal relation classification. We use various previously proposed graph node embedding algorithms to encode them such as random walk based embeddings (Goikoetxea et al., 2015), Path2vec (Kutuzov et al., 2019), matrix factorization based (Saedi et al., 2018) for WordNet and Uncertain Knowledge Graph Embeddings (UKGE) (Chen et al., 2019) for TEMPROB.

Next, we applied these approaches to obtain knowledge-aware mention representation for bridging anaphora resolution in Section 6.4. We combine knowledge graph embeddings with distributional text-based embeddings to produce improved mention representation. As pointed in Section 3.2.2, bridging anaphora resolution is commonly

considered as a classification problem. In this work, we take a different approach where we formulate bridging anaphora resolution as a ranking problem instead of classification perspective, for it to be less sensitive to class-imbalance, and making it focused on learning relative scores. Specifically, we train a ranking SVM model to predict scores for anaphor-candidate antecedent pairs, an approach that has been successfully applied to the related task of coreference resolution (Rahman and Ng, 2009). We observe that integrating node embeddings with text-based embeddings produces increased accuracy, substantiating the ability of graph node embeddings in capturing semantic information.

Afterwards, similar to knowledge-aware mention representation, we combine text-based representations and knowledge graph embeddings to produce knowledge-aware event representations for temporal relation classification in Section 6.5. We use current state-of-the-art (Wang et al., 2020) system based on RoBERTa (Liu et al., 2019b) embeddings and LSTMs (Hochreiter and Schmidhuber, 1997) to obtain text-based embeddings as well as for scoring temporal relations. We combine these text-based embeddings with graph node embeddings to improve event representation. Next, to train the neural model, a constrained learning objective that considers the accuracy of temporal relation predictions, as well as global temporal symmetry and transitivity constraint, is optimized. These constraints are applicable over temporal graph because of temporal algebra as described in Section 2.1.1.1. Further, we used Integer Linear Programming (ILP) inference to get globally coherent temporal relation predictions. Improvement in results over the use of *only* text-based embeddings also over a system with hand-engineered commonsense features, establishes the potency of our approach.

6.2 Commonsense knowledge

We refer commonsense as a broad knowledge that can not be *easily* acquired with only the given *linguistic context*. Thus, our definition of commonsense knowledge encompasses both linguistic and world knowledge. Linguistic knowledge can be any knowledge that is associated only with the linguistic units of the language. *Semantic knowledge* can be called a specific type of linguistic knowledge which involves semantic relations between words, phrases, or sentences meanings. For example, lexical relations such as synonymy, antonymy, hypernymy, etc. fall into this type of knowledge. On the other hand, *world knowledge* is broader information which is not specific to any language but shared by people. *Factual* or *encyclopedic* knowledge is a part of this kind of knowledge. For example, *Barack Obama was a president* is a world knowledge, independent of any language. Though making a clear distinction between linguistic knowledge and world knowledge is

difficult as different researchers define different boundaries to demarcate them (Ovchinnikova, 2012). In fact, commonsense knowledge is also a fuzzy term which can mean only *world knowledge* but in our work it refers to both linguistic and world knowledge.

Word embeddings like Word2vec (Mikolov et al., 2013a), Glove (Pennington et al., 2014), BERT (Devlin et al., 2019), etc. are considered to be capturing commonsense knowledge but only up to some extent (Chen et al., 2013; Da and Kasai, 2019; Ettinger, 2020; Talmor et al., 2020). Hence, various approaches have been proposed to enrich these unsupervised embeddings with commonsense knowledge contained by knowledge graphs. The proposed approaches can be broadly divided into two categories: 1. *Joint learning* of word embeddings with semantic constraints, and 2. Post-processing (retro-fitting) over unsupervised word embeddings.

Joint learning models put semantic lexicons as additional constraints while learning word embeddings. Many approaches fuse Word2vec with synonymy relations that reduce the distance between similar words (Liu et al., 2015; Yu and Dredze, 2014) whereas few approaches (Liu et al., 2018) also put constraints based on other lexical relations such as hypernymy-hyponymy relations from WordNet. Similar ideas have been applied over Glove by Bollegala et al. (2016), and Osborne et al. (2016). On the other hand, other models utilize similar words alternatively in the same context and learn models over the original and added context (Kiela et al., 2015; Niu et al., 2017). Recently, similar enhancements are also applied over BERT embeddings (Hao et al., 2020; Peters et al., 2019; Sun et al., 2020; Zhang et al., 2019b)

On the contrary to joint learning models, *post-processing* approaches take pre-trained word embeddings and retro-fit them with additional information. Faruqui et al. (2015) retrofit embeddings with information from WordNet with the addition of synonymy information, approaches like (Glavaš and Vulić, 2018; Mrkšić et al., 2016) go a step further and add antonymy information as well to increase the distance between dissimilar words. In addition to these relations, Vulić et al. (2017) leverage morphological information where they pull inflectional forms of the same word closer and push derivational antonyms farther.

So far, we mentioned approaches which produced generic word embeddings without focusing on solving any particular task. Now, we note a few approaches that learn representations with the addition of external knowledge to solve specific tasks. For instance, machine reading (Yang and Mitchell, 2017), Question Answering (QA) (Bauer et al., 2018; Sun et al., 2018), natural language inference (Chen et al., 2018), reading comprehension (Mihaylov and Frank, 2018; Wang and Jiang, 2019), and coreference resolution (Zhang et al., 2019a). In addition to these approaches, earlier approaches designed hand-crafted

features to inject commonsense knowledge into systems such as (Emami et al., 2018; Ovchinnikova, 2012; Rahman and Ng, 2011). Our approach too falls into this line of research where we inject commonsense knowledge to solve specific tasks.

The linguistic knowledge can be obtained from different sources. For lexical-semantic knowledge, WordNet (Fellbaum, 1998) is used extensively in NLP. In addition to WordNet, FrameNet (Ruppenhofer et al., 2006) and ConceptNet (Speer et al., 2018) are other popular semantic networks. FrameNet is based on *frame semantics* which briefly states that the meaning of the words can be understood from knowledge about the other related concepts. For example, meaning of the word *cook* is understood from *cooking frame* which contains other related concepts such as *food, bake, boil, apply heat*. FrameNet contains such 1200 frames containing more than 13000 words with different part-of-speech tags. In addition to that, it also contains semantic relations over frames. Other semantic network, ConceptNet consists of basic facts and understanding possessed by people. It contains more than 300,000 nodes and 1.6 million edges between them labeled by one of the 19 binary relations. ConceptNet is constructed by crowdsourced effort instead of manually creating it as opposed to WordNet and FrameNet.

In addition to these knowledge sources which contain semantic knowledge, knowledge graphs such DBPedia (Lehmann et al., 2015), YAGO (Hoffart et al., 2011) which are popular among many others contain generic world knowledge. DBPedia is an automatically created knowledge source by extracting factual information from Wikipedia pages and stored in a structured format. It contains all the information related to the entity present in Wikipedia pages, for instance, date of birth, place, occupation as well as a link to the Wikipedia page. YAGO is an another such knowledge base which possesses a collection of commonly known facts and information. It is also an automatically created knowledge base that uses a lot of other sources to build their knowledge such as Wikipedia, WordNet, Geonames, the Universal WordNet, and WordNet Domains. It contains knowledge of more than 17 million entities (like persons, organizations, cities, etc.) and more than 150 million facts about these entities.

Further, researchers have explored different sources other than knowledge graphs to acquire such commonsense knowledge like images (Cui et al., 2020; Li et al., 2019; Rahman et al., 2020), videos (Huang et al., 2018; Palaskar et al., 2019), or crowdsourced resources (Krishna et al., 2016). We use knowledge graphs among these sources, as they are specifically developed to hold world knowledge and are highly accurate in-comparison to other sources.

We discussed so far what we mean by commonsense knowledge, why it is needed for unsupervised word embeddings as well as for task-specific representation, and finally

we looked at different sources of linguistic and world knowledge. Now, we discuss why commonsense knowledge is important for event and mention representations.

6.2.1 Significance for effective representation

In Chapter 3 while discussing previously proposed work, we briefly talked about the significance of commonsense knowledge for temporal relation classification and bridging anaphora resolution. We further detail that here.

Temporal relation classification We have seen that temporal relation classification systems use tense, aspects or temporal markers to accurately predict temporal ordering between events. Sometimes, this information is not sufficient to make accurate predictions. More than these contextual clues, the system should be able to access the world knowledge which humans possess while reading the text. This is illustrated in the following examples:

(8) He graduated$_{e_1}$ with a computer science degree. He joined$_{e_2}$ a reputed software development firm.

(9) The government confirmed that 10 people died$_{e_3}$. The explosion$_{e_4}$ also damaged nearby homes.

In example 8, to establish temporal order between events e_1 and e_2, it is crucial to have commonsense information that *people generally join a firm after they graduate*. Similarly, in example 9, knowing that *people can die because of explosion* is useful in establishing precedence temporal relation between e_4-e_3.

Different approaches have been proposed to acquire such commonsense information for temporal relation classification systems. For better event-pair representations, D'Souza and Ng (2013) designed features based on WordNet and Webster dictionary. Specifically, they used four types of WordNet relations, namely hypernymy, hyponymy, troponymy, and synonymy to create eight binary features. A more advanced approach is taken by Ning et al. (2018a) by proposing TEMPROB knowledge source containing event verbs and prior probabilities of temporal relations between them. Ning et al. (2019, 2018a); Wang et al. (2020) used this knowledge source in their approaches. Ning et al. (2018a) used prior probabilities that are present in TEMPROB directly as one of the features in their system. Going away from this naive approach of injecting commonsense knowledge, Ning et al. (2019) trained Siamese network (Bromley et al., 1993) on the event pairs present in TEMPROB and their prior probabilities to produce embeddings for each verb in the graph. Next,

Wang et al. (2020) used a similar principle to acquire commonsense knowledge. They used partial relations from ConceptNet (Speer et al., 2018) in addition to TEMPROB knowledge. They selected few pairs from ConceptNet that possess "HasSubevent", "HasFirstSubevent", and "HasLastSubevent" relations as these relations encode temporal information. Then they trained two separate feed-forward networks, one over TEMPROB and the other over ConceptNet pairs, with contrastive loss to estimate the relations between these pairs. Once the models are trained verb embeddings are obtained from them and injected into their systems.

Bridging anaphora resolution Similar to temporal relation classification, commonsense information is crucial for bridging resolution. Standard text-based features either hand-crafted or automatically extracted from word embeddings (Mikolov et al., 2013a; Pennington et al., 2014), are not sufficient for bridging resolution (Hou, 2018b). The difficulty arises because, bridging indicates various relations between anaphor-antecedent pair for instance part-of relation, set relation, or many abstract relations. Consider the following examples:

(10) A car had an accident. **The driver** is safe, highway police reported.

(11) Starbucks has a new take on the unicorn frappuccino. **One employee** accidentally leaked a picture of the secret new drink.

In example 10, to establish bridging link between anaphor "The driver" and antecedent "a car", it is crucial to know that generally *a driver drives a vehicle* so "the driver" refers to "the driver of a car that had an accident" and not any other driver. On the same lines, in example 11, if the resolution system knows that *Starbucks* is a company and companies have employees, then it is easy to establish the link between "Starbucks" and "One employee".

Consequently, both rule-based, as well as machine learning-based systems for bridging resolution, have used external knowledge sources to get commonsense information. The rule based systems (Hou et al., 2014; Roesiger, 2018b) designed various rules by considering building parts to get part-of relation, job based rules to capture employee-employer relation, and meronymic relations from WordNet. The learning-based approaches (Hou et al., 2013a,b) also designed features with WordNet and Google queries (Poesio et al., 2004) to capture semantic relations. Recently, bridging-specific embeddings emb_pp (Hou, 2018b) were proposed by exploiting the preposition pattern (*X prep Y*) and possessive pattern (*X's Y*) of NPs. Her approach is better at capturing fine-grained semantics than *vanilla* word embeddings such as Word2vec (Mikolov et al., 2013a), Glove (Pennington

et al., 2014), etc. however, it still depends on the presence of the required noun-pairs in the corpus. The use of knowledge graphs, either manually or automatically constructed, can alleviate this problem as they contain general semantic and world knowledge.

All of these approaches, both for temporal relation classification as well as bridging resolution, extract only shallow features, capturing relations between pairs of nodes instead of taking advantage of broader information that is present in knowledge graphs. Moreover, attempting to extend these strategies to take into account a larger amount of information may translate into learning problems where the input space is of high dimension. It might be a hurdle especially in the case of bridging resolution due to moderate size datasets, for instance, ISNotes (Markert et al., 2012) and ARRAU (Uryupina et al., 2019) respectively contain 663 training pairs and 5512 training pairs. The only exceptions are approaches (Ning et al., 2019; Wang et al., 2020) proposed for temporal relation classification. They stand out among all previous approaches as they acknowledge the drawbacks of hand-designing features, therefore train models to get verb embeddings. But, their approach also captures shallow features as it only encodes pairwise relations so missing out on the information encoded by the whole graph topology.

6.2.2 Challenges in integration

We discussed in previous paragraphs that due to the limited capabilities of unsupervised word embeddings algorithms at acquiring commonsense knowledge various approaches have been proposed, some of the approaches were task-agnostic like (Faruqui et al., 2015; Peters et al., 2019; Sun et al., 2020), and some solved specific tasks (Bauer et al., 2018; Mihaylov and Frank, 2018; Sun et al., 2018; Wang et al., 2019). Our approach falls into the latter category where we use knowledge graphs specifically to solve the tasks. There lie some challenges in incorporating such knowledge from knowledge graphs. Though these challenges are generic and can be faced by any NLP system trying to inject knowledge from graphs, we focus our discussion on the challenges with respect to the tasks at hand: bridging anaphora resolution and temporal relation classification.

Integration with linguistic information Integrating knowledge held by knowledge graphs into NLP systems is not straightforward (recall the discussion in Section 2.6.2). Because the information in the knowledge graph is stored in a structured way whereas text is relatively unstructured [1]. Generally, knowledge graphs encode information in the form of triplets:

[1] We call text unstructured data only in the sense that it's not stored in pre-defined format, models, or schema, nor it is easy to process or analyze.

(h, r, t) where the head(h) and tail(t) are nodes and r denotes relation between them[2]. In addition to this, the topology encodes crucial information because of the connection between different nodes either directly or through other nodes. This whole information should be captured effectively and injected into the machine learning systems.

Event/Mention normalization The knowledge graph contains information about certain entities, for example, WordNet is a lexical knowledge graph containing different senses of words. This means we first have to normalize event or mention to a corresponding entity so that information about it might be present in the knowledge graph. Then the entity is used to acquire corresponding knowledge from the graph. However, it is tricky to get an entity from a given mention as a mention may contain words like quantifiers, prepositions, or modifiers in addition to the entity. Consider mentions like *the wall*, *one employee*, *beautiful lady* or *the famous scientist Einstein* which can not be matched with the entity in the graph. These should be normalized to *wall*, *employee*, *lady* and *Einstein*, respectively. Similarly, this issue exists in the case of events as well. Albeit, it is less severe, as they are are mostly verb phrases and contain only verbs with inflections (e.g. said, calling, reported). Though there are some cases of events being noun phrases, for instance *holy war*, *deadly explosion* which should be respectively mapped to *war*, *explosion*, they are relatively fewer.

Word sense disambiguation Once the event or mention is normalized, this normalized token can map to multiple entries in the knowledge graph, as the same word can possess different meanings, *senses*, or refer to multiple real world entities. This issue is pervasive over all the knowledge graphs, hence needs to be addressed irrespective of which graph is used. For example, in the case of mentions, *bank* can refer to *an institution related to finance* or *the land alongside river*, *Michael Jordan* can refer to *the scientist* or *the basketball player*. On the other hand, event verbs such as *book* can refer to *reserving tickets* or *recording a charge in police register*, *fall* can mean *descend* or *precipitate*. The different senses possess different knowledge, in other words different local structures in the graph. Thus, recognizing the correct sense is crucial to get the accurate information.

Absence of knowledge The opposite situation of the previous case is an absence of any node corresponding to the normalized event or mention. This can happen due to the inherent limitation of the knowledge graph or normalization error. It is crucial to handle these situations gracefully.

[2]There can be additional information as in TEMPROB where for an edge its strength is also added.

Choice of knowledge graph One of the least challenging but important aspect is a choice of the knowledge graph. As mentioned in earlier paragraphs, different knowledge graphs contain different information. So in a way, it becomes crucial to choose a knowledge graph that contains relevant information. One simple criterion for knowledge graph selection is to assess how many events or mentions can be mapped to the graph nodes. Then to select a knowledge graph which contains a higher percentage of event or mention mappings. Another aspect of this discussion is the use of multiple knowledge graphs to acquire commonsense information. Because required commonsense knowledge can be present in different knowledge graphs, it is prudent to use them all. In this case, the burden of selecting relevant knowledge falls onto the learning system instead of the designer of the system.

6.3 Our approach

We detail our approach for solving these challenges in the coming sections. First, we specify our approach of representing knowledge and specific knowledge graphs used in our work (Section 6.3.1). Then we describe simple rules used to normalize events and mentions to map to graph nodes (Section 6.3.2). Next, we proposed simple heuristics for the case of presence of multiple nodes (Section 6.3.3) or the absence of any node (Section 6.3.4) in the knowledge graph corresponding to these normalized tokens.

6.3.1 Knowledge graphs: WordNet and TEMPROB

To obtain external knowledge, we used WordNet (Fellbaum, 1998) for both tasks and TEMPROB (Ning et al., 2018a) specifically for temporal relation classification. As mentioned earlier, integrating the knowledge encoded by these graphs into machine learning systems is not easy. One of the naive ways of capturing information present in knowledge graphs is to design features or by executing queries over them. But these are inefficient approaches and do not capture the holistic information present in the graph. To remedy that, graph node embeddings were proposed to acquire the local and global structure of the graph effectively, as discussed in Section 2.6.2. Similarly, graph node embeddings learned over knowledge graphs can capture the encoded knowledge effectively. Therefore, here we learn graph node embeddings over WordNet and TEMPROB and use them in our systems.

In the following paragraphs, first, we briefly review WordNet, and then summarize different graph node embedding algorithms used over it, followed by a similar discussion on TEMPROB.

6.3.1.1 WordNet

As previously described in Section 2.6.1.1, WordNet (Fellbaum, 1998) primarily consists of *synsets*, i.e., a set of synonyms of words. The *synsets* which refer to the same concept are grouped together giving it a thesaurus-like structure. Each *synset* consists of its definition and small example showing its use in a sentence. The *synsets* are connected with different relations such as synonymy, antonymy, hypernymy, hyponymy, meronymy, etc. In addition, it also includes relations between real world entities like cities, countries, and famous people. This semantic information is already shown to be effective for bridging and temporal relations, which makes WordNet obvious choice for the tasks. Subsequently, the node embeddings learned on this graph automatically capture the commonsense information associated with the senses.

Now, we discuss different node embedding algorithms that are used to encode WordNet in our study. These algorithms are not specially designed for WordNet but have been proven to be effective at producing representations over it. We use random walk and neural language model based embeddings (RW) (Goikoetxea et al., 2015), matrix factorization based embeddings (WNV) (Saedi et al., 2018), and graph-similarity based Path2vec (Kutuzov et al., 2019) embeddings. These embeddings differ in learning strategies and more importantly the way different graphs are constructed over WordNet by varying types of either nodes or edges. For instance, different graphs can be constructed by considering actual synsets as nodes or corresponding words as nodes, similarly, in the case of edges, either by considering semantic relations between nodes or ignoring these relation labels. Because of these differences in graph constructions, the first two algorithms, RW and WNV, produce *word* embeddings whereas Path2vec produces embeddings corresponding to each *synset* present in WordNet. Because, RW and WNV conflate all the senses where they first map them to words, and then learn embeddings over words, thus lose finer semantic information in the process. But on the upside, they relieve the burden of sense disambiguation because now the mapping from events or mentions is to words and not to individual senses.

RW The approach proposed by Goikoetxea et al. (2015) is based on the well-known neural language model CBOW and Skip-gram (Mikolov et al., 2013c) which we described in Section 2.4.1.1. The main idea is to produce artificial sentences from WordNet and to apply the language models on these sentences to produce word embeddings. For this, they perform random walk starting at any arbitrary vertex in WordNet, then map each WordNet sense to the corresponding word to produce an artificial sentence. Each random walk produces a sentence, repeating this process several times gives a collection

of sentences. Finally, this collection of sentences is considered as the corpus for learning word embeddings by applying the same objective function as in Mikolov et al. (2013c).

WNV A different approach based on matrix factorization is taken by (Saedi et al., 2018) to produce these embeddings. The procedure starts by creating the adjacency matrix M from WordNet graph. The element M_{ij} in the matrix M is set to 1 if there exists any relation between words w_i and w_j. [3] Furthermore, words which are not connected directly but via other nodes should also have an entry in the matrix, albeit with lower weights than 1. Accordingly, a matrix M_G is constructed to get the overall affinity strength between words. In the analytical formulation, M_G can be constructed from the adjacency matrix M as $M_G = (I - \alpha M)^{-1}$ where I is the identity matrix and $0 < \alpha < 1$ decay factor to control the effect of longer paths over shorter ones. Following that, matrix M_G is normalized to reduce the bias towards words that have more number of senses and finally a Principal Component Analysis is applied to get vectors.

Path2vec Path2vec (Kutuzov et al., 2019) learns embeddings based on a pairwise similarity between nodes. The fundamental concept is that pairwise similarity between nodes of the graph should remain the same after their projection in the vector space. The model is flexible enough to consider any user-defined similarity measure while encoding. The objective function is designed to produce such embeddings for nodes which reduce the difference between actual graph-based pairwise similarity and vector similarity. It also preserves the similarity between adjacent nodes. Formally, for the graph $G = (V, E)$ where V, E denote a set of vertices and edges, respectively, the objective is:

$$\sum_{(a,b)\in V} \min_{\mathbf{v}_a,\mathbf{v}_b} \left((\mathbf{v}_a^T\mathbf{v}_b - s(a,b))^2 - \alpha(\mathbf{v}_a^T\mathbf{v}_n + \mathbf{v}_b^T\mathbf{v}_m)\right)$$

where n, m are adjacent nodes of nodes a, b respectively, $s(a,b)$ is the user-defined similarity measure between a, b and $\mathbf{v}_a, \mathbf{v}_b, \mathbf{v}_n, \mathbf{v}_m$ denote the embeddings of a, b, n, m, respectively. In their experiments, to show the ability of their model in adapting to different pairwise similarity measures, similarity function $s(a,b)$ is obtained with four distinct similarity measures: Leacock-Chodorow (Leacock and Chodorow, 1998); Jiang-Conrath (Jiang and Conrath, 1997); Wu-Palmer (Wu and Palmer, 1994); and Shortest path (Lebichot et al., 2018).

[3] They also experimented by weighting relations differently (e.g. 1 for hypernymy, hyponymy, antonymy and synonymy, 0.8 for meronymy and holonymy and 0.5 for others) but obtained the best results without weighting.

6.3.1.2 TEMPROB

In addition to WordNet, specifically for temporal relation classification, we explored the use of temporal information specific knowledge source: TEMPROB (Temporal relation probabilistic knowledge base) (Ning et al., 2018a). Though a detailed description of TEMPROB is given in Section 2.6.1.2, we quickly review it here. TEMPROB contains specific prior temporal knowledge. The knowledge is stored in the form of quadruples: $(u, v, r, f_{u,v,r})$ where u, v are semantic verb frame pairs, r is any temporal relation from set R containing temporal relations *after, before, includes, included,* and *undef (vague)*, and $f_{u,v,r}$ is the frequency of temporal relation r appearing between u, v. This frequency is measured as the number of times the classifier trained while constructing TEMPROB has predicted relation r for pair u, v on the corpus (1 million NYT articles). Also, recall that u, v are not verbs but semantic verb frames and there can be multiple semantic verb frames corresponding to a verb depending on its meaning, for instance, verb *sew* has multiple frames such as *sew.01*, *sew.02*, and more, depending on whether it is used for stitching *clothes*,*wounds*, or in another sense.

We observed that while constructing TEMPROB, verb pairs are selected as they appeared in the documents, so there are different valued edges between u, v and v, u. We aggregated them for *inverse* temporal relation pairs, *after–before, includes–included, equal–equal,* and *undef–undef*. We kept only one pair u, v and calculated frequency for relation r by adding the frequency of r as well as r' (inverse relation) as $f_{u,v,r} \leftarrow f_{u,v,r} + f_{v,u,r'}$. After that we converted these frequencies for each relation into probability with a softmax function:

$$p_{u,v,r} = \frac{e^{-f_{u,v,r}}}{\sum_{\hat{r} \in R} e^{-f_{u,v,\hat{r}}}} \tag{6.1}$$

Then, TEMPROB graph is modified to store quadruples containing these probabilities in-place of frequencies as $(u, v, r, p_{u,v,r})$. This modified graph is further used for obtaining node embeddings.

Uncertain Knowledge Graph Embeddings (UKGE) We used the UKGE (Chen et al., 2019) embedding algorithm to obtain TEMPROB node embeddings. The primary reason is that UKGE learns embeddings over a graph containing probabilistic (weighted) relations between nodes, while the previously proposed algorithms can only learn over deterministic edges. The graph considered in this algorithm is of the form $G = (V, E, R)$ containing set of vertices V, edges E, and relations R where $E = \{(l, s_l) | l = (h, r, t), h, t \in V, r \in R, 0 \leq s_l \leq 1\}$. It is the same as modified TEMPROB graph. The algorithm learns low-dimensional embeddings for h, t and r similar to translational models TransE (Bordes et al., 2013) such

that the predicted score between triplet (h, r, t) will be closer to the true score s_l. This is the core working of UKGE algorithm. Besides, in addition to the given links, UKGE also deduces new links with *soft logic* from the given (seen) links. Subsequently using them to train the model by calculating the training loss on both seen and deduced links. But while applying UKGE on TEMPROB, we did not deduce any new links and relied only on the seen links. Because TEMPROB contains edges which are obtained from the temporal relation classifier which is inherently error-prone, and by inferring new edges from these links can lead to further propagation of errors. Finally, the modified loss which is optimized to produce TEMPROB node embeddings is given as:

$$\mathscr{L}(\theta) = \sum_{(l,s_l)\in E} |f_c(l;\theta) - s_l|^2 \tag{6.2}$$

where $f_c(l;\theta)$ is the θ-parameterized confidence score based on the learned vector representations $\mathbf{h}, \mathbf{t}, \mathbf{r} \in \mathbb{R}^d$ as $f_c(l;\theta) = \psi(g(\mathbf{r} \cdot (\mathbf{h} \odot \mathbf{t})))$ such that $\cdot$ denotes inner product, $\odot$ denotes element-wise multiplication, and $\psi : \mathbb{R} \rightarrow [0, 1]$. The vectors $\mathbf{h}, \mathbf{t}$ are encoded with same function of the form $f_n : V \rightarrow \mathbb{R}^d$ to produce representations corresponding to nodes of the graph. Consequently, once the model is trained, function f_n is applied over nodes to get corresponding graph node embeddings.

6.3.2 Normalization: Simple rules and lemma

Mention normalization. A mention can be a phrase containing multiple words, and from these words we have to obtain an entity that can be mapped to the node in the graph or a key of the dictionary that contains knowledge graph embeddings. We propose to normalize them into a single word with the use of simple rules. For this, as a first step, we remove articles and commonly used quantifiers like *the, a, an, one, all* etc. from the mention. If we find an entry in the knowledge graph with this modified word then we get the corresponding embeddings, otherwise, we go a step further and extract the *head* of the mention and try to obtain embeddings for it. Specifically, we use the parsed tree of the mention, and Collins' head finder algorithm (Collins, 2003) to get the syntactic head. Recall the discussion from Section 5.4 where we discussed that the syntactic head approach fails for *coordinated* NPs (NPs containing coordinating conjunctions like *and*), therefore we used the semantic head in these cases which are obtained with Stanford CoreNLP toolkit (Manning et al., 2014).

Event normalization Though events could be phrases (verbs or nominals), the dataset is already annotated with headword of events. For instance, "the deadly explosion" phrase

is marked with headword "explosion", "holy war" as "war". As a result, the process of normalizing events is much simpler than mention normalization. We use this headword of event to map to the node in graph. For that, we obtain a lemma of the headword while considering its part-of-speech tag. This is especially useful in the case of verbs as they are inflected with suffixes such as *-ing, -ed*.

6.3.3 Sense disambiguation: Lesk and averaging

Once events and mentions are normalized to a single token[4], the string matching is done to map to graph nodes. This can yield multiple nodes for a single normalized token or no node at all. The case of multiple nodes arises due to multiple senses of the word. Now, we describe the solution for the case of multiple nodes and in the next section for the absence of any node. We devise different strategies depending on the kind of graph embeddings used.

Lesk We use Lesk algorithm (Lesk, 1986) to select an appropriate sense for a word depending on its context. A simplified variation of Lesk applied specifically to disambiguate senses present in WordNet relies on the corresponding definitions of senses contained in WordNet. It calculates the overlap between the context of the word and the definition of the sense by simply measuring the number of common words, and chooses a sense which has the highest number of matching words from the senses.

Averaging of all senses A simple heuristic to obtain all possible senses corresponding to a token and instead of narrowing down the sense of the word is to take an average over the embeddings of all these senses. We use this as an alternative to the above strategy.

Token matching If the embeddings are generated for the words instead of *actual nodes* (senses in case of WordNet) graph then there is no question of sense disambiguation. This is true in two of the graph node embeddings algorithm we used: RW and WNV. These embeddings internally map synsets to the words, creating a graph over words from WordNet and produce embeddings over these words itself. As a consequence, in these cases, the need for sense disambiguation disappears and with simple string matching, knowledge graph embeddings can be obtained.

[4]This is even true for the cases where, ideally we should get multiple tokens. For example, in the cases of named entities having multiple tokens like Hong Kong, Los Angeles are still mapped to a single token. We discuss these cases in the error analysis (Section 6.4.5.1).

6.3.4 Absence of knowledge: Zero vector

The opposite situation of mapping to multiple senses is mapping to no node at all. This might happen because of the inherent limitation of the knowledge graph or some normalization error. Consequently, it leads to the unavailability of the corresponding node embeddings. To tackle this, we use the zero vector of the same dimensions.

6.4 Improved mention representation for bridging resolution

So far, we have discussed the challenges of injecting commonsense knowledge and described our proposed approaches to solve them. Now, we apply these methods for improving mention representation by integrating commonsense knowledge. In Section 6.4.1, we detail our approach to obtain knowledge-aware mention representation which combines both text and commonsense information. Next, we describe our ranking model based on SVM and inference strategy in Section 6.4.2. Further, Section 6.4.3 describes our experimental setup and Section 6.4.4 presents results over various datasets. Lastly, error analysis is presented in Section 6.4.5.

6.4.1 Knowledge-aware mention representation

We propose a new, knowledge-aware mention representations for bridging resolution. These representations combine two components: (i) distributional embeddings learned from raw text data, and (ii) graph node embeddings learned from relational data obtained from a knowledge graph. Specifically, the final representation $\mathbf{m_i}$ for a mention m_i is obtained by concatenating the text-based contextual embeddings $\mathbf{g_i}$ and the knowledge graph node embeddings $\mathbf{h_i}$: $\mathbf{m_i} = \mathbf{g_i} \oplus \mathbf{h_i}$.

For the distributional embeddings $\mathbf{g_i}$, we use off-the-shelf word embeddings such as Word2vec (Mikolov et al., 2013a), Glove (Pennington et al., 2014), BERT (Devlin et al., 2019), or embeddings_pp (Hou, 2018b). Except for BERT, we average over embeddings of the mention's head word and common nouns appearing in the mention before the head, as mentioned in Hou (2018a). With BERT, mention embeddings are obtained by averaging over embeddings of all the words of the mention.

Whereas, for knowledge graph node embeddings $\mathbf{h_i}$ we use strategies described in the previous section. Briefly, we first normalize mentions, then map them to nodes in the

knowledge graph, use sense disambiguation strategies in the case of multiple mappings, and use the zero vector for no mapping.

6.4.2 Ranking model

Let $\mathscr{D}$ be the given document containing set of mentions, $\mathscr{M} = \{m_1, m_2, \cdots, m_{n_m}\}$, and $\mathscr{A} = \{a_1, a_2, \cdots, a_{n_a}\}$ be the set of all anaphors such that $\mathscr{A} \subset \mathscr{M}$. Let a be any anaphor in the set $\mathscr{A}$ and j be its position in the set $\mathscr{M}$, then E_a be the set of antecedent candidates for a which is defined as $E_a = \{m_i : m_i \in \mathscr{M}, i < j\}$. Let T_a and F_a be the set of true antecedents and false antecedent candidates of a such that $T_a \cup F_a = E_a$, $T_a \cap F_a = \emptyset$. Let $\mathbf{a}$ be the knowledge-aware represention of a, and $\mathbf{e}$ be the representation of $e \in E_a$. Then the goal is to predict a score $s(\mathbf{a}, \mathbf{e})$ between anaphor a and antecedent candidate e such that this score for true antecedent is higher than the wrong one. The score denotes the possibility of anaphor a having bridging relation with the antecedent candidate e, so a higher score denotes a higher chance of e being true antecedent.

The model is trained to reduce the ranking loss calculated based on the scores obtained between anaphor-antecedent candidates. The ranking strategy is fairly obvious: for an anaphor a high scoring antecedent candidate from E_a is ranked higher than the low scoring one. Let this prediction ranking strategy be r' and true ranking is given by r^*. For an antecedent candidate, if the predicted rank is not same as the true rank then it is called discordant candidate, otherwise concordant. The difference between true and predicted ranking strategy can be measured with Kendall's rank correlation coefficient: τ. Formally, concordant C, discordant D candidates and τ are defined as:

$$C = \sum_{(t,f)\in(T_a \times F_a)} \mathscr{I}_{s(\mathbf{a},\mathbf{t})>s(\mathbf{a},\mathbf{f})}\ , \quad D = |T_a \times F_a| - C \quad and \quad \tau(r^*, r') = \frac{C-D}{C+D}$$

where $\mathscr{I}$ is an indicator function which takes value 1 if $s(\mathbf{a}, \mathbf{t}) > s(\mathbf{a}, \mathbf{f})$ else 0, $\mathbf{t}, \mathbf{f}$ are knowledge-aware mention representations of t, f, respectively, and $|\cdot|$ denotes cardinality of the set. The empirical ranking loss (Joachims, 2002) captures the number of wrongly predicted ranks which is given as:

$$\mathscr{L} = \frac{1}{n_a} \sum_{i=1}^{n_a} -\tau(r_i^*, r_i')$$

Inference We consider all the anaphors in the test document separately. For each anaphor, we consider all previously occurring mentions as antecedent candidates and find out the compatibility score for each anaphor-antecedent candidate pair with the

above ranking model. We choose highest scoring antecedent candidate as the predicted antecedent. Formally, let a be any anaphor and E_a denote a set of antecedent candidates for a. Let $s(\mathbf{a}, \mathbf{e})$ be the score between a and e where $e \in E_a$. Let $\hat{e}_a$ be the predicted antecedent of a which is given as: $\hat{e}_a = argmax_{e \in E_a} s(\mathbf{a}, \mathbf{e})$

6.4.3 Experimental setup

Data We used ISNotes (Markert et al., 2012), BASHI (Roesiger, 2018a) and ARRAU (Uryupina et al., 2019) datasets for experiments. ISNotes and BASHI consist of 50 different OntoNotes documents, containing 663 and 459 anaphors, respectively. The BASHI dataset annotates *comparative* anaphors as bridging anaphors which are 115 in numbers, remaining are *referential* anaphors. Following the setup from Hou (2020a), we only consider 344 referential bridging anaphors in this work as well from the BASHI dataset.

In the experiments over ISNotes and BASHI datasets, we implemented nested cross-validation to select the best hyperparameter combination. The setup is: first we make 10 sets of train and test documents containing 45 and 5 documents respectively with 10-fold division. Then at each fold, 45 training documents are further divided into 5 sets of 36-9 actual training and development documents. Each hyperparameter combination is trained on these 5-sets and evaluated. The highest averaged accuracy over the 5-sets of development documents gives the best hyperparameter combination. Once the best hyperparameter setting is obtained the SVM model is re-trained over 45 documents (36+9). For each fold number of accurately linked anaphors is calculated. The accurately predicted number of anaphors over each fold is added to get the total number of accurately linked anaphors from the complete dataset. Thus, the system is evaluated by the accuracy of predicted pairs (Hou, 2020a).

For ARRAU dataset, the results are separately reported over different genres present: RST (news articles), PEAR (stories) and TRAINS (dialogues). We followed the similar setup on these datasets as previous studies (Roesiger, 2018b; Yu and Poesio, 2020). In that, different experimental setup is used for each genre: RST dataset is relatively big and there is train, dev, and test partition of dataset so model is trained on train while hyperparameters are tuned with respect to dev and finally evaluated on test. The samples for PEAR and TRAINS are small so for training 10-cross validation is done on train/dev set and final result is reported on test set.

For the training data, we have positive samples where we know true anaphor-antecedent pairs but no negative samples. We generate these pairs by considering all the noun phrases (NPs) which occur before the anaphor in the window of some fixed number of sentences. All the mention pairs which do not hold bridging relations are considered as negative

samples for training. Similarly, at the test time, for an anaphor, all the previous mentions in the window size are considered as antecedent candidates. Only the limited number of antecedent candidates are used instead of all, because in ISNotes 77% of anaphors have antecedent either in the previous two sentences or the first sentence of the document. So, considering all the previous mentions (without the restriction of window size) could result in way more false antecedent candidates and could lead to performance degradation. Though we use window size to restrict antecedent candidates, the window size is treated as a hyperparameter and the best value is chosen depending on the validation accuracy. The list of values are mentioned in the following section.

Implementation We obtained pre-trained 300-dimensional Word2vec (Mikolov et al., 2013a), 300-dimensional Glove (Pennington et al., 2014), 768-dimensional BERT (Devlin et al., 2019) and 100-dimensional embeddings_pp (Hou, 2018b) embeddings. For BERT, we specifically used spanBERT (Joshi et al., 2020) variation to get embeddings in our experiments as it gave better results for Hou (2020a). Also, we used pre-trained WordNet embeddings provided by respective authors of RW (Goikoetxea et al., 2015), WNV (Saedi et al., 2018), and Path2vec (Kutuzov et al., 2019). In the case of Path2vec (Kutuzov et al., 2019), 300-dimensional embeddings learned with different similarity measures such as: Leacock-Chodorow similarities (Leacock and Chodorow, 1998); Jiang-Conrath similarities (Jiang and Conrath, 1997); Wu-Palmer similarities (Wu and Palmer, 1994); and Shortest path similarities (Lebichot et al., 2018), are provided. We experimented with all the four similarity measures and found out that the shortest path based similarity measure produced better results most of the time, so used those embeddings in the experiments. We used the Python implementation of Lesk from *nltk*[5] library to select the best sense from multiple senses of the mention. Two sentences previous to mention, two sentences after the mention, and the sentence in which the mention occurs are given to this algorithm as a context for a mention.

Both anaphor and antecedent candidate's embeddings are obtained as mentioned above, afterwards, element-wise product of these vectors is provided to the ranking SVM. We also did preliminary experiments with the concatenation of the vectors but element-wise product gave better results. We used SVM^{rank} (Joachims, 2006) implementation for our experiments. In the experiments with SVM, we did grid search over C = 0.001,0.01,0.1,1, 10,100 with the use of the *linear* kernel. We also use the *random fourier features (rff)* trick proposed by Rahimi and Recht (2008) to approximate non-linear kernels. We found that the use of non-linear kernels slightly improved results in comparison to linear kernels so

[5]https://www.nltk.org/_modules/nltk/wsd.html

we reported only those results. We also varied different widow sizes of sentences: 2,3,4 and all previous sentences, in addition to NPs from the first sentence (salience), to get antecedent candidates for an anaphor. Out of these settings, the window size of 2 and salience have yielded the best results which are reported here.

6.4.4 Results

Comparison between distributional and graph embeddings is shown in Table 6.1 of our experiments section. Each section summarizes the results over datasets used in the experiment: ISNotes (Markert et al., 2012), BASHI (Roesiger, 2018a), ARRAU: RST, PEARS, and TRAINS (Uryupina et al., 2019). The first row corresponding to each dataset section shows the results with only text-based embeddings. We observe that on ISNotes, BASHI, and RST datasets the best performance is obtained with the use of BERT embeddings showing the efficacy of these embeddings when only one type of text-based embeddings is used (underlined values in these sections). It shows that the context of the mention plays an important role in resolving bridging anaphora, corroborating our observation from Chapter 5. In the case of ISNotes and BASHI, the second best scores with *only* text-based embeddings are obtained with embeddings_pp which are specially designed embeddings for the task. But this is not true for RST, the reason might be the difference of bridging types. Because embeddings_pp was designed for ISNotes which contains different annotations than RST. We also observe further improvement in the results when two best performing text-based embeddings: BERT and embeddings_pp are combined (noted as BEP [6] in the Table).

However, these observations do not hold in the case of PEAR and TRAINS datasets as the performance with BERT degrades drastically in comparison to distributional embeddings such as Word2vec or Glove. The best score with *only* text-based embeddings is obtained with Word2vec for both the datasets. The primary reason is probably the small size of these datasets in comparison to RST. TRAINS contains 98 documents whereas PEAR contains 20 relatively small compared to 413 documents in RST. This might be leading to the over-fitting of the learning model because of bigger BERT feature dimensions. This reasoning conflicts with the work (Yu and Poesio, 2020) where they used BERT successfully in their experiment over PEAR and TRAINS dataset. But the difference between their system and ours is of fine-tuning. We relied on the pre-trained BERT because of small training dataset whereas they fine-tuned BERT specifically for bridging resolution by leveraging the extra training data from coreference resolution with multi-task setup in their system.

[6] We combine BERT and embeddings_pp embeddings by concatenating both the vectors

Data		**Our Experiments**						**SOTA**	
		WV	GV	BE	EP	BEP	–	SYS	ACC
ISNotes	–	25.94	27.60	32.87	31.08	37.10	-	PMIII	36.35
	+ PL	26.40	28.61	34.39	31.81	43.87*	20.06	MMII	41.32
	+ PA	24.74	30.92	33.18	33.24	39.82*	19.53	EB	39.52
	+ RW	27.75	27.6	34.12	33.24	**46.30***	22.06	MMEB	46.46
	+ WNV	21.71	25.13	31.69	26.80	33.28	17.64	BARQA	50.08
BASHI	–	22.92	17.48	31.23	28.51	33.52	-	PMIII	-
	+ PL	30.95	21.49	35.53	29.26	36.68*	16.44	MMII	-
	+ PA	24.07	19.2	35.24	29.48	**38.94***	17.62	EB	29.94
	+ RW	26.64	18.91	34.38	28.91	38.83*	15.75	MMEB	-
	+ WNV	20.92	18.05	26.36	21.20	27.80	12.97	BARQA	38.66
RST	–	34.62	34.74	35.68	30.75	44.8	-	PMIII	-
	+ PL	38.36	33.84	41.11	37.83	48.06*	30.42	MMII	-
	+ PA	40.62	38.42	42.44	37.01	48.81*	31.7	EB	-
	+ RW	39.6	34.95	36.87	33.72	**49.28***	29.54	RULE	39.8
	+ WNV	34.59	33.35	36.17	28.83	41.54	22.98	MULTI	49.3
PEAR	–	42.09	40.6	21.95	20.9	21.95	-	PMIII	-
	+ PL	44.9	41.35	26.03	24.63	22.69	34.01	MMII	-
	+ PA	49.56	48.23	26.87	27.62	24.93*	34.57	EB	-
	+ RW	**54.53***	51.24	12.69	26.95	24.18*	38.13	RULE	48.9
	+ WNV	36.87	32.09	24.03	30.06	22.45	16.39	MULTI	50.9
TRAINS	–	37.92	34.26	15.68	29.86	16.42	-	PMIII	-
	+ PL	43.29	34.33	21.65	37.32	22.39	28.79	MMII	-
	+ PA	41.05	42.54	18.66	39.56	22.39	28.52	EB	-
	+ RW	39.56	**44.78***	26.87	36.72	19.81	25.94	RULE	28.2
	+ WNV	34.33	37.32	15.68	28.36	21.79	20.78	MULTI	61.2

Table 6.1 Results of our experiments and state-of-the-art models over popular bridging datasets: ISNotes, BASHI, ARRAU: RST, PEAR, TRAINS. In **Our Experiments** section, we present results for different text-based embeddings: Word2vec (WV), Glove (GV), BERT (BE), embeddings_pp (EP), BERT + embeddings_pp (BEP) and the last column – shows the absence of text-based embeddings. Also, in each row except the first row, WordNet node embeddings based on different algorithms, are added: Path2vec with Lesk (PL), Path2vec with averaged senses (PA), random walk based (RW) and WordNet embeddings (WNV). The bold-faced figures denote highest score over respective dataset and underlined figures indicate best scores only with the use of single text-based embeddings. **SOTA** section of the table shows results with previously proposed systems: Pairwise Model III (PMIII), MLN model II (MMII) (Hou et al., 2013b), embeddings_bridging (EB) (Hou, 2018a), the combination of embeddings_bridging and MLN model (MMEB) and the latest system, BARQA (Hou, 2020a). These previously proposed approaches do not have results over ARRAU, so compared with rule based (RULE) (Roesiger, 2018b) and multitask (MULTI) learning approach (Yu and Poesio, 2020). The results with $*$ are statistically signficant in comparison to the results based only on text embeddings with p-value $< 10^{-4}$ with McNemar's test and Wilcoxon signed-rank test.

The following rows (2-4) of Table 6.1 show the results obtained with the addition of WordNet information with different embeddings algorithms: Path2vec (PL and PA), random walk based embeddings (RW) and matrix factorization based embeddings (WNV). The results from these rows in comparison with the result from the first row prove the effectiveness of the external information and substantiates our claims. [7] Interestingly, it also shows that BERT though trained on a huge unlabeled corpus is not inherently efficient at capturing commonsense knowledge required for bridging anaphora resolution. Consequently, validating our claims done with qualitative analysis from the previous chapter. Moreover, external information seems to be complementing embeddings_pp embeddings which are custom tailored for bridging tasks, further consolidating our claims. Further, in each row of the second last column of the table, results obtained by combining external information with BERT embeddings and embeddings_pp show that even the best performing text-based embeddings can still benefit from the external information. We see a similar trend over other datasets as well when we compare results from first row of each dataset section with the rows 2-4.

Comparison between different WordNet embeddings We first examine the effectiveness of external knowledge without any text-based embeddings. These scores are noted in the last column of our experiments section against each WordNet graph node embeddings. The overall lower scores in this column in comparison with text-based embeddings reveal that the features learned with WordNet embeddings are not solely sufficient and should be complemented with the contextual features. Next, we compare results from Path2vec Lesk (PL) with Path2vec average (PA) to see which strategy of disambiguation is effective. But the observations are not conclusive, as in some cases the performance with the use of averaging strategy is better than choosing the best sense with Lesk. The reason is that Lesk is a naive algorithm which considers overlapping words in the context to get the best sense. Further, we consider results from averaged embedding over senses (PA) for comparing Path2vec with the other two embeddings as it is the closest analogous setting to correlate. This comparison shows that there is no best algorithm amongst these WordNet embeddings as sometimes we get better results with Path2vec and sometimes with RW embeddings. This result is surprising as even after losing some semantic information, RW

[7] But with the exception with the addition of WNV. Because, results with WNV are mostly inferior in comparison with only text-based embeddings. Lower coverage for WNV, around 65% as opposed to 90% for the other two embeddings as only 60,000 words were present in pre-trained WNV embeddings, might be the possible reason. Also, the vector dimension is significantly higher: 850 in comparison to 300 for the other two.

produces competent results compared to Path2vec. This might be happening because of errors in sense disambiguation with Path2vec (detailed explanation in Section 6.4.5.1).

Comparison with previous studies The results of different state-of-the-art systems on all the datasets are presented in SOTA section of Table 6.1. We compare our results over ISNotes and BASHI dataset with results obtained with Pairwise Model III (PMIII) and MLN model II (MLNII) that are proposed by Hou et al. (2013b), embeddings_bridging (EB) and EB with MLN model (MMEB) by Hou (2018a), and latest system BARQA (Hou, 2020a). Results from these systems are not available over RST, PEAR, and TRAINS datasets so we considered rule based system proposed by Roesiger (2018b) and multi-task learning system of Yu and Poesio (2020).

We observe that on ISNotes dataset, our model's performance is better than rule-based approaches from Pairwise Model III and MLN model II (Hou et al., 2013b), embeddings_bridging based deterministic approach from Hou (2018a) and competitive in comparison with the combination of MLN model and embeddings_bridging but lags to BARQA model. The reason might be that MLN model combines hand-crafted rules in addition to carefully crafted embeddings. On the other hand, BARQA system is trained on additional data obtained by forming quasi-bridging pairs. However, with BASHI dataset we observe the best results, as the model achieves significant gains in comparison with embeddings_bridging and moderate gains against BARQA.

Our proposed approach performs substantially better than rule-based (RULE) approach of Roesiger (2018b) over all the genres of ARRAU dataset. On the other hand, the results are mixed in comparison to multitask learning approach (MULTI) (Yu and Poesio, 2020). Over PEAR dataset our approach outperforms and yields competitive results over RST, but lags in TRAINS dataset. We think the noisy text in TRAINS dataset is the reason behind this gap. TRAINS contains dialogues, as a result, a lot of non-vocabulary words like "um", "uhhh" etc. are present in the text. Also few words are repeated as speakers can sometimes repeat themselves. This lead to noisy context which is completely different from the grammatically correct text data on which the word embeddings were trained. This difficulty does not appear in MULTI system because the embeddings are fine-tuned over this noisy data.

Dataset	Mention	Absent from WordNet (%)
ISNotes	9574	977 (10.20%)
BASHI	5933	482 (8.21%)
ARRAU	52206	3843 (7.39%)

Table 6.2 Number of mentions from the datasets and proportion of them absent in WordNet.

6.4.5 Error analysis

6.4.5.1 Mention normalization and sense disambiguation

We analyze the cases where normalized mention has failed to map to any sense in WordNet. We noted those numbers for each dataset in Table 6.2. We see that around 7 to 10 percentage of mentions were non-mappable to any WordNet node. There are broadly two reasons for this: 1. Normalization error, and 2. Inherent limitations of WordNet. We illustrate some of the examples from each category in Table 6.3. The first three mentions are wrongly normalized (Los Angeles to Angeles and Hong Kong to Kong) while both cities are present in WordNet. The cases like U.S.S.R shows a limitation of our simple normalization approach, the normalization should map U.S.S.R to Soviet Russia which is present in WordNet. The other three examples show the inherent limitations of WordNet as those entities are absent from WordNet.

WordNet contains multiple senses for a given word because of which we get on an average 7 senses for the given mention. We used a simple Lesk algorithm for disambiguation which takes into account the context of the normalized mention to determine the correct sense. We present some examples of disambiguation with Lesk in Table 6.3. It correctly disambiguates in the first three examples but fails for the following three. This is because of the count of overlapping words between sense's context and definition in WordNet. For example, the last example contains words like blood, breeder in the context because of which it selects sense as *a group of organisms* and not an *organization*.

6.4.5.2 Anaphor-antecedent predictions

We analyze a few anaphor-antecedent pairs which were identified incorrectly with BERT-based mention representations but with the addition of WordNet information, we were able to correct it. The underlined and bold lettered phrases denote antecedent and anaphor, respectively.

Mention Mapping Error		**Mention Sense Selection**	
Mention	Normalized Mention	Mention	Selected Sense
Los Angeles, Cali.	Angeles	[...] future generations of memory **chips**	electronic equipment
Hong Kong	Kong	The move by the coalition of political **parties** [...]	organization
U.S.S.R	U.S.S.R	[...] when the rising Orange River threatened to swamp the **course** [...]	route
IBM	IBM	[...] U.S. industry to head off **the Japanese**, who now dominate [...]	language
politburo member Joachim Herrman	Herrman	[...] potential investors at race **tracks** [...]	magnetic paths
U.S. district judge Jack B. Weinstein	Weinstein	The Thoroughbred Owners and Breeders **Association** [...]	a group of organisms

Table 6.3 **Mention Mapping Error** lists examples of mentions for which no entry is found in WordNet after normalization. The first three mentions are not found because of normalization error but the next three entities are not present in WordNet. **Mention Sense Selection** notes a few mentions and their senses selected by Lesk. For the first three mentions, Lesk disambiguates correctly but fails in the next three. The correct senses of the last three are *Japanese people*, *racecourse*, and *organization*, respectively.

(12) Staar Surgical Co.'s board said that it has removed Thomas R. Waggoner [...]. [..] that John R. Ford resigned as **a director**, and that Mr. Wolf was named a member of the board.

(13) So far this year, rising demand for OPEC oil and production restraint by some members have kept **prices** firm despite rampant cheating by others.

(14) One building was upgraded to red status while people were taking things out, and a resident who was not allowed to go back inside called up **the stairs** to his girlfriend, telling her to keep [...].

WordNet contains *company* and *director* with part-of relation. Also, the *OPEC oil* is stored as a corporation which in turn is related to *prices*, and *stairs* are part of *building*.

This information from WordNet has been used for resolving these pairs as opposed to relying only on the textual information in case of mention representation only with BERT.

Conversely, we also observed a few pairs where the addition of extra information has been detrimental. The italic faced phrase is the selected antecedent with WordNet based system but without WordNet correct antecedent (shown with underline) was selected for boldfaced anaphor.

(15) Within the same nine months, *News Corp.* [...]. Meanwhile, American Health Partners, publisher of American Health magazine is deep in debt, and Owen Lipstein, **founder**[...].

(16) [...] *the magnificent dunes where the Namib Desert meets the Atlantic Ocean* [...]Since this treasure chest [...] up a diamond from **the sand**.

(17) The space shuttle Atlantis landed [...] that dispatched *the Jupiter - bound Galileo space probe.* **The five astronauts** returned [...].

In example 15, *News Corporation* is closer to **founder** than Partners as head word is Partners for the long phrase. Thus, the system assigns higher scores to wrong antecedent candidate. Similarly, in example 16, the *dunes* are closer to **sand** than treasure chest. In the example 17, WordNet contains Atalantis as legendary island and not as a space shuttle thus **astronauts** is closer to space probe than island, thus receiving a higher score than the correct antecedent. These mistakes can be attributed to the process of normalizing mentions as well as limitations of WordNet. Interestingly, these examples show the inadequacy of BERT in capturing the *partOf* relation but efficacy of capturing some form of relatedness of the terms.

6.5 Improved event representation for temporal relation classification

In the previous section we described our approach to obtain knowledge-aware mention representation for bridging anaphora resolution. Now we apply conceptually similar approach to improve event representation for temporal relation classification. We combine text-based and knowledge graph based event representations to obtain knowledge-aware event representations in Section 6.5.1. We detail our neural model that is based on the latest work (Wang et al., 2020), learning objective and inference strategy in Section 6.5.2, our experimental setup in Section 6.5.3, and results in Section 6.5.4.

6.5.1 Knowledge-aware event representations

Our knowledge-aware event representation consists of two parts similar to the mention representation: 1. Text-based event representation, and 2. Knowledge-graph based representation. Let us look at them in the following paragraphs.

Text-based event representation We use state-of-the-art (Wang et al., 2020) BiLSTM based approach to get text-based embeddings. Let us suppose $w_1, w_2, \cdots, w_i, \cdots, w_n$ denote the sentence containing n-words. Let e_i be the event present in the sentence and w_i be its corresponding event word. This sequence of words is inputed to RoBERTa-base (Liu et al., 2019b) model to obtain pre-trained embeddings for each word. Let $\mathbf{w}_i$ be the RoBERTa embeddings for w_i. Additionally, with the use of part-of-speech (POS) tag of the word w_i, one-hot encoded $\mathbf{p}_i$ is also obtained. These embeddings are concatenated $\mathbf{v}_i = \mathbf{w}_i \oplus \mathbf{p}_i$ and used as an input to the forward and backward LSTMs. Let $\mathbf{f}_i, \mathbf{b}_i$ be the output corresponding to i^{th} word from the forward and backward LSTMs, respectively. Then the text-based event representation $\mathbf{g}_i$ is obtained by concatenating them: $\mathbf{g}_i = \mathbf{f}_i \oplus \mathbf{b}_i$.

Knowledge-graph based representation We obtain knowledge graph based representation for each event as detailed in Section 6.3. Briefly, we normalize event by using lemma of the event word and then map this normalized token to the graph node. Then corresponding sense embeddings are obtained. In case of multiple senses we averaged over all possible senses [8]. On the other hand, in case of non-availability of the node we used the zero vector of the same size. Let the knowledge graph-based embedding obtained by this procedure for an event e_i be given as $\mathbf{h}_i$.

Event-pair representation For getting event-pair representation, we obtain knowledge-aware *event* representation by concatenating the text-based representation and knowledge graph-based representation. For e_i it is given as $\mathbf{e}_i = \mathbf{g}_i \oplus \mathbf{h}_i$. Similarly, we obtain knowledge-aware *event* representation for an event e_j which is given as $\mathbf{e}_j$. Next, to obtain event-pair representation from these knowledge-aware representations, we follow similar approach used by Wang et al. (2020). They first concatenated event representations, then resulting vectors from subtraction and multiplication of event representations also concatenated to get the event-pair representation. Suppose, e_i, e_j are two events and $\mathbf{e}_i, \mathbf{e}_j$ be

[8] We have not used Lesk for disambiguation, as we observed in experiments for bridging anaphora resolution, there was no added advantage of using Lesk over averaged senses. Besides, it can not be directly applied over semantic verb frames of TEMPROB.

their knowledge-aware representation. Then the event-pair representation $\mathbf{e}_{ij}$ is obtained as:

$$\mathbf{e}^m_{ij} = \mathbf{e}_i \otimes \mathbf{e}_j \tag{6.3}$$

$$\mathbf{e}^s_{ij} = \mathbf{e}_i - \mathbf{e}_j \tag{6.4}$$

$$\mathbf{e}^c_{ij} = \mathbf{e}_i \oplus \mathbf{e}_j \tag{6.5}$$

$$\mathbf{e}_{ij} = \mathbf{e}^m_{ij} \oplus \mathbf{e}^s_{ij} \oplus \mathbf{e}^c_{ij} \tag{6.6}$$

6.5.2 Neural model

We extended the neural constrained learning model proposed by Wang et al. (2020) with the addition of knowledge graph-based embeddings. As mentioned earlier, the model is based on BiLSTM neural network which takes concatenated RoBERTa and POS tags embeddings as an input. We inject the commonsense knowledge with the knowledge graph based embeddings corresponding to each event at the output obtained from BiLSTM. Finally, this event-pair representation is fed to the scoring function which produces scores for each temporal relation showing confidence over each relation. This score is used by the model to optimize the aggregated loss from: pairwise classification loss, symmetry constraint loss, and transitivity constraint loss. At the inference stage, ILP problem is solved to produce globally coherent predictions.

Following the same notations from Section 2.1.1.1, we formally define the model as follows. Let D be the document containing events $\mathscr{E} = \{e_1, e_2, \cdots, e_{n_e}\}$ and true temporal relations between events $\mathscr{H} = \{(e_i, e_j, r_{ij}) | e_i, e_j \in \mathscr{E}, r_{ij} \in \mathscr{R}\}$ where $\mathscr{R}$ is possible set of temporal relations, so tuple (e_i, e_j, r_{ij}) denotes true temporal relation r_{ij} between e_i, e_j. Let the event-pair representation obtained with our approach (Eq. 6.6) be $\mathbf{e}_{ij} \in \mathbb{R}^d$, and $z : \mathbb{R}^d \rightarrow \mathbb{R}$ be the scoring function. Then, the pairwise confidence score parameterized over θ is given as $s_{r,i,j} = z(\mathbf{e}_{ij}; \theta) \forall r \in \mathscr{R}$. Based on this confidence score the pairwise classification loss, symmetry constraint loss, transitivity constraint loss, and cumulative loss is calculated as follows.

6.5.2.1 Constrained learning

Recall from Section 2.1.2.1 that temporal relations possess algebriac property, hence, symmetry and transitivity rules can be applied over them. The neural model takes into consideration these temporal constraints while learning model parameters. For that, a constrained learning approach is taken where in addition to pairwise classification loss,

losses incurred due to constraint violations are also considered while learning. We look at those losses one by one.

Pairwise classification loss This is a local loss that calculates the difference between actual temporal relation between event-pair and predicted temporal relation. The cross entropy is used to calculate it. The confidence score produced by a scoring function is used to get the loss. Suppose, $(e_i, e_j, r_{ij}) \in \mathscr{H}$ and the score produced by neural model for event-pair e_i, e_j is $s_{r,i,j} \forall r \in \mathscr{R}$, the pairwise classification loss is calculated as:

$$\mathscr{L}_p(\theta) = -\sum_{(e_i,e_j,r_{ij})\in\mathscr{H}} \sum_{r\in\mathscr{R}} y_{r,i,j} \log(s_{r,i,j}) \tag{6.7}$$

where $y_{r,i,j} = 1$ if $(e_i, e_j, r) \in \mathscr{H}$ else 0.

Symmetry constraint loss Temporal relations follow symmetry, therefore, if e_i is *before* e_j, it means that e_j is *after* e_i. This is because *after* and *before* are inverse to each other, whereas, *equal* and *vague* are inverse to themselves[9]. Let us suppose $\mathscr{R}_s = \{(r, \bar{r}) | r, \bar{r} \in \mathscr{R}$ and $r, \bar{r}$ be symmetric relations$\}$. Based on the symmetry constraint over all the event pairs, a logical rule with a conjunction ($\bigwedge$) of statements is given as:

$$\bigwedge_{\substack{e_i,e_j\in\mathscr{E},\\(r,\bar{r})\in\mathscr{R}_s}} r_{ij} \rightarrow \bar{r}_{ij} \tag{6.8}$$

Then the symmetry constrained loss is obtained as:

$$\mathscr{L}_s(\theta) = \sum_{\substack{e_i,e_j\in\mathscr{E},\\(r,\bar{r})\in\mathscr{R}_s}} |\log(s_{r,i,j}) - \log(s_{\bar{r},j,i})| \tag{6.9}$$

Transitivity constraint loss Temporal relation also exhibit transitivity property, due to that temporal relations between event-pairs can be obtained by composing temporal relations (denoted as $\circ$) of other pairs. For instance, suppose e_i is *before* e_j and e_j is *before* e_k, that implies, e_i is *before* e_k, $\forall\, e_i, e_j, e_k \in \mathscr{E}$. These transitivity rules are summarized in Table 6.4.

Based on these composition rules, logical conjunction rule can be formed as:

$$\bigwedge_{\substack{e_i,e_j,e_k\in\mathscr{E},\\r_{ik}=r_{ij}\circ r_{jk},\\\forall r_{ij},r_{jk},r_{ik}\in\mathscr{R}}} r_{ij} \wedge r_{jk} \rightarrow r_{ik} \tag{6.10}$$

[9]These are the only possible temporal relations between starting points of events.

$\circ$	a	b	e	v
a	a	-	a	-
b	-	b	b	-
e	a	b	e	-
v	-	-	-	-

Table 6.4 Composition rules on end-point relations present in MATRES dataset: *(a)fter*, *(b)efore*, *(e)qual*, and *(v)ague*. The temporal relations in the first row are composed with relations from first column to produce temporal relations at each row.

Opposite logical conjunction can be formulated which indicates non-possibility of composition:

$$\bigwedge_{\substack{e_i,e_j,e_k \in \mathscr{E}, \\ r'_{ik} \neq r_{ij} \circ r_{jk}, \\ \forall r_{ij},r_{jk},r'_{ik} \in \mathscr{R}}} r_{ij} \wedge r_{jk} \rightarrow \neg r'_{ik} \tag{6.11}$$

Both of these rules are considered while calculating transitivity loss:

$$\begin{aligned} \mathscr{L}_t(\theta) = & \sum_{\substack{e_i,e_j,e_k \in \mathscr{E}, \\ r_{ik} = r_{ij} \circ r_{jk}, \\ \forall r_{ij},r_{jk},r_{ik} \in \mathscr{R}}} |\log(s_{r_{ij},i,j}) + \log(s_{r_{jk},j,k}) - \log(s_{r_{ik},i,k})| + \\ & \sum_{\substack{e_i,e_j,e_k \in \mathscr{E}, \\ r'_{ik} \neq r_{ij} \circ r_{jk}, \\ \forall r_{ij},r_{jk},r'_{ik} \in \mathscr{R}}} |\log(s_{r_{ij},i,j}) + \log(s_{r_{jk},j,k}) - \log(1 - s_{r'_{ik},i,k})| \end{aligned} \tag{6.12}$$

Constrained Learning Objective All three losses: pairwise loss (Eq. 6.7), symmetry constrain loss (Eq. 6.9), and transitivity constrain loss (Eq. 6.12) are weighted to get constrained learning objective:

$$\mathscr{L}(\theta) = \mathscr{L}_p(\theta) + \alpha \mathscr{L}_s(\theta) + \beta \mathscr{L}_t(\theta). \tag{6.13}$$

where coefficients $\alpha, \beta \geq 0$.

6.5.2.2 ILP Inference

To enforce the global consistency over predicted temporal relations, the inference problem is formulated as an Integer Linear Programming (ILP) objective. The ILP constraints are again based on the composition rules mentioned in Table 6.4. The formulation is given as:

$$\underset{I_{r,i,j}}{\text{maximize}} \quad \sum_{\substack{e_i, e_j \in \mathscr{E}, \\ r \in \mathscr{R}}} s_{r,i,j} I_{r,i,j} \tag{6.14a}$$

$$\text{subject to} \quad I_{r,i,j} - I_{\bar{r},j,i} = 0, \qquad \forall e_i, e_j \in \mathscr{E}, (r, \bar{r}) \in \mathscr{R}_s, \tag{6.14b}$$

$$I_{r,i,j} + I_{r',j,k} - I_{\hat{r},i,k} \leq 1 \qquad \forall e_i, e_j, e_k \in \mathscr{E}, \hat{r} = r \circ r', \tag{6.14c}$$

$$I_{r,i,j} \in \{0,1\} \qquad \forall e_i, e_j \in \mathscr{E}, \forall r \in \mathscr{R} \tag{6.14d}$$

6.5.3 Experimental setup

Dataset Following recent work (Han et al., 2019a,b; Wang et al., 2020), we used MATRES (Ning et al., 2018b) dataset in our experiments, details of which are mentioned in Section 2.1.1.3, here we briefly restate them. This dataset is based on previously proposed TimeBank (Pustejovsky et al., 2003a), and AQUAINT (Graff, 2002) datasets. It annotates 275 documents with temporal relations between starting points of events as BEFORE, AFTER, EQUAL, or VAGUE. Instead of annotating any event-pair, their annotation process first divides events between four axes: main, intention, opinion, and hypothetical. And temporal relations are annotated only between event pairs that lie on the same axes and appear in the window of two adjacent sentences. These annotated documents are split into 183, 72, and 20 documents for train, development, and test, respectively. We followed the same setting for direct comparison with previous results.

Baseline Systems We implemented three baseline systems: 1. Without commonsense knowledge, 2. Commonsense knowledge injected with simple features, and 3. Commonsense knowledge learned from both ConceptNet and TEMPROB. All three systems are variations of our proposed model. The first system does not contain the knowledge graph embeddings part and relies solely on the context based embeddings learned from RoBERTa and POS embeddings with BiLSTM. The second system adds simple commonsense features such as prior probabilities for the event-pair obtained from TEMPROB on top of the text-based representation similar to the previous approach (Ning et al., 2018a). The third system is a much stronger baseline where commonsense knowledge is added from both ConceptNet (Speer et al., 2018) and TEMPROB graphs. To get the knowledge from both these knowledge graphs, we used an approach proposed by Wang et al. (2020). In that, *only* small portion of ConceptNet is used where only those nodes that are connected with specific relations such as “HasSubevent”, “HasFirstSubevent”, and “HasLastSubevent” are selected. These are considered as “positive” training examples, then the equal number

of node pairs possessing other than these relations are randomly selected and used as "negative" training samples. Then, auxiliary neural network (specifically, MLP) is trained to estimate the likelihood of temporal relations between these pairs. Similarly, another MLP is trained over TEMPROB as well. Once both MLPs are trained, their weights are not updated while learning the main system and are used only to get the knowledge graph features.

System with simple concatenation We experiment with another implementation of our proposed system where instead of obtaining a complex interaction with multiplication, and subtraction of knowledge graph embeddings, we simply concatenate them. This is done to understand the effect of complex interaction of knowledge graph embeddings.

Implementation We obtained officially released pre-trained RoBERTa embeddings (Liu et al., 2019b) and concatenated them with 18-dimensional one-hot encoded POS tag embeddings. These embeddings are given to two LSTMs, each having 1024 neurons. The output from LSTMs is concatenated with the knowledge graph-based embeddings to obtain event-pair representation. As mentioned in Section 6.5.2, we relied on WordNet and TEMPROB separately to capture such information. In the case of WordNet, we used the same embedding algorithms that were employed in the experiments for bridging anaphora resolution in the last section. Specifically, we used 300 dimensional vectors for random walk based (RW) (Goikoetxea et al., 2015), matrix factorization based (WNV) (Saedi et al., 2018), and Path2vec (PV) (Kutuzov et al., 2019) embeddings. In the case of Path2vec, embeddings learned with shortest path similarities (Lebichot et al., 2018) are used as those have produced better results in their paper as well as in our experiments on bridging resolution. We used officially released RW and WNV embeddings, but in the case of Path2vec, the officially released embeddings are not trained with verb information so we retrained the whole WordNet to get embeddings for all nodes. In the case of TEMPROB, we trained UKGE embeddings with the procedure mentioned by the authors that produced 300-dimensional vectors corresponding to each semantic verb frame of the graph. Finally, two fully connected layers with 1024 and 4 neurons are used over the event-pair representations. The output of the final layer is considered as a score for four temporal relations.

For training the model, the AMSGrad (Reddi et al., 2018) optimization algorithm is used with 0.0001 learning rate. We kept the values of α, β (loss coefficients) to 0.2, same as (Wang et al., 2020). The epoch value is kept at 50 which is sufficient for model convergence. At the end of each epoch, the model is evaluated against the validation set and parameters

of the epoch which produce the best validation score are stored. The best performing model is evaluated against the test set and those results are reported.

Evaluation We report the micro-average of precision, recall, and F1 scores on test set similar to previous studies (Han et al., 2019a,b; Wang et al., 2020). In addition to that, we calculate temporal awareness (UzZaman and Allen, 2011) based precision, recall, and F1 score.

6.5.4 Results

Comparison with baseline systems As noted in the previous section, we implemented three baseline systems: first, without any commonsense information but keeping the same neural model, in the second system we added commonsense information but only prior probabilities between event-pairs, whereas in the third system we added commonsense information by employing a sophisticated approach. The results of the experiments are shown in the initial three rows of Table 6.5.

Now, we compare results obtained with only text-based embeddings i.e. without addition of any commonsense information (Table 6.5: row 1) with commonsense knowledge added with our approach (Table 6.5: section c). We see an increase in pairwise F1 scores from 70.62 to 72.12, 71.36, 73.39, and 73.67, respectively with RW, PV, WNV, and UKGE embeddings. This shows that the addition of commonsense information with knowledge graph embeddings is effective over the system with only text-based embeddings, proving the efficacy of our approach and substantiating our claims for temporal relation classification task as well.

Second, we compare results obtained with addition of commonsense information (Table 6.5: row 2 and 3) with the results from our model (Table 6.5: section c). When we compare results of baseline (Table 6.5: row 2) that adds simple commonsense features with results from our system (Table 6.5: section c), we see significant improvements. This further confirms our claims that knowledge graph embeddings encode better information than simple hand-crafted commonsense features. However, in comparison to the next baseline (Table 6.5: row 3) where we added sophisticated commonsense features from two knowledge graphs, we see slight or no improvement in the results. The highest score obtained with TEMPROB (UKGE) (Table 6.5: section c) is only better by 0.72 F1 points whereas WNV embeddings over WordNet produce just 0.44 F1 points gain. Further, the other two embeddings: RW and PV produce lower results than the baseline. We present reasons of this lower performance in the discussion section 6.5.5.

Systems		Pairwise Evaluation			Temporal Awareness		
		P	R	F1	P	R	F1
(a) Baselines	Without CS	65.81	76.18	70.62	63.76	60.44	62.06
	With simple CS	67.31	75.04	70.96	62.53	59.97	61.22
	With CS	72.29	73.62	72.95	64.47	62.62	63.53
(b) Simple concatenation	+ RW	70.44	75.04	72.67*	63.52	61.69	62.59
	+ PV	70.83	70.93	70.88	59.82	59.35	59.58
	+ WNV	71.8	71.49	71.65	60.95	61.06	61.01
	+ UKGE	71.94	74.19	73.05*	62.89	61.69	62.28
(c) Our model	+ RW	69.43	75.04	72.12*	62.34	62.15	62.25
	+ PV	70.82	71.92	71.36	61.3	60.6	60.95
	+ WNV	71.94	74.9	73.39*	63.29	61.69	62.48
	+ UKGE	70.47	77.17	73.67*	64.42	62.47	63.43
(d) Previous studies on MATRES	CogCompTime	61.6	72.5	66.6	-	-	-
	Perceptron	66.0	72.3	69.0	-	-	-
	LSTM+CSE+ILP	71.3	82.1	76.3	-	-	-
	JCL	73.4	85.0	78.8	-	-	-

Table 6.5 Results of the experiments over baseline systems, systems with a simple concatenation of knowledge graph embeddings, our model, and previous studies. WordNet embeddings are obtained with three different algorithms random walk based (RW), Path2vec (PV), and matrix factorization based(WNV) whereas UKGE algorithm is used for TEMPROB node embeddings. Section d shows results with previously proposed systems: CogCompTime (Ning et al., 2018c), Perceptron (Ning et al., 2018b), LSTM+CSE+ILP (Ning et al., 2019), and Joint Constrained Learning (JCL) (Wang et al., 2020). The results with $*$ are statistically significant in comparison to the results obtained without commonsense information with p-value $< 10^{-3}$ with McNemar's test.

The trend remains the same even when we compare the results obtained with the simple concatenation of knowledge graph embeddings (Table 6.5: section b) with baseline results (Table 6.5: section a). The performance of the system is better than the system without any commonsense information (Table 6.5: row 1) but modest in comparison to systems with commonsense information (Table 6.5: row 2,3). Also, when we compare results with simple concatenation (Table 6.5: section b) and results from with our model (Table 6.5: section c) we do not see the effectiveness of interaction obtained with subtraction and multiplication. The reason might be that in both cases the interaction is obtained with linear operations. Therefore, additional interaction with subtraction and multiplication does not add more value than simple concatenation. This indicates that

the complex non-linear interaction learning approach that we developed in Chapter 4 can be further useful.

Next, we compare two baseline systems with each other (Table 6.5: row 1 and 2), to check the effect of commonsense in these systems. Recall that the second baseline system is similar to the first one, the only difference is the addition of commonsense knowledge. We see a small difference in their performances. The reason might be that only prior probability information from TEMPROB is added naively. But this improvement is lower in comparison to the improvement of 5.9 F1 points with pairwise evaluation and 7.1 points with temporal awareness shown in the original paper (Ning et al., 2018a). The reason behind these lower gains might be the difference of evaluating datasets, as they evaluated over TBDense dataset, whereas we evaluated over TE-Platinum. Above all, their text-based event representation was not as sophisticated as used here, and the learning model was also weaker, which might be the reason behind their comparatively large gains.

Comparison between different graph node embeddings Now, we compare results obtained with different graph node embeddings with each other to understand which embedding strategy or which knowledge graph is better suitable for temporal relation classification. From the results of Section c of Table 6.5, we see TEMPROB and WordNet are both comparable in the way they capture commonsense information for temporal relation classification. This also shows that semantic relations such as meronymy, hypernymy, synonymy, etc. are equally useful for classification as prior probability information encoded in TEMPROB. Within WordNet embeddings, WNV and RW approaches produce slightly better results in comparison to Path2vec. The reason might be that with the use of Path2vec, there is an explicit need of doing sense disambiguation but as the other two embeddings produce word embeddings rather than sense embeddings the extra step of sense disambiguation is not required.

Comparison with previous studies In Table 6.5: section d, we present results of previous studies done over MATRES: CogCompTime (Ning et al., 2018c), Perceptron (Ning et al., 2018b), LSTM+CSE+ILP (Ning et al., 2019), and Joint Constrained Learning (JCL) (Wang et al., 2020). Though our proposed approach performs better than CogCompTime and Perceptron approach, it lags by more than 2 F1 points in comparison with LSTM+CSE+ILP and more than 5 points with JCL. One of the reasons might be that both approaches added sophisticated commonsense knowledge by learning embeddings over TEMPROB (similar to our baseline 3). In the case of JCL, the original model is jointly trained with general event relation (e.g. Parent-child, coreference, etc.) classification task. This joint

training and cross task constraints have been shown to be beneficial in their ablation studies. In our experiments, we omitted this part of joint learning, as our primary goal was to assess the effectiveness of commonsense information injected with knowledge graph embeddings and not to achieve state-of-the-art result.

6.5.5 Discussion

We observe from the results that our approach of injecting commonsense information with knowledge graph embeddings produces better results in comparison to the system without any external knowledge as well as with the addition of simple commonsense features, however, our approach is ineffective in comparison to the carefully learned commonsense knowledge. To understand the reasons behind this ineffectiveness, we first checked how many events were mapped to WordNet and TEMPROB nodes. We observed that out of a total 10190[10] events, 195 were missed with WordNet whereas with TEMPROB only 37 events were missed. This shows high coverage for events in both knowledge graphs which clears the doubt that the absence of knowledge is not the reason behind the ineffectiveness. Further, we believe the following factors might have contributed to the moderate performance gains in comparison with the commonsense injection approach of Wang et al. (2020).

Firstly, the commonsense knowledge extracted by (Wang et al., 2020) contains knowledge from ConceptNet (Speer et al., 2018) which we have not explored in our experiments. It might be possible that the event information encoded in ConceptNet is more beneficial for temporal relation classification than the external knowledge encoded in WordNet or TEMPROB. In addition to that, they encoded knowledge from multiple sources, i.e. they used both ConceptNet as well as TEMPROB to get commonsense information. This might have benefited them as well.

Further, we think the simple heuristics used to circumvent the need for sense disambiguation might be another reason. We simply averaged embeddings over all the senses of the word to get Path2vec WordNet embeddings, similarly in the case of TEMPROB embeddings. We think learning an appropriate sense of word instead of relying on the simple heuristics can improve the system performance further.

Lastly, the graph node embeddings that are used in our system are learned in a task-agnostic way. This means they are not specifically designed to capture information for temporal relation classification. These embeddings may capture irrelevant information

[10] Though we have total 12366 events in MATRES, all of them are not unique verbs also not all the event pairs are annotated with temporal relations. This is the reason behind a small number of events in comparison to all events.

that might not be useful for the task. We think instead of relying on pre-trained static graph node embeddings, learning them jointly with text-based embeddings in the process of learning model parameters can be useful for the system.

All in all, we think that the use of other knowledge graphs such as ConceptNet which encodes event specific information, or Verbocean (Chklovski and Pantel, 2004) which possess temporal relation between verbs can be beneficial. The other promising way can be to use multiple knowledge sources instead of relying on a single source of information. Further, disambiguating senses while training the model for classification can also produce better results. Lastly, we think the joint learning of knowledge graph embeddings rather than using pre-trained embeddings can be beneficial.

6.6 Conclusion

We added commonsense knowledge into bridging resolution and temporal relation classification systems. For acquiring such knowledge, instead of relying on hand-engineered features or partially selected pairs from knowledge graphs like previous approaches we used graph node embeddings. We proposed a simple approach for mapping events and mentions to the nodes of knowledge graphs to obtain corresponding graph node embeddings. Specifically, we used WordNet for both tasks, and TEMPROB, particularly for temporal relation classification.

We observed significant gains in the results with the addition of knowledge graph embeddings in the system compared with only text-based representations for both bridging anaphora resolution and temporal relation classification when evaluated on standard datasets. This shows that both contextual and commonsense information are needed for these tasks, establishing our central claim. Secondly, the results prove that word embeddings learned with only text data are inadequate at capturing commonsense information, hence, must be complemented with commonsense information explicitly. This also corroborates our observations from the last chapter. Further, our gains with knowledge graph embeddings also show that node embeddings learned over knowledge graphs are an effective way of encoding knowledge graphs in comparison to hand-crafted approach. Apart from this, we observed similar gains with the use of WordNet and TEMPROB for temporal relation classification, showing semantic relations such as meronymy, hypernymy, synonymy, etc. encoded by WordNet are equally useful for classification as specific temporal information present in prior probabilities between events.

Though the systems performed well, there are a number of ways to improve them further. First, the sophisticated approach for mention and event normalization and

sense disambiguation instead of heuristics can be beneficial. Next, the use of multiple knowledge resources instead of depending on a single source of knowledge can be useful for the system's performance. Further, we think learning knowledge graph embeddings and text-based embeddings jointly can be valuable.

Chapter 7

Conclusions

Identifying temporal relations between events and establishing bridging links between mentions is crucial for automatic discourse understanding. For that purpose, obtaining effective events and mentions representations is necessary for NLP models employed to determine these relations. We argued that contextual information and commonsense information is crucial for such effective representations. The previously proposed computational approaches to determine these relations were inadequate at capturing both this information simultaneously. This thesis solved that problem by developing efficient ways to incorporate contextual and commonsense information to improve event and mention representations.

We developed a neural network based approach for learning rich event representations and interactions (Chapter 4). We used the context of the event in the window of n-words and represented each word as pre-trained word embedding. Then provided this as an input to RNN to produce context rich event representations. Further, we added morphological information by concatenating character embeddings of the event headword. At last, we employed deep CNN to obtain rich interactions between the event representations. The empirical results proved the efficacy of this approach, as we obtained better results than local models that relied on *only* event headword representations or simple interactions. More importantly, the results demonstrated that contextual information is needed to accurately predict temporal relations between events. Additionally, the study showed that interaction learning over event representations is also important for the task.

Next, we investigated pre-trained transformer language models (e.g. BERT, RoBERTa) for bridging resolution as an alternative way of capturing contextual information (Chapter 5). We developed two complementary approaches to achieve that. First, we investigated each attention head of transformer models individually to assess the amount of bridging signal captured by them. Then, we developed *Of-Cloze test* to understand the

efficacy of the whole model. We found that pre-trained BERT models are significantly capable of capturing bridging inference though it depends on the provided context. Also, our qualitative analysis showed that BERT is inadequate at capturing commonsense knowledge.

Finally, we combined both contextual and commonsense information for better event and mention representations (Chapter 6). We acquired commonsense information with knowledge graph embeddings learned over WordNet (Fellbaum, 1998) and TEMPROB (Ning et al., 2018a). We used simple methods to get knowledge based representations for events and mentions based on the node embeddings. Then these representations are combined with contextual representations to get knowledge-aware event and mention representations. We evaluated our proposed approach over standard datasets for both bridging anaphora resolution and temporal relation classification. We observed substantial improvements with the addition of commonsense information in the results in comparison to *only* text-based representations for both tasks. These results show that graph node embeddings learned over knowledge graphs are capable of encoding the commonsense knowledge required for these tasks. The gains over text-only embeddings by the addition of knowledge graph embeddings also substantiate the findings from the investigation of pre-trained transformer models that transformer models lack at capturing commonsense information. Above all, the results validate our claim that both contextual and commonsense information is required to effectively represent events and mentions, which is consequently necessary for accurately solving temporal relation classification and bridging anaphora resolution.

We can see a few immediate ways of extending our work. From the findings of the investigation of pre-trained transformer models, we can build a better system for bridging anaphora resolution. We observed that the last layers and a few individual attention heads target bridging information, so making specific use of these elements for bridging instead of whole BERT can be an interesting exploration. Next, we can dynamically learn the linking of mentions and events to knowledge graph nodes while addressing the issue of sense disambiguation as well. This procedure can reduce the effects of normalization and disambiguation errors which we identified in our analysis. Further, we believe that graph node embeddings learned in task-agnostic way can project nodes that are less probable to possess bridging relation into nearby space (e.g. cat-dog) because of their proximity in the actual graph. A similar problem may occur for temporal relations as well where the generic node embeddings algorithm may encode some noisy information. Therefore, learning graph embeddings specifically for these tasks can be beneficial for getting relevant knowledge.

More generally, we can extend the findings from this thesis for the other two tasks of discourse understanding: discourse relation classification and coreference resolution. These tasks being highly related to the tasks we solved, the insights gained from the thesis can be useful. In fact, there have been attempts of making use of other relations while proposing systems for particular relations (D'Souza and Ng, 2013; Ng et al., 2013; Yu and Poesio, 2020), so it can also be interesting to go a step further to learn all of them jointly with shared context and commonsense knowledge to exploit learnings from one another. Apart from that, in our work, we focused on including commonsense knowledge but have not worked on the reasoning capabilities of the systems. We think in addition to commonsense knowledge, reasoning over it can lead to further accurate solutions.

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