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Exploration des interactions humaines pour la modélisation de l'influence dans les réseaux sociaux

Monika Rakoczy

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Exploring Human Interactions for Influence Modeling in Online Social Networks

Thèse de doctorat de l'Université Paris-Saclay
préparée à Télécom SudParis

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To my Mom and Dad

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Abstract

Online social networks are constantly growing in popularity. They enable users to interact with one another and shifting their relations to the virtual world. Users utilize social media platforms as a mean for a rich variety of activities. Indeed, users are able to express their opinions, share experiences, react to other users' views and exchange ideas. Such online human interactions take place within a dynamic hierarchy where we can observe and distinguish many qualities related to relations between users, concerning influential, trusted or popular individuals. In particular, influence within Social Networks (SN) has been a recent focus in the literature. Many domains, such as recommender systems or Social Network Analysis (SNA), measure and exploit users' influence. Therefore, models discovering and estimating influence are important for current research and are useful in various disciplines, such as marketing, political and social campaigns, recommendations and others. Interestingly, interactions between users can not only indicate influence but also involve trust, popularity or reputation of users. However, all these notions are still vaguely defined and not meeting the consensus in the SNA community. Defining, distinguishing and measuring the strength of those relations between the users are also posing numerous challenges, on theoretical and practical ground, and are yet to be explored. Modelization of influence poses multiple challenges. In particular, current state-of-the-art methods of influence discovery and evaluation still do not fully explore users' actions of various types, and are not adaptive enough for using different SN. Furthermore, adopting the time aspect into influence model is important, challenging and in need of further examination part of the research. Finally, exploring possible connections and links between coinciding notions, like influence and reputation, remains to be performed.

In this thesis, we focus on the qualities of users connected to four important concepts: influence, reputation, trust, and popularity, in the scope of SNA for influence modeling. We analyze existing works utilizing these notions and we compare and contrast their interpretations. Consequently, we emphasize the most important features that these concepts should include and we make a comparative analysis of them. Accordingly, we present a global classification of the notions concerning their abstract level and distinction of the terms from one another, which is a first and required contribution of the thesis. Consequently, we

then propose a theoretical model of influence and present influence-related ontology. We also present a distinction of notion not yet explored in SNA discipline – micro-influence, which targets new phenomena of users with a small but highly involved audience, who are observed to be still highly impactful. Basing on the definitions of the concepts, we propose a practical model, called Action-Reaction Influence Model (ARIM). This model considers type, quality, quantity, and frequency of actions performed by users in SN, and is adaptive to different SN types. We also focus on the quantification of influence over time and representation of influence causal effect. In order to do that, we focus on a particular SN with a specific characteristic - citation network. Indeed, citation networks are particularly time sensitive. Accordingly, we propose Time Dependent Influence Estimation (TiDIE), a model for determining influence during a particular time period between communities within time-dependent citation networks. Finally, we also combine two of the abovementioned notions, influence and reputation, in order to investigate the dependencies between them. In particular, we propose a transition method, ReTiDIE, that uses influence for predicting the reputation. For each of the proposed approaches, experiments have been conducted on real-world datasets and demonstrate the suitability of the methods.

Key-words: Social Networks; Influence; Reputation; Trust; Popularity; Social Networks Analysis;

Résumé

De nos jours, la popularité des réseaux sociaux (RS) est en constante progression. En effet, de plus en plus d'utilisateurs interagissent dans le monde virtuel, soit en y exprimant des opinions, en partageant des expériences, en réagissant aux avis d'autrui ou encore en échangeant des idées, en fonction de leurs qualités : influents, populaires, dignes de confiance, etc.. Dans la littérature, l'influence a fait l'objet d'une attention particulière ces dernières années. En effet, de nombreux domaines, dont l'Analyse des Réseaux Sociaux (ARS) et les systèmes de recommandation ont étudié l'influence, sa détection, la propagation de son effet et sa mesure. Ainsi, des modèles d'identification et d'estimation de l'influence sont aujourd'hui largement utilisés dans de nombreuses applications dédiées au marketing, aux campagnes politiques et sociales, etc. De plus, les interactions entre utilisateurs indiquent non seulement l'influence mais aussi la confiance, la popularité ou la réputation. Cependant, ces notions sont encore vaguement définies et il n'existe pas de consensus dans la communauté ARS. Définir, distinguer et mesurer la force de ces relations entre les utilisateurs posent également de nombreux défis, à la fois théoriques et pratiques, qui restent à explorer. La modélisation de l'influence pose de multiples défis et les méthodes actuelles de découverte et d'évaluation n'explorent pas encore pleinement les différents types d'interactions et ne sont en général pas applicables à plusieurs RS. En outre, la prise en compte de la dimension temporelle dans le modèle d'influence est importante, difficile et nécessite un examen plus approfondi. Enfin, l'exploration de liens possibles entre des notions, telles que l'influence et la réputation, reste un sujet ouvert.

Dans cette thèse, nous nous focalisons sur les quatre concepts qualifiant les utilisateurs : influence, réputation, confiance et popularité, pour la modélisation de l'influence. Nous analysons les travaux existants utilisant ces notions et comparons leurs différentes interprétations. Par cette analyse, nous mettons en avant les caractéristiques essentielles que ces concepts devraient inclure, et nous en effectuons une analyse comparative. Cela nous permet d'établir une classification globale des différentes interprétations des notions selon leur niveau d'abstraction et leurs divergences ; cela constitue la première, contribution de cette thèse. En conséquence, nous proposons un modèle théorique de l'influence ainsi qu'une ontologie associée décrivant ce concept. Nous présentons également une variante

de l'influence, inexplorée à ce jour dans le domaine de l'ARS, la micro-influence. Celle-ci cible un phénomène nouveau dans les RS que sont les utilisateurs avec une faible audience, mais fortement impliqués ; ces derniers apparaissent en effet comme ayant un impact fort malgré tout. En s'appuyant sur ces définitions, nous proposons ensuite un modèle pratique dénommé ARIM (Action-Reaction Influence Model). Ce modèle considère le type, la qualité, la quantité et la fréquence des actions réalisées par les utilisateurs, et ce en étant compatible avec différents RS. Nous abordons également la quantification de l'influence au cours du temps et la représentation de ses effets de causalité. Pour cela, nous considérons un type spécifique de RS: les réseaux de citations, particulièrement sensibles au temps. Ainsi, nous proposons un modèle, TiDIE (Time Dependent Influence Estimation), qui détermine l'influence, sur une période de temps, entre les communautés de ces réseaux. Enfin, nous combinons l'influence et la réputation avec le modèle TiDIE, afin d'étudier les dépendances entre elles. Nous proposons une méthode de transition, ReTiDIE, utilisant l'influence pour obtenir la réputation. Pour chacune de nos approches, des expérimentations ont été menées sur des jeux de données réels et ont montré la pertinence de nos méthodes.

Mots clés: Réseaux Sociaux; Influence; Réputation; Confiance; Popularité; Analyse de Réseaux Sociaux

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Chapter 1

Introduction

1.1 Research Context

While Social Network Analysis (SNA) exists since the mid-1930s, it is recent years that brought the momentum to the discipline. This SNA growth has been matched by an increasing advancement of the tools that are accessible to users. Easy access to the Internet and the emergence of services that allow people worldwide to interact enabled the researchers to collect and access to massive amount of social network data. This, in turn, allowed for examination and analysis of social networks on the scale never seen before.

Abovementioned social media services include ever-growing base of users. To-date, it is estimated that 2.77 billion people are registered on various online social network platforms, a number which is expected to rise above 3 billion in 2021 [1]. The increase of numbers of users registered on social network sites from 2010 can be seen in Figure 1.1. One of the consequences of such ubiquitous use of social networks is the drastic change in our daily habits and the way we interact with our environment – friends, families, co-workers and so on. Social networking platforms offer wide range of different usages: from networking and interacting with people (known or unknown in real life), getting news and updates, collaborating and sharing opinions, photos and videos, publishing different contents (videos, photos, articles), discussing and communicating, to finding and buying products (see Figure 1.2).

Depending on the portal and its functionalities, users interact with their network in various ways, which also leads to a variety of data that can be obtained from these portals. Using such data, SNA research can tackle multiple different issues, some of which are: gathering information about the structure of social networks, structuring social networks, discovering patterns of connections and information flow, analysis and characterization of social relations or uncovering ways of resource exchange. Accordingly, the results of the research done up

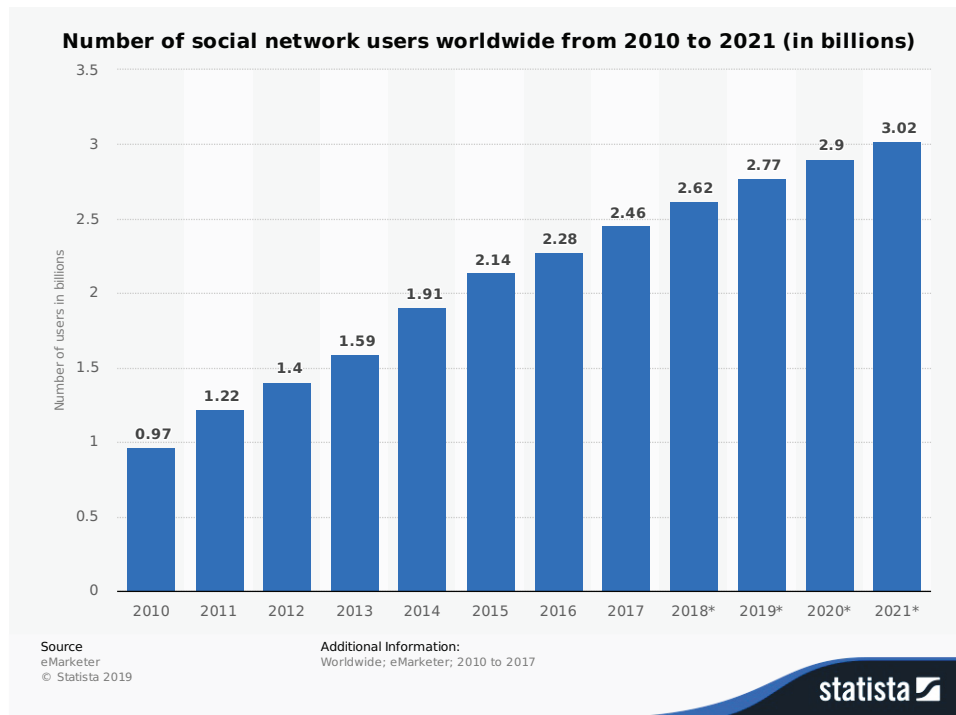


Fig. 1.1 Number of social network users globally (in billions), Statista [1]

until now have led to usages and applications in multiple disciplines, such as recommender systems, targeted advertising, data mining, and others. For example, Amazon¹, a multi-billion dollar behemoth of a lot of online retailers, utilizes user past transaction, search history, products' similarity information and other to make recommendations and sell more items. Similarly, Facebook², while enabling people to connect and interact, also collects vast amounts of user data, that are then used to target specifically-tailored advertisement to selected users. Furthermore, the advance in research has also led to an increasing number of businesses reaching to social media for finding people that can promote their products. Consequently, the number of creators targeting a career based on advertising brands and companies using only networking sites such as Youtube³ has risen as well.

The constant flow of information within social networks also results in determination of numerous important user roles and relations with regard to their activity, interactions, and impact on the community they have. While identifying some social roles can depend on the network or analysis context, there are also a few ones that are critical for social networks in general. Among them, we can distinguish relations such as trust, influence, reputation, and popularity. All of these notions play a significant role in Social Network Analysis.

¹<https://www.amazon.com/>

²<https://www.facebook.com/>

³<https://www.youtube.com/>

Social Media Landscape 2018



Fig. 1.2 Landscape of different social media services as of 2018, FredCavazza.net [2], no copyright infringement is intended.

Evaluation of both trust and reputation for social networks is particularly important for avoidance of spam and irrelevant content spreading, prevention of service resources abuse, and protection against malicious users. Moreover, information about the level of trust also can help to decide about accepting new connections, or taking somebody's opinion into consideration while purchasing a product. Similarly, knowledge about company reputation can prevent or encourage users to use their services. Simultaneously, evaluation of influence and popularity not only takes part in users decision making but also is a constant focus of companies and other organizations searching for means of promoting services or products. Imagine a non-profit organization, looking for easy and possibly not expensive way of advertising social campaign to society, using limited resources. The issue they will face is how to select social media users to share the event, which not only have (possibly large) audiences, but also the audience that would be involved in the campaign – which is exactly the task of detection of users showing the potential of being influential and popular.

Nevertheless, while the importance of abovementioned roles is undeniable, and much of the research done so far is actively applied to use, there is still plenty of room for improvement and extension for methods concerning investigation, modelization, and evaluation of interactions between users in social networks.

1.2 Motivation and Research Problems

Undoubtedly, the examination of social relations is an important part of Social Network Analysis discipline and has drawn much attention of researchers over the years. However, there are still multiple issues and branches that require deeper studies and understanding.

One of the major issues of analyzing any social relations is that they are subjective. Influence or trust between users, as well as one's popularity or reputation, are elusive to quantify. Accordingly, those notions are still unclear and imprecise in the literature, and therefore often confused with one another. The first issue we target is: *How to define each of notions: trust, popularity, influence, and reputation, how to differentiate them and what properties each of them?*. Additionally, note that both influence and reputation describe an overall, generally held opinion about a particular entity. Hence, another connected subchallenge we tackle relates to the issue of: *How to link together those two notions, in order to use the evaluation of the first, to infer information about the later?*.

Moreover, a clear distinction of abovementioned terms is a crucial, first step towards appropriate influence modeling. As mentioned before, the issue of discovery and selection of users who are influential is particularly of broad and current interest. Nevertheless, influence detection itself poses various challenges. In the first place, there is the general issue of how and in what way modelize and evaluate influence in social networks. Influence in a social network is definitely a compound notion. Considering this, the second issue we tackled is: *How to modelize and evaluate influence in order to capture its complexity?*. At the same time, the data obtained from online social networks on which influence is calculated will always be finite and somehow limited. Moreover, depending on the particular online service and social network type, the way in which users can express their appreciation for the content can vary. Therefore, the subproblem of *how to sufficiently modelize the notion of influence so that the final model can be expressive enough to seize influence while being adaptive to different social network types* remains open. The vast development of different online social network services and sites has also caused the emergence of multiple ways in which users can express themselves, interact with each other, and react to each other posted content. For instance, publishing on an online service can include text, photo, audio, video, and others. Simultaneously, a user impressed by somebody's else content might react to it by liking, commenting, or sharing it forward to her friends. Thus emerges the question – *in what way to model influence estimation so that we consider those numerous methods of social interaction?* What is more, works considering the discovery of influential users focus on aspects favoring entities being widely known, and therefore highly connected. Accordingly, an issue of *how to find promising entities who could still have influence but are invisible (as*

they are less connected)? remains an unexplored area of research that we addressed in this thesis.

The nature of influence also poses another problem for influence discovery and evaluation methods – it is highly dependent on time. Time-dependency is one of the most compound and difficult aspects of influence, especially since depending on the type of social network, the dynamic properties will change. For instance, micro-blogging networks like Twitter⁴ will have a big number of interactions between users happening in a short time span such as days or even minutes. On the other hand, social networks based on posting long texts (e.g. blogs) or publishing articles (e.g. citation networks) will be connected to less dynamic changes, where interactions happen less frequently. As a result, we addressed further questions related to time such as: *how to quantify influence over time?* and *how causal effect on entities influence can be represented?*.

The research challenges presented in this section designate the issues intended to be tackled in this work.

1.3 Thesis Contributions

As discussed in the previous section, there are multiple complex research challenges surrounding exploration and investigation of social networks interactions. Here, we recall the abovementioned research questions and pair them with our proposed solutions aiming to answer them.

- (i) First of all, we target the issues of, first, how to differentiate the notions describing social roles, namely trust, reputation, popularity and influence, and, second, what properties each of them has. In order to tackle those problems, in Chapter 2, we present a literature review about each of the notions, which specifies their properties. Then, the core of the issue is tackled in Chapter 3, where we propose a general classification of the considered notions, as well as the theoretical modelization of influence, including an ontology providing the influence-related context. This contribution was published in the following article:

(1) Monika Rakoczy, Amel Bouzeghoub, Katarzyna Wegrzyn-Wolska, Alda Lopes Gancarski *Users Views on Others – Analysis of Confused Relation-Based Terms in Social Network*, OTM 2016 Conferences: Confederated International Conferences: CoopIS, C&TC, and ODBASE 2016, Springer, 2016.

⁴<https://twitter.com/>

(ii) The next problem we address is the matter of how to modelize and evaluate influence in social networks. As mentioned previously, this issue can be divided into two subproblems: firstly, how to make the model expressive enough to seize influence while being adaptive to different social network types and secondly, in what way to model influence estimation so it can consider various types of interaction. We tackled this problem, in Chapter 4, by proposing an instantiation of the abovementioned theoretical influence modelization, that is both adaptive to different types of social networks and inclusive of various kinds of users' reactions. This work was published in:

(2) Monika Rakoczy, Amel Bouzeghoub, Katarzyna Wegrzyn-Wolska, Alda Lopes Gancarski, *Exploring Interactions in Social Networks for Influence Discovery*, 22nd International Conference on Business Information Systems (BIS), 2019.

(iii) Then, we aim to challenge the question of how to find entities who, although are not visible (considering the number of connections), they still influence their network. We address this problem by first proposing a definition of the influence of such case in Chapter 3, and then in Chapter 4, we test the proposed theoretical approach by performing experiments on two real-world datasets. Work including this contribution was published in:

(3) Monika Rakoczy, Amel Bouzeghoub, Katarzyna Wegrzyn-Wolska, Alda Lopes Gancarski, *In the Search of Quality Influence on a Small Scale – Micro-influencers Discovery*, OTM 2018 Conferences: Confederated International Conferences: CoopIS, C&TC, and ODBASE 2018, Springer, 2018.

(iv) Next, we deal with the questions of how to quantify influence over time, and how can the causal effect on entities influence be represented. We deal with it in Chapter 5, where we describe the proposed model aiming at time effect on influence evaluation which uses the second instantiation of the abovementioned theoretical model, that targets highly time sensitive type of social network – citation networks. This work was gathered into the following publications:

(4) Monika Rakoczy, Amel Bouzeghoub, Katarzyna Wegrzyn-Wolska, Alda Lopes Gancarski, *Influence in Time-Dependent Citation Networks*, 12th International Conference on Research Challenges in Information Science (RCIS), IEEE, 2018;

(5) Monika Rakoczy, Amel Bouzeghoub, Katarzyna Wegrzyn-Wolska, Alda Lopes Gancarski, *Time-Dependent Influence Measurement in Citation Networks*, Complex Systems Informatics and Modeling Quarterly (CSIMQ 17), Volume 17, 2018.

- (v) Finally, a subchallenge questioning the linkage between influence and reputation was targeted in Chapter 5 by investigation of both influence and reputation. We propose a transition method, that uses existing influence information from the social network in order to predict the reputation. The work was published in:
- (6) Monika Rakoczy, Amel Bouzeghoub, Katarzyna Wegrzyn-Wolska, Alda Lopes Gancarski, *Reputation Prediction using Influence Conversion*, 17th IEEE International Conference On Trust, Security And Privacy In Computing And Communications (IEEE TrustCom-18), IEEE, 2018.

1.4 Thesis overview

The remainder of this thesis manuscript is organized as follows:

- **Chapter 2: Related work** provides a review of current *state-of-the-art*. We first briefly describe of Social Network Analysis scope in general. Then, each section presents the related works connected to each of the notions on which we focus: influence, population, trust, and reputation. In each part, we discuss the meaning and properties of one term in the literature and present a spectrum of different SNA methods dealing with the term.
- **Chapter 3: Social Network Interactions Modeling** presents our proposition of the general hierarchy of the terms, considering their complexity. In the chapter, we also propose the terms typologies and discuss the differences between the notions. Having a clear understanding of the terms, we then focus on the influence modelization, providing a theoretical model of influence. In particular, we introduce an Action-Reaction concept on which we base afterward, propose an ontology containing and binding the influence and influence-related concepts, and present their definitions. We also propose and discuss differentiation between macro- and micro-influence, as well as show the proposition providing a link between influence and reputation computation.
- **Chapter 4: Proposition of General Model of Influence** shows the first instantiation of the established theoretical model from Chapter 3, which is an influence evaluation model called ARIM. The model incorporates different influence components, such as intensity, spread, engagement and time. At the same time, it remains general in the sense of possible application to different types of social networks and flexible in regard to being able to work using various types of social network reactions. We performed experiments with the use of ARIM, which were performed using three real-world

datasets, and applied both macro- and micro-influence evaluation issues, which in Chapter 3 we discussed and defined.

- **Chapter 5: Proposition of Time-focused Influence Adaptation** presents the second instantiation of our theoretical proposition introduced in Chapter 3. While the previous chapter showed a general aspect model, the model proposed in this chapter is an extension of influence modelization targeted particularly on time component. To achieve this the model, called TiDIE, was applied to particularly time-sensitive social networks type – citation network, and takes into account time from the causal relation perspective. It was validated by experiments using scientific articles dataset, which showed the applicability of our model. Moreover, we further utilized TiDIE to explore the link between influence and reputation described in Chapter 3. Combining the two, we created and experimented with an extension of TiDIE, called ReTiDIE, dedicated to assessing reputation based on influence information.
- **Chapter 6: Conclusion** summarizes our work, as well as discusses some of the research issues that we encountered during the thesis. We also present the future research directions aiming to indicate possible later extensions of the work presented in this dissertation.

Chapter 2

Related work

2.1 Introduction

Social Network Analysis (SNA) deals with a wide spectrum of topics, from structures of networks and ways they form to users and their individual behavior within social networks. This work is primarily dedicated to the analysis of the interactions between the users within the social networks. The findings of such analysis can be used in a variety of disciplines, e.g. peer-to-peer networks [10, 11], spam detection systems [12], medical usage [13] or combined with Semantic Web [14, 15]. Moreover, the methods for relations between users discovery are particularly broadly and extensively used in advertising [16, 17] and recommender systems [18]. Interestingly, in recommender systems, typically the goal of such systems is to predict the users' rating of the items. However, the analysis of relations between users, e.g. whether users influence or trust one another, cannot only reinforce the process of recommendation but also provide the extra sources of information [19].

Naturally, the basis of the interest in relations between users (or, better say: humans), lies in Social Sciences, which long studied and still studies characteristics of social relationships such as *connectedness*, *relation strength*, *trust* and others [20]. The rapid expansion of ways in which people can make and maintain virtual contact transformed and evolved these inter-human relations. However, while some of these notions and relations characteristics were adjusted into computer science context, others still remain the hot topic for research. In this work, we will explore three of such important, yet not fully examined and studied concepts. Specifically, we will investigate influence, reputation, and trust between users within social networks.

While several notions were thoroughly studied in psychology, philosophy and sociology, it has been shown that the concepts of *influence*, *reputation*, *popularity* and *trust* are particularly subjective and hard to qualify. For this reason, the task of finding methods capable of

automatically capturing and evaluating reputation or influence between the users basing only on raw data tends to be daunting and challenging. Obviously, while there have been attempts at creating methods that explore users' relations like trust or popularity, the need for general and precise ways of estimation of these concepts is still very current.

In this chapter, we discuss these *state-of-the-art* methods. In Section 2.2 we briefly describe the origin and general concepts connected to Social Network Analysis. Section 2.3 reviews methods dealing with influence. Then, we analyze approaches focusing on popularity in Section 2.4. Sections 2.5 and 2.6 are dedicated to models dealing with trust and reputation, respectively. We close the chapter with the conclusion taking into consideration influence, reputation, trust, and popularity.

2.2 Social Networks

The discipline of Social Network Analysis (SNA) has been studied and developed for many decades. The precursors of the field, Durkheim and Tonnies, created the foundations of Social Network Analysis as early as 1800s [20]. The present SNA is believed to have evolved mainly from three studies: two of them were carried out in the 1930s – one involved research around correspondence between well-being and social life; second, done at Harvard University, was concerned about investigation of cliques within social groups; the third, performed principally at Manchester University, looked into informal social relationships [21].

Later, the use of algebraic models led to further development and formalization of the field [22]. Importantly, until the late 1990s, the research involved collecting data by using groups of paid and unpaid volunteers that filled questionnaires. This meant not only the general difficulty in obtaining the data but also a small sample of the gathered data, which made it harder to reason from it.

The big shift in the SNA domain was noted with the development of the Internet, especially during the arrival of so-called Web 2.0. Previously, Web 1.0 was dominated by personal websites and very basic communication between the users (by email) without the habit of participating in the interactions, building connections and developing the collective content [23]. Meanwhile, the quick development and evolution of Web to Web 2.0 led to the emergence of social sites offering their users the means of communication and possibility of establishing relations between them, enabling more interactive participation of users within the Web. Using these social networking services (SNS), users started to interact with each other virtually, leaving massive data in the form of "traces" of their activity. This big amounts of data attracted social network analysis, who could utilize much bigger and more widely sampled datasets that originated exactly from these social networking sites.

In this section, we introduce the fundamentals of the current SNA scope, describing the most popular representations of social networks and characterizing the SNA data sources – the social network sites.

2.2.1 Models of Social Networks

Throughout the years, in order to analyze the information included in social networks, the methods of modeling social networks have progressed and diversified. First ones were developed by sociologists, including sociograms, dyads, and triads.

Graphs

The most common method of modeling social networks is by using graph theory. By using graphs, the networks can be represented compactly and systematically. As it is a very intuitive structure, it enables easy and quick storing, managing and manipulating of the network data with the use of a computer.

A network is a graph $G = (V, E)$ where V is the non-empty and finite set of vertices (nodes) and E is the finite set of edges (pairs of elements from node set). In the context of social networks the nodes represent actors, e.g. people, and the edges correspond to ties (relations or activities) between them, e.g. Facebook friendship or message exchange. We can distinguish two types of graphs using the edge type criteria [21]:

- Directed – the set of edges is ordered, and each edge e_{ij} leads from node i to node j ,
- Undirected – the set of edges is unordered and edge e_{ij} equals e_{ji} .

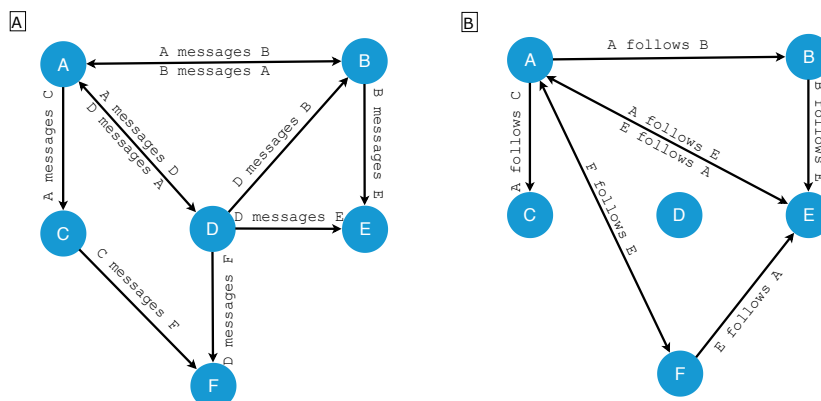


Fig. 2.1 Illustration of two different networks created using same set of users {A,B,C,D,E,F}: A) as edges we consider the messages exchanged between the users, B) the edges represent the "follow" relation

There are multiple properties of graphs resulting from graph theory, such as the degree of the node, the distance between two nodes, etc. In general, nodes in graph symbolize subjects and edges represent the link between them, which can be any relation-type concept, e.g. friendship, action, transaction, etc. It is important to notice that the graph representation can model completely different networks. For instance, in some cases, the nodes will represent users and edges between them will signify friendship notion appointed by users themselves. In another case, the edges can mean the exchange of messages. Else, graphs can also represent blogosphere, where posts are nodes and links are edges, or a network where nodes are bloggers and edges are comments written in response to bloggers' posts by other users. Examples of such situation can be seen in Figure 2.1. Therefore it is crucial to identify and make initial assumptions about the graph and hence the meaning behind edges and nodes.

Sociograms and Sociomatrices

Sociograms represent persons' social links, created to show preferences in groups. In sociograms, nodes are people with links that represent relations between them. Similarly to graphs, we can distinguish undirected and directed sociograms. Undirected sociograms represent symmetrical relations and do not include arrows. On the other hand, directed sociograms are used for asymmetrical relations, where the direction of the relation is represented by an arrow. Moreover, valued sociogram is a sociogram in which the thickness of the link between people is used to signify the strength value of a relation. Sociograms can be also dichotomized – the link between people is only drawn if the relation value exceeds a particular threshold, in order to simplify the sociogram graphically [3]. Figure 2.2 shows on the left a dichotomized undirected sociogram and an undirected valued sociogram, and on the right a dichotomized directed sociogram. Information about persons' social links visualized by sociograms is

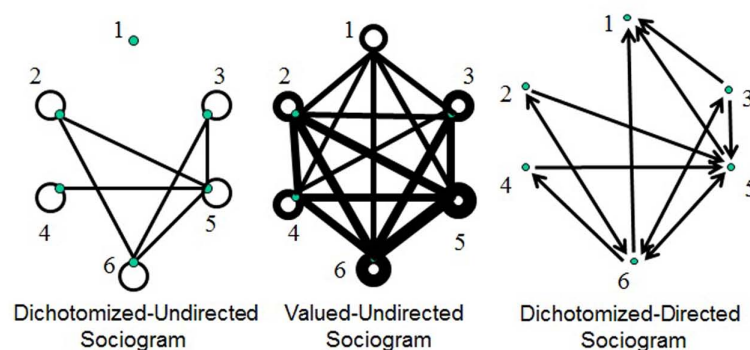


Fig. 2.2 Example of two undirected sociograms – left one being dichotomized, and the middle one valued on, and on the right a directed sociogram [3]

Shared Knowledge (cutoff = 0.5)						
Mbr	1	2	3	4	5	6
1	0.37	0.37	0.33	0.37	0.37	0.37
2	0.37	0.57	0.43	0.46	0.57	0.56
3	0.33	0.43	0.56	0.33	0.56	0.54
4	0.37	0.46	0.33	0.52	0.51	0.48
5	0.37	0.57	0.56	0.51	0.91	0.84
6	0.37	0.56	0.54	0.48	0.84	0.84

Symmetric Sociomatrix

Knowledge of Who Knows What						
Mbr	1	2	3	4	5	6
1		0.10	0.20	0.20	0.30	0.10
2	0.20		0.00	0.46	0.57	0.56
3	0.60	0.43		0.33	0.56	0.54
4	0.37	0.46	0.33		0.51	0.48
5	0.60	0.30	0.20	0.30		0.80
6	0.60	0.80	0.60	0.90	0.80	

Asymmetric Sociomatrix

Fig. 2.3 Example of symmetric and asymmetric sociomatrices. The values were normalized to scale [0,1]; bold signifies the values above the threshold value 0.5 according to which the sociograms (created based on these sociomatrices) can be dichotomized (from work[3])

organized using sociomatrices. Sociomatrices are "*key quantitative artifacts used in network analysis*" [3]. Sociomatrix contains one row and one column for each member. Depending on the relation that is depicted by particular sociomatrix, the diagonal cells either can be a recursive relation of a person to themselves, or can be left blank signifying no value. Figure 2.3 is an illustration of two different sociomatrices.

While using graphs, sociograms and sociomatrices are the most popular representations of social networks, there are also some other structures used to describe social networks and relations within. For instance, dyads and triads are groups of respectively two and three people, that can be observed in social networks and particularly interesting are the way they form. Other structures considering social networks comprise entities such as subgroups, and blockmodels.

2.2.2 Characteristics of Social Network Sites

In general, social network sites are made in order to enable users to create and share content or to participate in social networking. While they differ by usage and functions, they are all growing in popularity. Figure 2.4 shows 20 most popular social network sites ranked by the number of active users (as of January 2019).

Social networking sites can be classified according to their use [24]:

- Social networking sites – they focus on building relationships between users. Their primary functions are connecting (befriending) people and building individual profiles of users. A profile helps other users to recognize the person; the profile can be public or semi-public. These sites enable to create connections between both strangers and

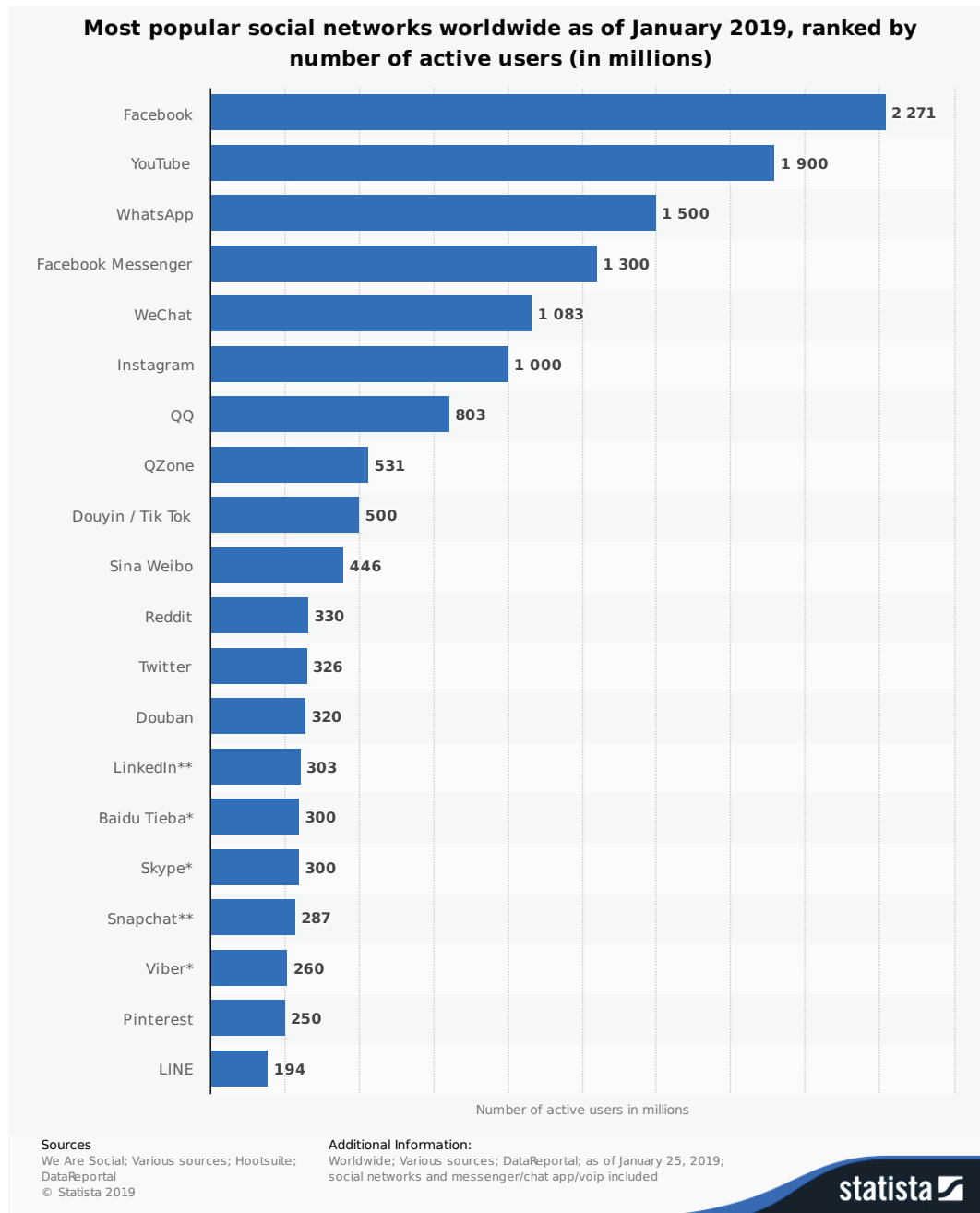


Fig. 2.4 Twenty most popular social networks ranked by number of active users in millions (as of January 2019) [4]

known people, however, the surveys showed that users are more likely to befriend “latent ties” [25], so users that they “share some offline connection” [24]. Examples: Facebook¹, Google+². We can also distinguish a subcategory:

- Business networking sites – based on the same principle of connecting users, but on the basis of creating a wide, global business network by getting acquainted in terms of business contacts. They allow users to generate business opportunities (new business deals, job opportunities, etc.). Examples: LinkedIn³, Viadeo⁴.
- Content sharing sites – portals focused on sharing content, e.g. photographs, music, texts. Users can comment and upvote the content in reaction to the shared content. There can be two subcategories distinguished:
 - Photo sharing – focused solely on sharing photos, examples: Instagram⁵, Pinterest⁶.
 - Video sharing – allow publishing and sharing videos, examples: Youtube⁷, Vimeo⁸.
- Blogging platforms – allow users to create personal space, dedicated to publishing articles. Each user, called a blogger, is a registered user who writes texts – called posts. The content of a blog is dated and displayed on the Web in the reverse chronological order. The interaction between users is established by the possibility of commenting the content (by bloggers or by anonymous visitors of the page) as well as linking to each other’s posts. Examples: Wordpress⁹, Medium¹⁰. Additionally to blogging platforms, we can also recognize an important subcategory:
 - Microblogging platforms – while they still do root in the idea of sharing, the text that the user can produce is limited. They are also allowing users to connect to each other (similarly to social networking sites), and are much more based on the

¹<https://www.facebook.com/>

²<https://plus.google.com/>

³<https://www.linkedin.com/>

⁴<https://fr.viadeo.com/>

⁵<https://www.instagram.com/>

⁶<https://www.pinterest.com/>

⁷<https://www.youtube.com/>

⁸<https://vimeo.com/>

⁹<https://wordpress.com/>

¹⁰<https://medium.com/>

real-time, or almost real-time users' reactions to the published content. Examples: Twitter¹¹, Weibo¹².

- Collaborative sites – they provide the ability of information gathering and sharing collectively by the Internet community. Creation of content is done simultaneously by many end-users, thanks to applications which allow multiple users to add, remove and change the content [26]. Example: Wikipedia¹³, Yelp¹⁴.
- Interest-based networks – the portals connected to a particular topic or domain that enable multiple users to participate in a shared space, where the interaction is made. The shared space is constantly changed and developed by users [26]. Example: SecondLife¹⁵.
- Educational sites – they provide educational materials, such as online courses, that allow users to widen their knowledge in various disciplines. Examples: Coursera¹⁶, Udacity¹⁷.
- Commerce sites – the sites are based on the services enabling commerce that allow trading and buying products and services with the use of the Internet. Examples: Amazon¹⁸, AliExpress¹⁹.
- Company-sponsored sites – they are connected with both companies and their campaigns, and their main purpose is to help companies to advertise and promote themselves. Example: Apple Support Communities²⁰.

However, it is important to notice that, with the growth and development of SNS, many sites can fall into multiple categories. For example, Facebook can be considered as both social networking and photo sharing site; Twitter, besides its microblogging nature, also allows photo and video sharing, etc. Depending on SNS main function, they enable users to perform a variety of actions. Although sites differ in provided services, many of them provide a similar set of ways for users to interact. The most popular social activities are:

¹¹<https://twitter.com/>

¹²<https://www.weibo.com/>

¹³<https://www.wikipedia.org/>

¹⁴<https://www.yelp.com/>

¹⁵<https://secondlife.com/>

¹⁶<https://www.coursera.org/>

¹⁷<https://www.udacity.com/>

¹⁸<https://www.amazon.com/>

¹⁹<https://www.aliexpress.com/>

²⁰<https://discussions.apple.com/welcome>

- Content publishing – the content shared in the space of the site includes texts, videos, and photos.
- Commenting – the activity performed in reaction to other users' activities, e.g. posting a photo, involving written texts (sometimes of limited length).
- Upvoting – the reaction on the content of others, it usually has a positive connotation. However, many sites provide multiple emotion connected with votes, for instance Facebook has 6 different emoticons including *like*, *love*, *angry*, *sad* and *haha*.
- Content sharing – the act of re-publishing the content already posted by another user on other social networking sites, e.g. using an external link.
- Friendship creation – creating a link between two users.
- Messaging – the majority of SNS provide a built-in messaging function allowing users to exchange private messages.

Each of such activity can provide some knowledge about the social network and can potentially lead to general observations about the population. Understanding the behavior of users is important to multiple entities [27]. Internet service providers are focused on the extraction of information about the structure and evolution of online social networks (OSNs) in order to maintain the infrastructure needed for Internet services. OSN service providers can improve the user experience by ameliorating and adding functionalities and services on the website based on the analysis of users behavior. Moreover, based on the traffic data and information about users geographic distribution, OSN providers are able to sustain and optimize the use of data centers. The behavior study is also highly utilized in political and social campaigns for sharing and spreading information, in e-commerce for targeting groups of selected users and products to advertise, and in recommender systems to filter various information for end-user. Furthermore, the users' behavior analysis can be also used in applications such as security, e.g. malicious users identification, business intelligence, textual analysis, machine learning, etc.

Remark

As mentioned, in this thesis, we are particularly focused on the analysis of users' behavior, and we target four concepts: *influence*, *trust*, *popularity* and *reputation*. These notions can be characterized as defining relations between the users, but they also affect the structure of the network, the spread of information within the network and the willingness of the users to cooperate. In the next sections, we will address the works connected to each of these notions.

2.3 Influence-based Approaches

In this section, we investigate the influence notion. We first recall definitions of influence. Then, we focus on influence properties and features that specify and distinguish the term from other notions. Next, we present an overview of literature dealing with influence in SNA scope. We then shortly discuss the issue of influence valuing. Finally, we show a synthesis of the presented *state-of-the-art* methods, focusing on their inclusion of showed before influence properties.

The term *influence* is widely known and used. Merriam-Webster Dictionary [28] defines it as "*the act or power of producing an effect without apparent exertion of force or direct exercise of command*". Sociology gives even clearer definition, describing *influence* as a process of changing both feelings and behavior of a particular person, due to the interaction with others. The result of such influence interactions varies from an adaptation of one's opinions, believes revision to change of the behavior [29].

Although intuitively the term is well understood in social context, in social network analysis *influence* seems to be an ambiguous term that depends strictly on the presumed assumptions. For instance, Kempe et al. [30] focused on influence in the information flow and spread sense. On the other hand, other works, e.g. [31, 32], dealing with the quantity aspect of influence targeting mainly users in a central position in social networks.

2.3.1 Influence Properties

In order to get a closer look at the influence, we present the assumed influence properties taken from literature [33–35]. We have classified these properties into three categories, depending on the object they describe: influence itself, influential users, and influential content. The properties are as follows:

1. Influence properties– these are properties strictly concerning the way influence is modeled.
 - Asymmetry – the impact goes from the subject to the object of the influence.
 - Time-dependency – influence of one person is changing with time. Moreover, depending on the length of time considered, we either focus on influence trend (short time observations) or long term observations.
 - Event sensitivity – influence, especially considered in online social networks, is highly sensitive to all events happening, both in the real and virtual world.

- Transitivity – it can be observed that influence can be transitive, e.g. in case of influential content sharing, the act of sharing can occur not only directly between post author and followers, but also between further followers of the followers, and, in fact, it is the author's influence that will increase.
2. Influential users properties – these are the attributes that users can have in order to be influential.
 - Being popular – many users are more influential when they are well known (connected).
 - Immediacy – the distance or strength between influential users and the person being influenced is an important factor that partially defines the weight of potential *influence*.
 - Eloquence – according to [36], influential users are often eloquent. This also matches intuition of the fact that the more attractive the users' content is, the higher the probability of them to be persuasive.
 3. Influential content properties represent the factors that describe content (posts, photos, etc.) that we can call influential.
 - Content Recognition – the content has to be noticed by many people in order to be influential.
 - Activity generation – apart from the content being generally known, it also has to make impression (positive or negative), e.g. content commenting, retweeting, linking, etc.
 - Content Propagation – the target is to track the way the influential content spreads out in the network.

Note

Obviously, it is desired for the influential user, if applicable, to generate the influential content. The presented division of influence properties into several perspectives is important since, in order to actually model influence, the influence evaluation method has to capture this "layered" nature of influence.

2.3.2 Methods for Influence Evaluation and Diffusion

The research involving influence and influential users is an important part of social network analysis. Notably, the analysis of influence is a cross-discipline domain involving not only

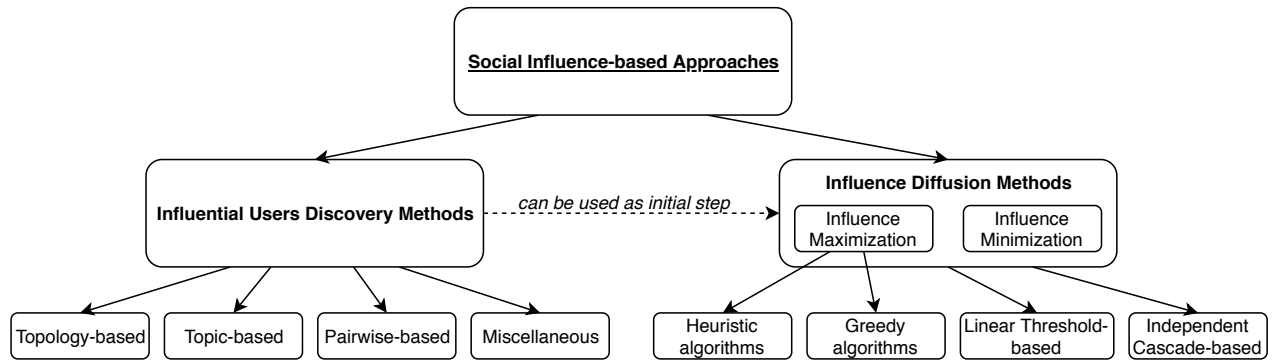


Fig. 2.5 Division of influence methods into (i) approaches with influential users discovery and (ii) influence diffusion methods

SNA but also the newest information from social sciences, e.g. sociology, usage of graph theory, statistics and others [35]. The existing *state-of-the-art* methods considering influence presented here are divided into two categories: approaches dealing with influential users discovery and influence diffusion methods, as can be seen in Figure 2.5. The former category includes methods aiming to find the users that can be regarded in some aspects as influential, while the latter involves approaches that deal with information spread within the network with a particular focus on the optimized way to maximally diffuse the information in the social network.

Importantly, influential users discovery approaches can be used as an initial step for many influence diffusion methods. This is due to the fact that diffusion methods frequently use the pre-defined seed of users who then diffuse the influence further. This seed of users could be obtained by applying influential users discovery methods. As in this work we target relations between users, we particularly focus on the first category of the methods – the approaches for influential users discovery. Nevertheless, in this section, we describe both approaches – first the methods for influential users discovery, and then we briefly discuss influence diffusion approaches.

Influential Users Discovery Approaches

The methods for influential users discovery are a wide range of approaches that try to find users that are affecting the network and other users in some way (structurally, by adding information to the network, etc.). Such methods try to answer the following question: Which users (i.e. influentials) are in such position and are affecting other users in a way that the structure of the network and their behavior, actions or preferences is changed? To keep in mind is the fact that the methods differ not only in the used techniques (statistical

or probabilistic techniques, graph theory, etc.) but more importantly also in defining the influence itself. Some methods focus only on the central position of the user (topology-based approaches). Others, more complex ones, involve more aspects of influence, e.g. user's history, therefore considering more of the influence properties that were listed previously. We identified four main approaches for influential users discovery approaches: (i) topology-based, (ii) topic-based, (iii) pairwise-based, and (iv) miscellaneous approaches. We detail them in what follows.

(i) *Topology Based*

These approaches are focusing on the position of the user within the social network. They have emerged from graph theory and were the first methods to be applied in the context of capturing users' influence.

The three most basic topology based measures, that are frequently used as influence measure, or as a metric contributing to measuring the influence are: *degree centrality*, *closeness centrality* and *betweenness centrality*. The *degree centrality* measures the importance of the node (user) v_i depending on its number of neighbor relations. This means that the bigger number of edges one has, the higher rank it gets. In undirected graphs the degree centrality can be defined as [37]:

$$C_d(v_i) = d_i \quad (2.1)$$

where v_i is a node and d_i is its number of adjacent edges. In directed graphs degree centrality can alternatively be defined in three ways as follows:

$$C_d(v_i) = d_i^{in} \quad (2.2)$$

$$C_d(v_i) = d_i^{out} \quad (2.3)$$

$$C_d(v_i) = d_i^{in} + d_i^{out} \quad (2.4)$$

where d_i^{in} is the number of incoming adjacent edges and d_i^{out} is the number of outgoing adjacent edges. Hence, in terms of social networks, the influential user means the user that has a lot of connections to others (e.g. a large number of friends), no matter the importance of the connections.

On the other hand, *closeness centrality* measures the average shortest path to all other nodes in the graph. The smaller average of the node, the higher the node is ranked.

The definition of closeness centrality is as follows [37]:

$$C_c(v_i) = \frac{1}{L_{v_i}} \quad (2.5)$$

where L_{v_i} is the *average shortest path* for node v_i to all other nodes and is defined as:

$$L_{v_i} = \frac{1}{n-1} \sum_{v_j \neq v_i} L_{i,j} \quad (2.6)$$

and $L_{i,j}$ is the shortest path from v_i to v_j , and n is the number of nodes in the graph. For the non-existent paths the measure is 0. Consequently, the influential user in terms of closeness centrality is defined as the user that has the most central place in the whole network.

Finally, *betweenness centrality* measures the importance of the node by considering the information flow in the graph. In other words it checks the frequency of node v_i appearing in the shortest path of two other nodes. The formal definition [37] is the following:

$$C_b(v_i) = \sum_{j \neq k \neq v_i} \frac{l_{j,k}(v_i)}{l_{j,k}} \quad (2.7)$$

where $l_{j,k}$ is the number of shortest paths between nodes v_j and v_k , and $l_{j,k}(v_i)$ is the number of shortest paths between nodes v_j and v_k that go through v_i . Therefore betweenness centrality defines the influential user as the user that is the *connector* or a *hub* to many other users.

Both HITS [38] and PageRank[39] are algorithms created initially in order to find and rate web pages. HITS is a link-based algorithm also used to rate web pages. It depends on two scores: hub score and authority score. *Hubs* are the nodes that have high outgoing degree while *authorities* are the nodes with high incoming degree. The algorithm is based on the assumption that high ranked hubs are pointing to the nodes with high authority score and vice versa. Finally, the high rank is based on high authority scores.

Each node has two values assigned: a_v is the authority score and h_v is the hub score. Initially, all the values are equal to 1, and later they are changed iteratively according to the equations ([38]):

$$a_v = \sum_{i=1}^m a_i \quad (2.8)$$

$$h_v = \sum_{i=1}^n h_i \quad (2.9)$$

where m in Equation 2.8 is the number of nodes connected to v and n in Equation 2.9 is the number of nodes that v connects to. The lack of changes in parameters is the stop condition for both values computation.

PageRank is the algorithm created by Larry Page and Sergey Brin from Google, that ranks web pages and it is often used by search engines. It is based on the assumption that the more edges a particular node has, the higher score it should get. Moreover, it takes into consideration the importance of edges – the weight of the particular edge is higher if the node from which it goes out is an important node. The formal definition in matrix form of PageRank score (C_p) is as follows (based on [37]):

$$C_p = \beta(I - \alpha A^T D^{-1})^{-1} \cdot \mathbf{1} \quad (2.10)$$

where β is a constant coefficient added to the measure of each node, I is an unit matrix, α is the parameter that specifies the importance of β in the final rank (it should be positive), A^T is the transposed adjacency matrix, D is a diagonal matrix defined as $D = \text{diag}(d_1^{\text{out}}, d_2^{\text{out}}, \dots, d_N^{\text{out}})$, -1 signifies the operation inverting the matrix, and $\mathbf{1}$ is a vector of all 1's. Additionally, all the nodes' degrees d_j^{out} should be non-zero. As the centrality of the zero-degree node does not have an effect on any other nodes, the zero degree should be changed to a constant value of 1. Thus, the users' influence is based on the influence of their neighbors.

(ii) **Topic Based**

One group of the *state-of-the-art* methods include the approaches that separate topic detection process from the analysis of the influence. For example, a paper by Haveliwala et al. [31] proposed an extension of PageRank, called Topic Sensitive PageRank (TSPR). The main idea of TSPR is to calculate the set of scores with respect to various topics for each node, and then to use the combination of the scores, while utilizing the hierarchy of topics. The method requires a pre-defined set of hierarchic topics and is computationally challenging. Similar works that are based on PageRank followed [40–42]. For example, Cataldi et al. [42] proposed calculating the influence for a user basing on a retweet graph, that is created for a pre-defined topic. Alternatively, there are also some works that have used additional information provided directly from users about the topic, namely hashtags. RetweetRank and MentionRank [32] are examples of such approaches that are using hashtag information in order to group users together according to subjects. Both methods are similar, using as a base for the network either retweets or mentions. The underline assumptions of these methods are that, firstly, an influential user is surrounded by other influential users, and secondly, the increasing

number of retweets or mentions signifies the increase of influence. These approaches indeed try to tackle the dependence of influence topic problem, however, they require a preprocessing involving gathering the topics.

On the other hand, we can also distinguish another group of influence models that combines the analysis of influence with topic discovery at the same time. Paper [43] focuses on users' opinions on some topics, in order to predict their future views on other topics. For each user, the method estimates the sentiment of the user towards different topics based on the number of times the user expressed positive or negative opinion (in the form of verb or adjective) about this topic. Topics are discovered using the Latent Dirichlet Allocation method that estimates their distribution. Authors combine estimated opinion of the user with the opinion of neighbors using the tie strength. A similar method, Fellowship-LDA (or FLDA) was proposed by Bi et al. in [44]. Here, the influence of the user is a combination of two parts: topic-specific influence and content-independent popularity. In order to evaluate the former, the algorithm implements the Bayesian-Bernoulli-Multinomial mixture, thanks to which we can obtain the probability distributions of: first, user mentioning some subject; second, the user's statement belonging to the subject; and third, the likelihood of the user being followed by another user because of the subject. The additional value of content-independent popularity covers the cases in which the user is followed for an unknown, not related to any topics, reasons (e.g. she is a celebrity). While indeed performing topical computing of influence, FLDA is particularly complex. Additional inclusion of topic-level influence propagation was introduced in [45], where the overall influence value was a sum of influence value provided by the user and indirect influence value obtained by assuming influence transitivity.

As we could see, more complex topic based methods need the analysis of the content created by users, which increases their computational and data requirements.

(iii) *Pairwise Based*

Another group of works tackling analysis and evaluation of influence proposes models that are focused on pairwise influence between users. Such approaches, instead of measuring influence globally, deal with point-to-point relations between users, investigating possible differences between ties made by various users, by utilizing information about their interactions, the frequency of those interactions and other parameters.

In many ways, the study of Kwak et al. [46] was a pioneer study, in which the authors have analyzed the follower-following relations basing on Twitter. One of the important

discoveries of the papers is the non-power law distribution of followers, as well as their low reciprocity. A comparison of PageRank and a ranking proposed by Kwak et al. based on a number of followers was performed as well, and it led to the conclusion of the two being very similar. The models aiming to assess the pairwise influence frequently utilize both structural properties of the network and information about users' behavior, as done in [47]. In this work, authors proposed a model (called AWI) aimed to estimate the influence basing on user's neighbors and combining it with the information about the frequency of performing both posting and re-posting (reciprocity) in the network. They additionally consider the time dependency of such networks, using the snapshot of data at a time. Another interesting approach was presented in [48]. Li et al. proposed a method that dealt with identifying influential users within a research network. They divided the issue into two: (1) discovery of academic influence – basing on the assumption that an influential scientist has popular publications, and (2) discovery of social influence – basing on the assumption that an influential user in a network is both well connected and has easiness to propagate information. The authors have addressed the first issue by combining parameters such as the total number of readers of a user, a number of readers per paper, etc. To calculate the social influence they have used Euclidean norm of degree, closeness and betweenness centralities. Chikhaoui et al. [49] have introduced the model determining the direction of pairwise influence between two communities, understood as two conferences, for a particular time period. In their work, the authors have introduced a model of influence in which they incorporated the concept of Granger Causality²¹ from work [50] and tested on a citation network. They have focused on influence between groups and utilized in their calculations normalized citation weights as a measure to represent citation influence. The calculated values of citation influence are used in Granger causality test in order to determine the influence. Similar works have been done in [51, 52] – their approach was further extended by a topic-discovery preprocessing step, which was used in order to determine communities.

(iv) *Miscellaneous*

Additionally to the approaches presented above, there are obviously other works that as well deal with the influence evaluation. In the famous work of Hirsh [53], the author presents a metric that aims to calculate the influence of research, based on his/her publications. The basic metric proposed in the paper is as follows:

²¹A concept of causality based on the prediction. See Chapter 5

$$\text{h-index}(p) = \max(\min(f(i), i)) \quad (2.11)$$

where f is the function that corresponds to the number of citations for each publication, and i is the position of the publication p in the set of ordered publications by descending citation number. Based on this work, other similar metrics were created, including g-index [54], Google invented i-index [55], o-index [56], etc. Important to mention is also the work of Agrawal et al. [34]. The main goal of the method presented in the paper is to measure the influence of the posts and their authors within the blogosphere, by first evaluating the post influence (influential content), and then determining the influence of the user who wrote it. The rank for post p is calculated using the following formula:

$$\text{InfluenceFlow}(p) = w_{in} \sum_{m=1}^{|I|} I(p_m) - w_{out} \sum_{n=1}^{|\theta|} I(p_n) \quad (2.12)$$

where w_{in} and w_{out} are weights determining the importance of incoming and outgoing links (the number of times the post p was shared or shared something respectively), p_m is the number of posts that link to the post p and p_n is the number of posts to which post p links to.

The total rank for post p is given by the equation:

$$I(p) = w(\lambda) \times (w_{com}\gamma + \text{InfluenceFlow}(p)) \quad (2.13)$$

where $w(\lambda)$ is the weight function dependent on the post length λ and w_{com} is the weight used to adjust the contribution of the number of comments on the post. The influence score for each user is then calculated by selecting the maximal rank value from all posts N of each author U :

$$\text{Influence}_U = \max(I(p_i)) \quad (2.14)$$

where $1 \leq i \leq N$, and N signifies the number of all posts. Based on Agarwal et al. approach, several other approaches were proposed [57, 58]. Impossible to omit are also several working web applications that aim to measure the influence of different people based on their activity in the World Wide Web. Examples of such systems are Klout [59], or PeerIndex²². It is important to notice that the criteria and the parameters used by such systems are unknown and not transparent [60]. Rao et al. system called Klout

²²<https://www.brandwatch.com/p/peerindex-and-brandwatch/>

is a cross-platform system that considers properties, both topological and activity-like, in order to evaluate the influence. However, none of the articles published by Klout team reveals enough details about the metric to really have inside into their work. For example, in their article [59] they mention using both weights and more than three thousand features to calculate the final score, however, they do not include any details about them.

Influence Diffusion Approaches

The issue of influence diffusion is a general problem of how the information spreads within a network. It can be treated as a specific case of epidemic problem. The assumption of most influence diffusion approaches is that the network consists of users (nodes) that are connected by edges, and the edges already signify the influence.

As shown in Fig. 2.5, within influence diffusion problem we can distinguish two sub-problems: influence maximization and influence minimization. Influence maximization is a particular subproblem originating directly from influence diffusion problem, that is particularly interesting and widely studied. We will first discuss some of the most important works dealing with influence diffusion problem and then move to methods dealing with influence maximization.

As mentioned before, in this work we focus in particular on approaches for influential users discovery. However, even though influence diffusion approaches are not of our primary interest, we still present a brief overview of the most important methods dealing with influence diffusion. Two main categories of influence diffusion approaches are: (i) Linear Threshold, and (ii) Independent Cascade, which we detail in what follows:

(i) *Linear Threshold*

In the Linear Threshold (LT) model [30] the nodes can be idle or activated (infected). Initially, the activation threshold for each node is randomly chosen. Then, the node can be activated by its already active neighbors, if the sum of the weights of the neighbors is bigger than the activation threshold of the node. Once activated the node remains active until the end of the process.

Improvements of LT model followed. Mohammadi et al. [61] proposed a Delayed LT (DLT) model, where a node has a third possible state – latent active. The node has to go through this middle-state in order to be activated. The introduction of the state has improved the diffusion effect of the influence, however, it made the whole model more complex. On the other hand, in [62] Liu et al. proposed a LT extension in which both diffusion and containment of the influence is considered.

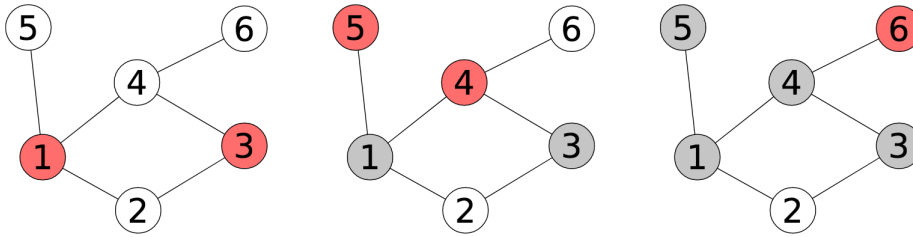


Fig. 2.6 An illustration of the Independent Cascade Model [5]. I is a set of infected nodes. At $t = 0$ (left graph), $I_0 = \{1, 3\}$, both infected nodes fail (due to their random "infection" probabilities) to infect node 2, but successfully infect nodes 4 and 5. At $t = 1$ (middle graph), $I_1 = \{4, 5\}$ nodes 1 and 3 are now inactive; 5 has no susceptible neighbor and stops propagating the contagion, while 4 successfully infects 6. At $t = 2$ (right graph), $I_2 = \{6\}$, but since 6 has no susceptible neighbor the contagion process stops there. [5]

(ii) *Independent cascade*

The first step in the Independent Cascade (IC) model [30] is to activate an initial seed of nodes. Then, at each step, nodes can activate their outgoing and inactive neighbors with an independent probability (chosen randomly). A node, once activated remains activated until the end of the process. Moreover, if a node fails to activate its neighbor, it cannot try to activate it until the end of the process. The influence diffusion process ends when no node can be activated. An example of IC model can be seen in Figure 2.6.

IC model was further developed and extended [63, 61, 64]. For example, Chen et al. [63] considered additionally time-delays for IC model. Moreover, a Delayed Independent Cascade (DIC) model, similar to the DLT model for Linear Threshold, was proposed [61].

Influence Maximization Subproblem

Approaches for influence maximization deal with NP-hard problem defined as follows: given a social network modeled as a graph $G = (V, E)$, and a non-negative number k , where nodes are users and edges are labeled with influence probabilities among users, the influence maximization problem is to find a set of k seed nodes that maximizes the influence propagation scale in the social network under a given diffusion model [35]. In other words, such issue can be translated into the following question: Which users to target for spreading some information in order to have maximum possible users in a social network talking/knowing about this information? Hence, such methods aim to find users that will most widely share the information (propagate it further). On the contrary to approaches for the influential users discovery, these methods are strictly connected with the diffusion of information. The

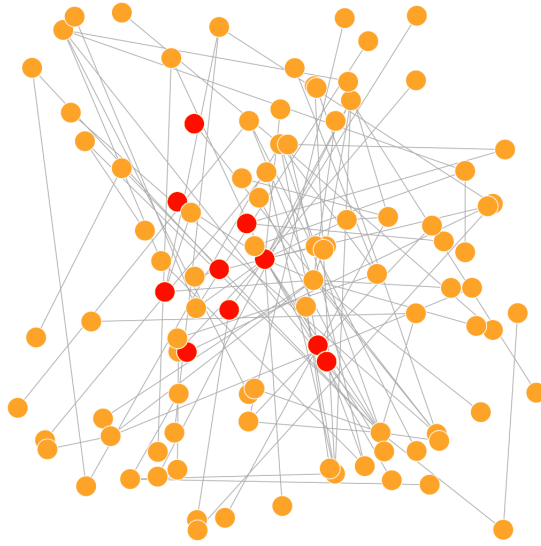


Fig. 2.7 Visualization of influence maximization problem: based on the set of red nodes, how to spread the information in quickest way?

illustration of this issue can be seen in Figure 2.7. We distinguished two main categories of methods dealing with Influence Maximization:

- *Greedy algorithms* – These are the methods where the selection of the nodes to activate are chosen based on the maximal gain towards the state of the current iteration. The accuracy of such approaches is relatively high [65], however, both complexity and execution time are high as well. Various algorithms were proposed, e.g. greedy climbing approximation algorithm by Kempe et al. [30], Cost-Effective Lazy Forward Approach [66] and others.
- *Heuristic algorithms* – Such methods base the selection of the nodes to activate on a specific heuristic. Kempe et al. [30] proposed heuristic algorithms for influence maximization using Random, Degree and Centrality metrics. Other examples include Local Directed Acyclic Graph (LDAG) heuristic algorithm [67], Two-phase Influence Maximization (TIM) [68] amongst others.

Influence Minimization Subproblem

Interesting to mention is also the problem of Influence Minimization. It can be considered as a dual problem of Influence Maximization [65]. The goal is, obviously, to limit the number of infected (activated) nodes in the network, by blocking initially k -nodes (similarly to maximal infection of nodes with initial k -infected for influence maximization). A real-world application of this problem can be seen in the issue of limiting the fake news spreading.

2.3.3 Influence valuing

It is essential to mention also the judgment of the concept influence in terms of being positive or negative. While considering the term basing on the real world meaning, having an influence on somebody does not imply either positive or negative value. The evaluation of influence is only added by attaching an adjective to the whole phrase. For instance, one can say that some person (e.g. a parent) has a *good influence* on her/him; on the other hand, an ill-behaved child can have *bad influence* on another kid. However, the fact that one is regarded as *influential* does not necessarily imply that the influence itself is positive or negative. Additionally, none of the described properties guarantees favorable attitude of influenced users towards the impacting source. Not only influence can be both good or bad, but also we acknowledge that it is possible to distinguish the "zero stage" of influence, where the source does not have any impact on the target at all. It is also important to notice that inclusion of the "judgment" by assigning a positive or negative label to influence can not only be biased or be incorrect (e.g. ironic comments), but also can be undesirable from the application point of view.

One of the examples of works utilizing valuing influence is proposed by Bigonha in [69]. In this paper, the analysis of polarity of users has been included, assigning them to one of two groups: evangelists and detractors, depending on the sentiment analysis of user's messages. On the other hand, Zhang et al. [70] have used only positively evaluated influence in order to maximize its spread.

2.3.4 Synthesis of Influence Evaluation Methods

We considered the discussed methods within the scope of influence properties, showed previously. As our focus is on influential users discovery and not on influence diffusion approaches, in this synthesis, we only included the of-interest approaches for influential users discovery. Table 2.1 includes all the methods examined from the perspective of solely influence attributes. Then, Table 2.2 reviews if the methods are considering the properties of influential content and properties of an influential user. Additionally, Table 2.3 gathers further information about the methods, such as database used for experiments, utilized technique and metrics, and the application of the method.

It can be seen that all the methods consider influence to be asymmetric. Transitivity and topic-dependency are also sometimes included in the works. However, aspects such as time-dependency and propagation are rarely examined. Particularly surprising is the lack of consideration of time aspect of the methods, as influence is deeply time sensitive. As mentioned before, the characteristics of the influence will change with time, meaning depending on the length of time span considered for the influence calculation, we can

Table 2.1 Comparison of influence properties in *state-of-the-art* methods

Method	Asymmetry	Transitivity	Topic de- pendency	Time de- pendency	Event Sen- sitivity
Degree Centrality	yes	no	no	no	no
Closeness Centrality	yes	no	no	no	no
Betweenness Centrality	yes	no	no	no	no
HITS [38]	yes	yes	no	no	no
PageRank [39]	yes	yes	no	no	no
TSPR [31]	yes	yes	yes	no	no
<i>Cataldi et al. [42]</i>	yes	yes	yes	no	no
RetweetRank [32]	yes	no	yes	no	partially
MentionRank [32]	yes	no	yes	no	partially
TOIM [43]	yes	yes	yes	no	partially
FLDA [44]	yes	yes	yes	no	no
<i>Liu et al. [45]</i>	yes	yes	yes	no	no
AWI [47]	yes	no	no	yes	no
<i>Li&Gillet [48]</i>	yes	no	no	no	no
<i>Chikhaoui et al. [49]</i>	yes	no	no	yes	no
<i>Chikhaoui et al. [51]</i>	yes	no	no	yes	no
H-index [53]	yes	no	no	no	no
iFinder [34]	yes	no	no	no	no
ProfileRank [58]	yes	no	no	no	no
Klout [59]	yes	no	no	partially	no

either observe long-term or short-term influence. Moreover, influence is considered to be deteriorating with time, which is also an important aspect to consider when modeling influence evaluation methods. A related to time-dependency feature – event sensitivity – is also rarely covered by the methods. Furthermore, as can be noticed in Table 2.2, many methods utilize features connected with network topology. This emphasizes the connection of terms influence and popularity. Nevertheless, these methods omit influence aspects such as eloquence or activity generation. However, most of today’s influential users and content tends to be viral, i.e. particularly generate multiple reactions from users. Both recognition and immediacy are included frequently in the approaches. The least used property for influential discovery is eloquence. This is due to the fact that it is a highly subjective, hard to define and measure feature. The only methods that actually included eloquence (iFinder [34]) calculated it basing on a simple assumption that the longer text is more eloquent. However, this assumption might not only be not universally true (e.g. very long texts might be actually less eloquent than shorter straight-to-the-point ones), but also can be impossible to measure at all (e.g. some social networking sites have an upper limit on the number of characters used in post or message).

We can also observe in Table 2.3 that, while there are variety of databases used in the *state-of-the-art*, the microblogging sites such as Twitter or Weibo are used the most frequently. Moreover, multiple methods base on the PageRank method. We can also see by analyzing methods applications that most methods target the detection of influence by itself, however, such discovery obviously has further use in marketing, advertising, recommending, etc.

Note

In comparison, the model that we propose tries to combine multiple important aspects of the influence, including popularity, recognition, immediacy and activity generation. Thanks to this, we have a more versatile set of influential users, as we focus on different indicators of influence. The details can be found in Chapter 3. On top of that, we also investigated a novel phenomenon called micro-influencers. These are the users generating influential content, however not having an enormous number of connections, hence not being in top-popular users. Modelization of the notion can be seen in Chapter 3. We also instantiated the theoretical model from Chapter 3 and tested it on multiple social networks as well as investigating the micro-influencers notion (see Chapter 4). Additionally, we also focused on one particular social network type, in order to focus on the time aspect of influence (Chapter 5).

Table 2.2 Comparison of influential content and user properties in *state-of-the-art* methods

Method	Popularity	Eloquence	Recognition	Immediacy	Activity generation
Degree Centrality	yes	no	no	no	no
Closeness Centrality	yes	no	no	yes	no
Betweenness Centrality	yes	no	no	yes	no
HITS [38]	yes	no	yes	yes	no
PageRank [39]	yes	no	yes	yes	no
TSPR [31]	yes	no	yes	yes	no
<i>Cataldi et al. [42]</i>	yes	no	yes	yes	no
RetweetRank [32]	no	no	no	no	yes
MentionRank [32]	no	no	yes	no	no
TOIM [43]	no	no	yes	yes	no
FLDA [44]	yes	no	yes	no	no
Liu et al. [45]	yes	no	yes	no	no
AWI [47]	no	no	no	no	yes
Li Gillet [71]	yes	no	yes	no	yes
<i>Chikhaoui et al. [49]</i>	yes	no	no	no	yes
<i>Chikhaoui et al. [51]</i>	yes	no	no	no	yes
H-index [53]	yes	no	no	no	yes
iFinder [34]	yes	yes	yes	yes	no
ProfileRank [58]	yes	no	yes	no	no
Klout [59]	yes	no	yes	unavailable	yes

Table 2.3 Detailed methods information including dataset, used technique, metrics and application concerning *state-of-the-art* influence methods

Method	Dataset	Technique	Metrics	Application
TSPR [31]	Stanford WebBase	Extended PageRank		Importance of Web pages
<i>Cataldi et al. [42]</i>	Twitter	Probabilistic	Ngrams, PageRank	Influential users within a subject
RetweetRank [32]	Twitter	Probabilistic	PageRank based	Influential users within a subject
MentionRank [32]	Twitter	Probabilistic	PageRank based	Influential users within a subject
TOIM [43]	Weibo	Probabilistic	Gibbs sampling	Detect and analyze the public opinions around some topics.
FLDA [44]	Twitter, Weibo	Probabilistic, Bayesian	Bayesian Bernoulli-Multinomial mixture	Marketing
Liu et al.	Digg, Twitter, citation network	Probabilistic	Gibbs sampling, LDA	User behavior prediction
AWI [47]	Sina Microblog	Probabilistic	Binomial distribution assumption	Influential users discovery
Li Gillet [71]	Mendeley dataset	Statistic	max/min functions	Influence of researcher
<i>Chikhaoui et al. [49]</i>	DBLP	Statistic	Granger causality	Conferences influence discovery
<i>Chikhaoui et al. [51]</i>	DBLP, Yelp	Statistic	Granger causality	Influence of communities
H-index [53]	citation based	Statistic	max/min functions	Influence of researcher
iFinder [34]	Unofficial Apple Weblog	Statistic	linear	Influential bloggers discovery
ProfileRank [58]	MySpace	Statistic	linear	Influential bloggers discovery
Klout [59]	multi-platform	unavailable	unavailable	Influential users discovery

2.4 Popularity-using Approaches

Popularity – the state of being popular, is a term relating to the audience or the general public. Social psychology divides the concept into two issues: *sociometric popularity* and *perceived popularity*. *Sociometric popularity* refers to the persons who are liked by others, while *perceived popularity* is connected to entities "who are well known and socially central" [72]. However, in social networks analysis, it is broadly assumed that the concept of *popularity* is narrowed and is understood only as *perceived popularity* in the sociological sense. In this context, there are multiple works dealing with measuring popularity within social networks.

2.4.1 Methods measuring Popularity

Using the abovementioned definitions in social networks area, *popularity* of users is usually connected with the number of links they have. Various works use metrics connected to a number of in-coming and out-going nodes. In work by Nagmoti et al. [73], the authors defined a measure called FollowerRank for a user a , as follows:

$$FR(a) = i(a)i(a) + o(a) \quad (2.15)$$

where $i(a)$ is user's in-degree (i.e. the number of followers) and $o(a)$ is user's out-degree (i.e. the number of users followed by user a). It is also important to notice that Nagmoti et al. in their work assume that FR rank is measuring *influence*, however, the method is only connected to users' links, hence is measuring only popularity. Similarly to FollowerRank, metrics such as degree centrality, closeness centrality or betweenness centrality should be, in our opinion, considered as popularity (see Chapter 3). The same measure as FollowerRank, but called Structure Advantage (SA) was also proposed in work by Cappelletti et al. [74]. In their work, the authors also provided a threshold value when SA value was greater than 0.5 signified a user being popular and called them an "*information provider*". In comparison, SA smaller than 0.5 represented an "*information seeker*", as the user was following more users than followed them.

Some works also included popularity metrics as one aspect considered within the estimation of influence. For instance, Bigonha et al. [69] created a Twitter Follower-Followee (TFF) Ratio, that is an arithmetic mean of combination of betweenness centrality, eigenvector centrality and in-degree measure. TFF ratio is then used as a part of the final formula to obtain influence value. The advantage of using TFF is that it can additionally eliminate potential spammers, that possibly have little to no followers but a lot of followees. On the other hand, in [75] popularity was used as a part of equitation aiming at calculating "opinion

leadership". Popularity was calculated using the following formula:

$$Popularity(a) = 1 - e^{-\lambda \#Followers} \quad (2.16)$$

where λ is a variable used for tuning the total score. In their work, Aleahmad et al. targeted finding the opinion leaders, by combining popularity with factors such as topics about which a user discussed.

2.4.2 Misconceptions about Popularity

Importantly, *popularity* is frequently confused with the term *influence*. Many works aiming to create metrics dealing with influence, use only the high connectivity of the user. To illustrate, the authors in [60] give as an example the account of Clint Eastwood on Twitter, having 60,000 followers, the account is completely inactive (no tweets, no followees). While undoubtedly the character of Clint Eastwood is popular and recognized, there can be no discussion about the impact of this person within the network.

What is important to acknowledge is that, while being popular can be an important aspect of being influential, it is not a necessary and sufficient condition. This important observation was recognized for example in work [76], where authors define popular users as those highly-connected within the network, however, they stress that while having many connections, those users are not important in the sense of information dissemination in a network.

Due to this crucial need for distinguishing popular and influential users, we have proposed a novel categorization of *state-of-the-art* methods, which we discuss in Chapter 3.

2.4.3 Popularity Properties

As could be seen before, current *state-of-the-art* works consider only the connectedness of users, or, as social psychology calls it, *perceived popularity*, while considering their popularity score. While *perceived popularity* is strictly connected with the in-coming and out-going links within social networks, there are no specific popularity properties that we can consider here. However, when considering *sociometric popularity*, so the feature of being liked by others, we can distinguish various factors impacting the sociometric popularity score.

Basing on the sociological research [72, 77], we enumerate some popularity properties. It is important to notice that not all of them are easy to adapt and measure while using social

networking sites, due to limitations such as privacy issues or high subjectivity of a factor. The distinguished properties that should suggest high popularity of a user include [72, 77]:

- High-connectivity,
- Large number of shared links or posts,
- Participation in self-promotional groups,
- Inventive profile,
- Having a picture on a profile,
- High frequency of profile information change,
- Routine in social networks sites use.

Moreover, the authors in [72] also stress the fact that, at least in some social networking sites, users who exchange many messages and posts with friends of opposite gender also seem to have higher popularity score.

2.4.4 Synthesis of Popularity methods

Considering a previously presented literature overview it can be observed that in general *popularity* is measured by utilizing in-coming and out-going links in social networks. Most works [73, 74, 69] have used a variation of the ration of followers and followees, sometimes combined with other centrality metrics as in case of [69]. One work [75] utilized a bit more complex approach, where to calculate popularity they applied an exponential function with the number of followers as a parameter.

It is also important to realize that discussed methods do not explicitly acknowledge that their metrics calculates popularity. As showed in the case of metrics used simultaneously in two works [73, 74], one work called it *popularity*, while the other claimed it to be *influence*. We discuss this issue of incorrect assumption of what a particular method is actually calculating, and distinguish between methods that actually deal with both *influence* and *popularity* in Chapter 3.

It can also be observed that popularity is a much less complex notion, in comparison to previously discussed *influence*. As long as the research considers only *perceived popularity*, the methods for calculating it will only consider the topology of the network, using the link ratios.

2.5 Trust-based Approaches

In this section, we detain and describe the notion of trust, first by presenting its general definition. Then we focus on the notion classification and we specify its properties. Next, we present a literature overview of various works dealing with trust. We also briefly discuss the distinction between trust and distrust. Finally, we show the synthesis of the presented *state-of-the-art* works, utilizing the properties of trust presented before.

The ever-present interactions between users using OSNs, both private and business-motivated, have led, among others, to the problem of evaluating trust about a particular user or product. Many interactions involve around cooperating with strangers, believing or not their opinions, etc. The studies that concern trust include multiple disciplines, from social sciences (sociology, psychology [78]), to economics [79], up to computer science. While trust is a cross-disciplinary concept, there is no consensus on the exact meaning, properties or definition of trust.

Considering some pioneer computer science works, there are multiple trust definitions. Golbeck et al. defined trust as "*a commitment to an action, based on a belief that the future actions of that person will lead to a good outcome*" [80]. On the other hand, Josang et al. used the following interpretation "*the subjective probability by which one user expects that another user performs a given action*" [81], somewhat similar to the one in Ruohomaa and Kutvonen work claiming trust to be "*the extent to which one party is willing to participate in a given action with a given partner, considering the risks and incentives involved*" [82]. The concept of trust can be as well characterized in particular context, for example in the recommender systems domain, it can be described as "*confidence towards other people in their capacity of giving valuable ratings for potentially interesting products to be recommended*" [83].

Importantly, we can derive the similarities of the above-mentioned definitions — the trust relation involves expectations about some behaviors of the parties involved. However, it is also clear that the problem of measuring and evaluating trust is a very challenging task, that depends on the taken assumptions, the environment in which we consider the issue, the profile of the actors involved, the purpose of measuring trust and so on.

Moreover, various existing models use different ranges to quantify trust. For example, it can be measured in continuous scale $[0, 1]$ as presented in multiple works, e.g. [84, 6, 85]. Other publications use discrete values, e.g. work [80] used scale $[1..10]$, while systems such as Amazon [86] utilized $[1..5]$ value scale.

2.5.1 Trust Classification

Basing on the literature [87, 88], we distinguished several classification criteria for trust, which we aggregated into a taxonomy, depicted in Figure 2.8. The classification criteria for trust are as follows:

- Number of people involved in the *trust* evaluation process:
 - Local – *trust* can be observed between two users (point-to-point connection), hence every relation will have a separate and independent value,
 - Global – *trust* is the resultant of deposing of the many users' opinions towards one particular user, therefore each user will have only one value, independently of the number of the connections one may have.

Note

Importantly, since *global trust* implies considering opinions of many people, this *trust* type is always implicit. Furthermore, it is crucial to notice that *global trust* is the overall judgment of one person, therefore it is connected to the intuitive meaning of *reputation* and this term is used also in the literature instead of *global trust* [89]. To our understanding, *reputation* is better and more clear term for the aforementioned concept. We discuss the reputation notion in Section 2.6.

- Way the connections between users are regarded:
 - Direct – considered connections are only those where users are directly connected, usually meaning that they are "friends" in SNS;
 - Indirect – the assumption is that *trust* between the users can exist even if they are not in relation, but they have connection through another user (e.g. friend of a friend); in other words, *trust* is considered to be propagated through direct connections, hence using indirect connections always implies utilizing the direct ones.
- Method of obtaining trust values:
 - Explicit – the value is directly given by users;
 - Implicit – the value is based on users activity and behavior, according to the available data and made assumptions; the process always implies computation.

Like in any system that involves engagement of the users, the systems using explicit trust values face the problem of a small amount of data provided. What is more, given

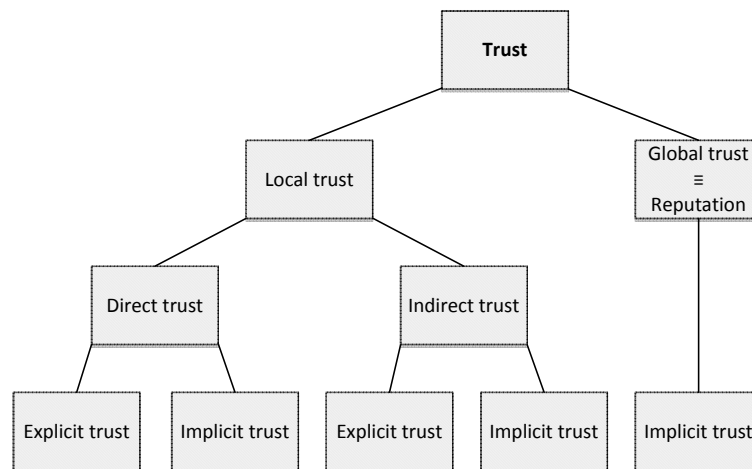


Fig. 2.8 Taxonomy of *trust*.

information can be noisy due to the fact that most users have a tendency to rate only very trusted or very untrusted parties (so the opposite values) and thus the distribution of the values is not regular/even. In comparison, implicit trust models deal with this issue, since the trust is inferred for all users and based on their behavior. The similarity between users' ratings is used to correlate it with the trust value, as it was done in several approaches [90–92]. However, authors in [93] notice that most of these surveys do not compare the outputs of methods – computed implicit trust values with the explicit one to see how close their results are to user-supported values.

2.5.2 Trust Properties

In order to specify the concept of trust, it is very useful to describe its properties. Authors in [94, 36], on the base of trust theory, have distinguished several properties for precisely defining trust:

- **Direction** – *Trust* depends on individual feelings towards another person and the existing *trust* of a user towards a trustee does not imply the trust the other way around.
- **Asymmetry** – *Trust* is subjective to each person. The fact that user *a* trusts user *b* does not imply that user *b* trusts user *a* at the same level (or even at all, hence the importance of including direction in the first place). Additionally, asymmetry implies the relations to be directed.
- **Transitivity** – It is very common for one person, while searching for advice (or recommendation), to not only ask the directly known (connected) persons but also to take

into account the opinion of a friend of a friend, which leads to the conclusion that transitivity is an important *trust* feature.

- **Dynamicity** – The users relations, especially in case of *trust*, are highly dependent on time: *trust* is built over time and, accordingly to the collected experience, its value can increase or decrease.
- **Context dependence** – *trust* is also very strictly dependent on the context in which user *a* trusts user *b*. Obviously, people have interests, hobbies, or work, concerning one group of subjects while other subjects will be completely unknown to them. Because of that, one usually trusts the advice of a particular person in one subject (e.g. computers) but not necessarily in others (e.g. cars).

In order to give a better understanding of these properties, we compare these features with their opposite characteristics. Figure 2.9 depicts all the above-mentioned properties using graph examples, where nodes symbolize users while edges – *trust* values between them. The direction property of *trust* is represented by a directed graph, opposed to undirected one; asymmetry is depicted as directed relation with two different values, combined with a symmetric feature where the trust values are equal no matter the direction; transitivity shows the trust propagation between two users not connected directly; dynamicity shows possible changes in time in the network; finally, context dependence is depicted as a graph with different connections and *trust* values are depending on the topic, contrary to the case of no context dependence where there are constant trust values.

2.5.3 Methods evaluating and using Trust

Since trust is a complex concept, its definition and the way of calculating it can vary depending on the particular assumptions taken. There are many ways in which methods dealing with and using trust can be categorized. For instance, Sherchan et al. [95] proposed to group existing methods according to the used concepts in the models, resulting in three groups: (1) network-based trust models, (2) interaction-based trust models and (3) hybrid trust models. On the other hand, we also can use trust type for categorizing the models, resulting in: direct trust and inferred (indirect) trust models. We can also look at these models from the perspective of usage, where we can distinguish two main categories of models: used in recommender systems and used in the security domain.

Having the above in mind, we chose to group the models of trust focusing on the way the actual trust value is obtained. Basing on this, we divided models into three groups: (i) models basing on user-defined trust values, (ii) models computing trust values and (iii)

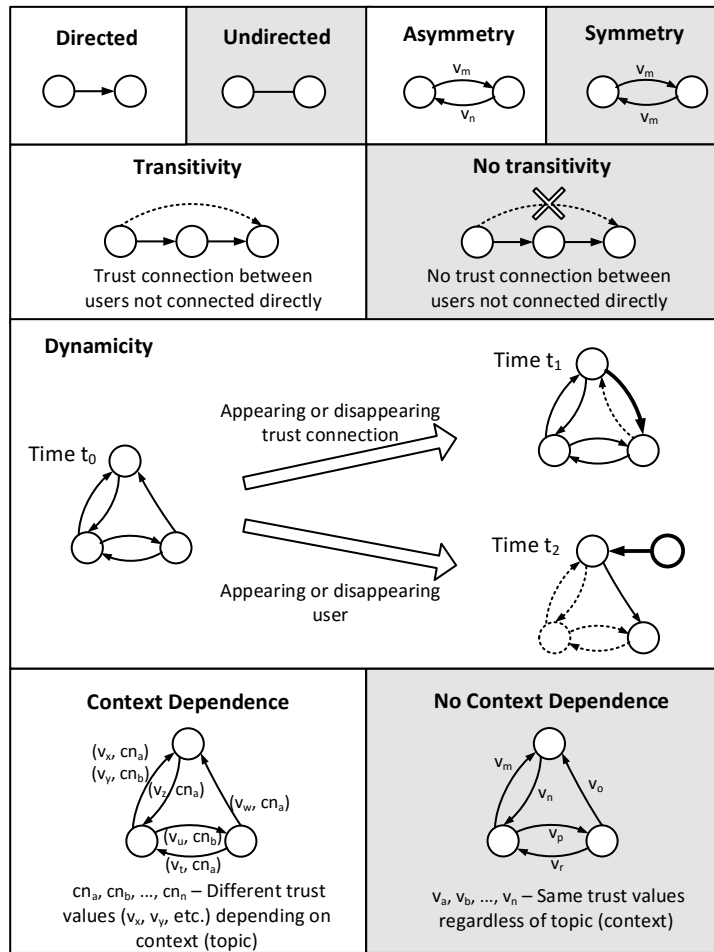


Fig. 2.9 Example of graph visualization of selected *trust* properties (white boxes indicate trust properties).

models assuming the existence of trust information. We provide an overview of the methods from each group in what follows:

(i) *Models using user-defined trust*

There are multiple working systems that utilize the trust value, that is directly obtained from the information given by users. Most of the shopping websites, such as Amazon, or AliExpress, let the users evaluate both products and sellers. They are using some scale (e.g. the above-mentioned services are all using 1 to 5 scale) that enables users to assess the quality of the product, compatibility of the product with the description, time of delivery, etc. Another example is the website TrustPilot²³, that aims to evaluate businesses, companies, websites and such. Similarly to previous systems, users are able to leave the reviews and evaluate the entities by assessing a 1 to a 5-star review. Importantly, TrustPilot problem was malicious users trying to game the system by flooding it with not real reviews. This is possible due to the fact that a user is able to leave the review without any proof of actually using the reviewed service. In comparison, both AliExpress and Amazon, since they are connected to a particular company servicing the sells, are at least partially attack-resistant to such situations, as the evaluation by a user is only possible after a finished transaction.

It is also important to notice that each user using these services is assessing the trust level to the site, business or transaction. However, the overall evaluation scores, in case of those evaluated as an average of all the individual grades, have more to do with the reputation of the evaluated entity (see Section 2.6).

Worth to mention are also hugely popular, but not existing anymore systems that utilized direct trust values. For instance, a non-existing social media site called Orkut enabled the users to assess the trustworthiness value on scale 1 to 3 to his/her friends.

Epinions was another example of a website on which users could review products, similarly to TrustPilot. However, in order to tackle the problem of malicious users, the "Web of Trust" feature was introduced. Thanks to it, the users were able to create the white lists of users that they trust and block lists where users were untrusted (thus their reviews were never shown). The site is currently being re-launched as shipping.com.

(ii) *Models calculating trust*

This group consists of methods that integrate the way of calculating the trust into the model. These approaches, in order to calculate trust between two users, take into

²³<https://www.trustpilot.com/>

consideration information such as the strength of tie between the users, domains of interest of users, etc.

Having said that, the basis on which trust is calculated is sometimes very weak. For example, a work [96] by Jamali et al. introduces TrustWalker. TrustWalker is a recommender system utilizing trust. Trust is evaluated using explicit friendship information and, for two users u and v , is given by the formula [97]:

$$t_{u,v} = \frac{1}{|out(u)|} \quad (2.17)$$

where $|out(u)|$ is the number of out-degree connections of user u (or, in other words, the number of user u friends). Measured trust is therefore strictly local and considered to be of topological nature. Another approach, basing on TrustWalker, called MWalker [92], aims to predict ratings for k -top items utilizing trust in order to narrow down the number of profiles that are used afterward to predict ratings. The trust measure in this system is local and combines two parameters: explicit binary friendship value (assuming that it is "explicit trust") and similarity between users (measured by checking the similarity of tags between the users' profiles). The formula for trust calculation is as follows:

$$t_{u,v} = \text{Explicit Trust}_{u,v} \times \text{similarity tag}_{u,v} \quad (2.18)$$

The ratings prediction is done basing on matrix calculations. Nevertheless, the work considers a very simple model of trust existence basing on the binary relation of friendship between users. Another work, described in [90], used the random walk fashion to traverse the trust network, in order to recommend new items to the target user. To estimate the trust, the authors have used a combined measure of explicit information about the existence of the friendship with the similarity of users, in addition to the weight criteria for both parameters. Interestingly, they have assumed that trust has direction, but also is transitive — they considered as trusted the users that were friend-of-a-friend of the target user, and were similar to the target. Their experiments included Epinions database and shown good results in terms of novelty and diversity.

On the other hand, the authors in [98] proposed a measure of trust that is a combination of similarity and confidence, where confidence between two users is based on the number of common rated items. Using the trust network, the system uses "ants" to move around and searches for the most trustworthy users. The aim is to recommend the set of items to a user, basing on the ratings of those most trustworthy users. Interestingly, the work additionally utilized the well-connected users as the default "trustworthy users"

in order to deal with the cold start problem by using it for the new user. The work of *Sarda et al.* [99], aimed to predict rating for a particular item after some time t . The authors have defined two types of trust: friendship trust and trail levels. The former is defined to be irrespective of context, information about friendship/trust between users (binary metric). The latter is a context-sensitive notion, based on the assumption that friends giving good recommendations for a certain product should maintain the level of those recommendations for similar products. Basing on these notions, the authors create the trust network, where every node has trust information about all other users and sends the request in order to get to know the rating of a particular item from other participants. Then, the node tracks the quality of the responses from the nodes. The recommendation is the resultant trusted neighbor nodes ratings, while the system ignores the recommendations that come from the nodes that are trusted below some value.

The problem of trust is tackled from another angle in work [100], where the authors propose a measure of trust basing on different types of interaction on Twitter, namely: following, retweeting, and mentioning. The authors define trust by the frequency of these interactions between two users, which can be propagated forward as well. The trust from i towards j is defined using the following formula:

$$t_{ij} = \frac{wN_{ij}^{(m)} + (1-w)N_{ij}^{(rt)}}{N_i} \quad (2.19)$$

where N_{ij} is the number of interactions from i to j , N_i is the number of total interactions originated by i , and w is the weight assigned to retweets (rt) against mentions (m). The system also incorporates the notion of decay, which means that the newer updates have higher importance. Additionally, the authors measure also the horizon of trust – the notion that direct, close friends should be considered more valuable for trust calculation than the propagated acquaintances.

(iii) *Models assuming the existence of trust*

Many works in the literature propose systems basing on the trust values, assuming that the information about them is already given. Those approaches usually deal with the problem of transitivity of trust and its inference. The main objective of these works is to infer the trust between two distant (not directly connected) users. To achieve this, the models are discovering the trust paths and aggregating trust values along these paths in order to maximize the confidence of estimation. The propagation of trust poses some problems. To illustrate, Figure 2.10 shows an example of a trust network.

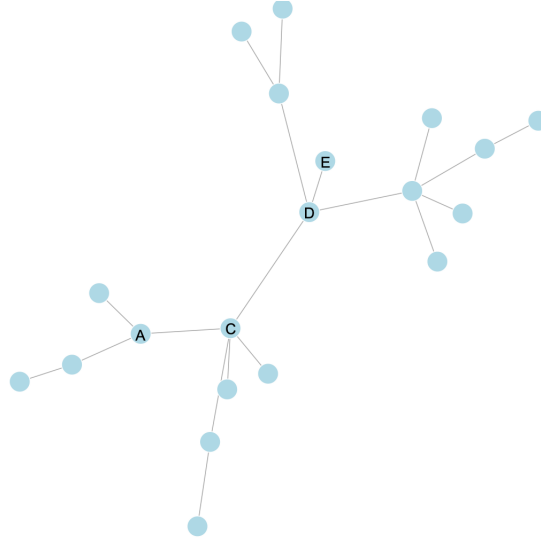


Fig. 2.10 Example of trust network – links between the nodes signify trust

We can see that using pairs A trusts C , C trusts D and D trusts E . Then, can and to what extent A would trust E ? We discuss here the main works that deal with inferring trust, assuming the existence of direct trust information between users beforehand. The *state-of-the-art* for trust inference consists of various works. For instance, a method utilizing a flow approach is presented in [6] as GFTrust. Figure 2.11 shows the trust graph and the flow of trust paths using GFTrust. The authors, additionally to using the general flow approach, model the decay of trust by simulating leakage of the node. To achieve this, they utilize four functions that imitate four possible decay patterns for a node. In order to avoid the problem of reusing the same paths while traversing the network in the search of inferred trust values, the node has assigned capacity, that is decreasing each time the path is passing via this node.

A very known model proposed by Golbeck et al. was presented in [80]. The algorithm, TidalTrust, aims to generate the inferred trust value by creating trusted paths. Similarly to works before, they traverse the networks using Breadth-First-Search and utilize only the shortest path between users. The trust value is calculated using the neighbors trust information, but only those that have high trust value – the neighbor group is limited by a threshold. The trust between users s and f is calculated using the following formula:

$$t_{s \rightarrow f} = \frac{\sum_{i \in \text{Adj}, t_{s \rightarrow i} \geq \max} t_{s \rightarrow i} t_{i \rightarrow f}}{\sum_{i \in \text{Adj}, t_{s \rightarrow i} \geq \max} t_{s \rightarrow i}} \quad (2.20)$$

where Adj is the neighbor set of user s , and \max is the threshold value for trust. While consideration of the shortest path is limiting the computational space, it also can lead

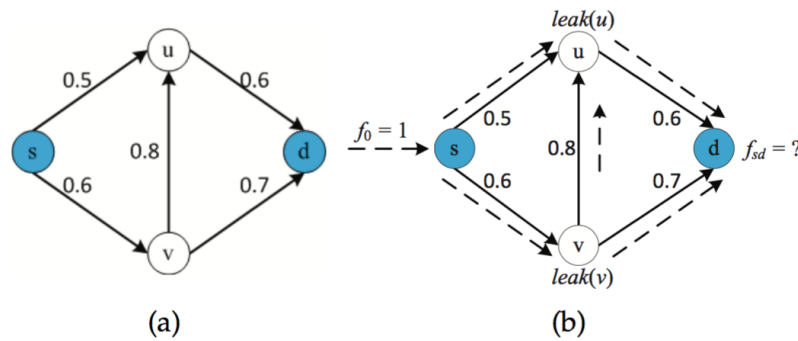


Fig. 2.11 Depiction of the way GFTrust method is working [6]. While (a) is an example of trusted graph, (b) shows idea of GFTrust: Initial flow at node s with flow $f_0 = 1$ which represents full trust, while f_{sd} represents total aggregated trust at d . In the algorithm, at each node other than s and d , a certain percentage of incoming flow will be leaked before redirecting to outgoing links (e.g., $leak(u)$ and $leak(v)$), in order to obtain the final value at f_{sd}

to the information loss. To omit this problem, Wang&Wu [101] proposed a multi-dimensional evidence based trust evaluation system, MeTrust. The model evaluates trust using multiple paths. Trust value is obtained by using the weighted average from combination of all the paths. In order to guarantee that each link in the graph is used only once, the authors presented multiple algorithms to simplify the trust graph.

As mentioned before, using only the shortest path might lead to information loss, while using more (or even all) paths can cause the reuse of information. Therefore, in [102] the authors compared four aggregation methods and concluded that the best strategy is to utilize all trust paths with exclusion on longer paths.

2.5.4 Co-existence of trust and distrust

Along with the notion of *trust*, we cannot omit the discussion about *distrust*. Although it is often discarded, it undoubtedly should be acknowledged while defining the term *trust*. The meaning of *distrust* is also not clear in the literature. For example in [103, 104] the term is often defined as being symmetrical and opposite to *trust*. Merriam-Webster Dictionary claims *distrust* to be "*lack of trust or confidence*" [105]. We argue however, that *distrust* is not simply lack of *trust* – following the Oxford Dictionary definition, it is "*The feeling that someone or something cannot be relied upon*" [106], which clearly suggests that the term is not symmetric to *trust*. Moreover, works [103, 107] point three important observations about trust and distrust that show the difference of concepts: "*a) they separate empirically, b) they coexist, and c) they have different antecedents and consequents.*"

Table 2.4 Comparison of trust properties in *state-of-the-art* methods

Method	Direction	Asym	Transitivity	Dynamicity	Context dependency	Depen- dency
TrustWalker [96]	yes	yes	yes	no	no	
MWalker [92]	no	no	no	no	no	
Alexandridis <i>et al.</i> [90]	yes	yes	yes	no	no	
TARS [98]	yes	yes	yes	yes	no	
Sarda <i>et al.</i> [99]	yes	yes	yes	no	yes	
Lumbreras <i>et al.</i> [100]	yes	yes	yes	yes	no	
GFTrust [6]	yes	yes	yes	yes	no	
TidalTrust [80]	yes	yes	yes	no	no	
MeTrust [101]	yes	yes	no	partially	no	
Kim&Song [102]	yes	yes	yes	no	no	

It is also important to emphasize the properties of *distrust* in comparison to *trust*. Although the concepts are both directional, asymmetric and context-dependent, the transitivity must be differently interpreted. As said earlier, in case of *trust*, the propagation is simple: if user *a* trusts *b* and *b* trusts *c*, then also user *a* should trust user *c*. On the other hand, the transitivity of *distrust* is not that straightforward: if *a* distrusts *b* and *b* distrusts *c*, then the relation between *a* and *c* is neutral, as pointed out in [108]. Other works [109, 91] also emphasized the importance of exploiting the terms separately. Importantly, while *trust* is being a positive term, and *distrust* is negatively evaluated, there also can be distinguished as a "null-value stage", where the user is neutral towards the person.

2.5.5 Synthesis of Trust methods

Methods evaluating and using trust were compared and classified according to the properties described before. The results are compiled in Table 2.4. It can be observed that most methods [96, 90, 98–100, 6, 80, 101, 102] include asymmetry and direction properties of trust. Transitivity is considered by all but two works ([92, 101]). However, dynamicity and context dependency is barely ever included. In fact, context dependence is only fulfilled by [99] and it is based on the assumption of knowing the product category (the assumed context of *trust*), however, the process of obtaining this information is not explicitly explained. On the other hand, dynamicity is used in only a few works: [98, 100, 6, 101].

Furthermore, we categorized the methods using the taxonomy of *trust* shown in Figure 2.8. The results can be seen in Table 2.5. Methods [96, 90, 99] use explicit trust values, which has a big advantage because there is no need to create alternative ways of obtaining trust values. However, there are some problems concerning explicit values [94]. Firstly, they are prone to

attacks by "fake" users, giving false *trust* information. Secondly, the use of this information creates the need for publicly available datasets containing users' *trust* information, which poses a risk of privacy violation. Finally, usually users are reluctant to provide the system with the *trust* values for all their friends (e.g. they might feel uncomfortable with evaluating the strength of their relations), hence the number of *trust* values are pretty small in comparison to the whole network.

Methods using implicit trust values obviously require additional information for calculation (indicated as column "Additional Information" in the Table 2.5). The drawback of the implicit approach is that the trust calculation is then dedicated towards a particular system for a particular application. What is more, most methods treat trust locally, which seems to be more fitted to definitions presented at the beginning of this section.

We also compared the trust methods looking at the information they require in order to work, and the type of computational model of trust they require, seen in Table 2.6. Two works using explicit trust [96, 90] utilized trust as part of other application, which we included as well, e.g. [96] uses explicit trust values to improve the random walk model for recommendations. Some works [90, 98–101] also use user history in order to ameliorate the final trust value. Additionally, in order to calculate implicit trust values, work [90] used similarity information, while several others [92, 90, 98–101] utilize social information such as friendships.

2.6 Reputation-using Approaches

This section is dedicated to the reputation. We first describe the notion. Then, we present the properties of reputation. After, we discuss *state-of-the-art* works that utilize and evaluate reputation. Next, we briefly discuss the issue of reputation valuing. We finish by synthesizing the presented literature, targeting in particular the properties that we showed before.

As previously mentioned, the meaning behind the term *reputation* is closely related to *trust*. *Reputation* is broadly understood as an "*overall quality or character as seen or judged by people in general*" [110], which implies that the concept is a resultant of opinions of a group or gathering, considered collectively. Josang et al. defined reputation as "*what is generally said or believed about a person's or thing's character or standing*", additionally suggesting that the reputation scores, obtained from the underlying social network, have to be globally visible to all members of the network. A similar definition can also be found in [111], where authors stress that reputation connects to "*what character others think someone has*".

Table 2.5 Categorization of *state-of-the-art* methods of trust using taxonomy

Method	Global/local	Explicit/im plicit	Additional information
TrustWalker [96]	Local	Explicit	-
MWalker[92]	Local	Implicit	Based on Social information (friendship) and similarity between users
<i>Alexandridis et al.</i> [90]	Local	Explicit information about trust and similarity information	Social information and similarity of previous rating
TARS[98]	Local	Implicit	Based on similarity of ratings of items
<i>Sarda et al.</i> [99]	Local	Explicit information about friendship trust and implicit trust called trail level	Social and previous ratings
<i>Lumbreras et al.</i> [100]	Local	Implicit	Based on interactions on Twitter: following, retweeting, mentioning
GFTrust [6]	Local	Implicit	Explicit trust graph assumed to be known, calculation of transitive trust basing on flow information
TidalTrust [80]	Local	Implicit	Implicit: aggregation of neighbours' explicit trust values (weighted) based on shortest path
MeTrust [101]	Local	Implicit	Based on explicit ratings of transactions between users, combined with decay function
<i>Kim&Song</i> [102]	Local	Implicit	Based on aggregated explicit trust values from all trustees and trusted users

Table 2.6 Additional information considering *state-of-the-art* trust methods

Method	Social info	Similarity info	User History	Computational Model
TrustWalker [96]	no	no	no	explicit trust used on random walk model for recommendation
MWalker [92]	yes	no (considered in calculation later)	no	matrix multiplication
<i>Alexandridis et al.</i> [90]	yes	yes	yes	explicit trust, used for clustering
TARS [98]	yes	no	yes, called clicked history	
<i>Sarda et al.</i> [99]	yes	no	yes, classified in categories for trail levels trust	
<i>Lumbreras et al.</i> [100]	yes	no	yes (history of the interactions with age notion)	linear model
GFTrust [6]	no	no	no	network flow
TidalTrust [80]	no	no	no	linear model
MeTrust [101]	yes	no	yes	linear model
<i>Kim&Song</i> [102]	no	no	no	path search

This leads to the conclusion that the so-called *global trust*, which is connected with overall values of *trust* of one user gathered from the rest of the community, is equivalent to *reputation*. Nevertheless, reputation is often used as a synonym of trust. For instance, in [112], the authors explicitly say that "*Reputation is synonymous with the measure of that trust*". This misuse of words leads to confusion and even more difficulties with defining and describing both terms.

Although the concepts are similar and take into consideration related sociological phenomenon, thus are definitely connected, they have to be distinguished. Indeed, there are works that stress that need. In [113], there is clear stress that reputation is a "*collective measure of trustworthiness (...) based on the referrals or ratings from members in a community*". Furthermore, in [114], it is pointed out that, while *trust* and *reputation* themselves are separate, their values should affect one another. For example, the occurrence of a new member in a group implies unknown values of both *trust* and *reputation*. However, if in time some users trust and interact with this user, the value of her or his overall opinion in the group, hence reputation, will increase as well.

2.6.1 Reputation Properties

Basing on the literature and the definitions showed above, we describe the following reputation properties:

- Collectivity – in order to compute reputation, the *local trust* values (from point-to-point connections) of the user for whom the reputation value is specified must be known (they can be both *direct* or *indirect*) – the *local trust* values will serve as basis of the reputation computation.
- Dynamicity – the process of gaining reputation is continuous and dynamic in time.
- Long-term – reputation is an incremental process, hence the study of reputation evolution should involve long time spans.
- Context-dependent – while reputation is an overall quality of a group or person, it can be considered context sensitive.

While reputation and trust are closely related, the properties of the two notions are definitively distinct. Moreover, it can be observed that trust properties such as direction and asymmetry are not applicable to reputation, due to the collective nature of reputation – reputation value is global and connected to the user (contrary to *trust* where the value is correlated with particular point-to-point connection).

Furthermore, because of the fact that trust is derived directly from users' opinions, it can be sometimes referred to as "subjective" [115]. On the other hand, the aggregated value of reputation could be, in comparison, called "objective" (at least in the sense of averaging out many individual opinions).

2.6.2 Methods for Reputation Calculation

There are multiple reputation methods used by various systems. We divided them into several categories [116]: (i) average-based ratings, (ii) fuzzy-based methods, (iii) Bayesian-based methods and (iv) miscellaneous. As was mentioned before, the terms trust and reputation are sometimes used as synonyms. Therefore, in this section, we provide an adequate comment about what exactly the presented method measures if appropriate.

Each aforementioned category of reputation methods is detailed in what follows.

(i) *Average-based ratings*

There are numerous systems using the simple form for computing reputation by averaging or summing the trust scores [111]. For example, services mentioned in Section 2.5 as Amazon and AliExpress utilize reputation rank created by averaging all the users' opinions (trust rates) for a particular seller and product. The formula for reputation score is as following:

$$\frac{\sum(\text{positive feedback ratings})}{\sum(\text{all feedback ratings})} \quad (2.21)$$

On the other hand, the service on Epinions included not only the average reputation score for each product based on users' reviews but also a reputation ranking system, where users could rate reviews (*Not Helpful*, *Somewhat Helpful*, *Helpful*, *Very Helpful*). These reviews grades were summarized over a period of time and were used to give high accomplished users different statuses e.g. *Advisor*, *Top Reviewer*, etc., which served as a type of reputation score. Another working reputation metric is used on StackOverflow ²⁴, a question and answers site dedicated for developers. For each action on the site, such as asking or answering the questions, a user can gain or lose the reputation points. The reputation score for each user is a sum of all reputation points. The higher number of points gives a user more privileges and accessibility to site features. A similar approach was used by [114], where authors for obtaining reputation between two nodes first calculated all trust paths between them, and to get the final reputation score used simply weighted arithmetic mean of those paths.

²⁴<http://stackoverflow.com/>

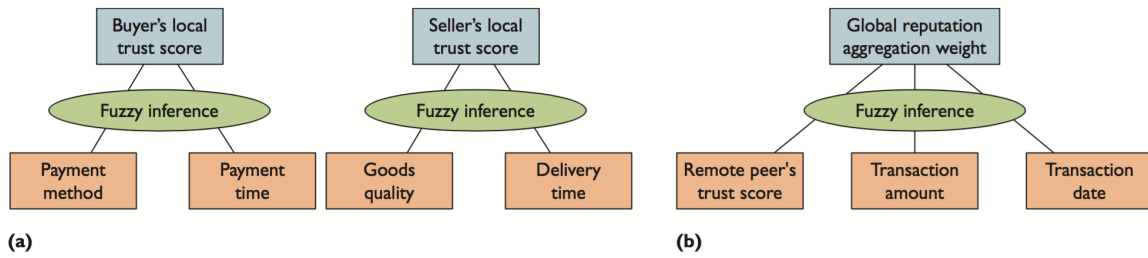


Fig. 2.12 Illustration of local trust and global reputation mechanism of FuzzyTrust [7]: (a) gathering information about payment in order to calculate buyer and seller local trust values; (b) using fuzzy inference for computing global reputation score with the use of transaction information and trust given by other users

(ii) *Fuzzy-based methods*

In order to assess the reputation of a user, some works proposed to use fuzzy logic. Hamdi et al. [117] developed a Fuzzy Clustering Reputation (FCR) algorithm. In this work, authors assume that the trust network is already given. To aggregate the trust values and obtain reputation value, FCR aggregates the values and classifies the user into several clusters, with assigned fuzzy value for each cluster (*Very Low*, *Low*, *Medium*, *High*, *Very High*). Then, by using the maximum membership function, the algorithm assigns the user to one cluster that responds to their reputation value. Another work [7] used fuzzy logic utilizing eBay transaction data as a test case. The system, FuzzyTrust, has two main inference steps: local score trust calculation and global reputation aggregation, showed in Figure 2.12. The trust score is generated using the fuzzy inference based on different scores given by users (e.g. evaluating payment, quality of product and delivery time for sellers). Using this information, the reputation is evaluated by aggregating all trust scores assigned by users to each transaction, using additionally weights. The weight for each transaction is based on the transaction amount and date (how much time has passed since the transaction took place).

(iii) *Bayesian-based models*

Bayesian-based methods utilize probability density functions (PDFs) in order to model the reputation score. Binomial Bayesian reputation systems utilize binary space (*Bad*, *Good*) corresponding to the direct evaluation of the entity for which reputation is calculated. To model the certainty of the reputation score, a Beta PDF is used. The reputation is calculated and updated by combining every new rating with the prior reputation score. On the other hand, Multinomial Bayesian reputation systems allow

modeling multiple possible values of rating. In comparison, the Dirichlet PDF is used to model evidence reputation. The example of models utilizing Binomial Bayesian reputation model and Multinomial Bayesian reputation model can be found in [118].

What is more, the aggregation of the ratings can also include the notion of time, e.g. in work [119] a time decay factor was proposed, that was modeled both as a function and a parameter. This time decay factor aimed to penalize the older ratings on the basis of them being not fresh enough.

(iv) *Other miscellaneous models*

In addition to the methods shown above, there are other methods utilizing various different techniques. For instance, a work by Lee et al. [120] introduced a Reputation Management for Social Agents (ReMSA) algorithm. The reputation is calculated and then updated every time a new interaction between two users takes place. The reputation score considers old reputations scores, history of interactions, frequency of interactions and time decay of previous reputations. Interestingly, the aggregation of point-to-point trust values uses the voting system, where each agent "votes", and this vote counts to the overall final reputation score.

Worth noticing is also the work by Jha et al. [121], evaluating reputation for sellers in e-shopping using transactions scores. The system utilizes several techniques: Beta Probability Density for rating connected to criteria by which each user evaluates the transactions (trust values) and weighted multiplication method for aggregating the reputation. However, most interesting is combining those two techniques with opinion mining. The authors propose to extract opinion expressions from the text of reviews and discretize the opinions in order to use them as a weight (mentioned before) for calculating the final reputation score. The work [122] proposed an algorithm dedicated to recommender systems. The authors introduce a Topic-level trust, which is a collective measure that represents the overall degree of trust that lets particular user to make correct recommendations on specific topics. The value of Topic-level trust is an average-based rating that relies on recommendation trust between the target user and any other user that validated the item belonging to this topic. The authors assume the pre-defined existence of topics taxonomy. A similar approach was also presented in [123]. O'Donovan&Smyth proposed two notions: item-trust that measures the percentage of correct recommendations for a particular item, and profile-trust, the measure for correct recommendations of a particular user for a particular item. They combined the measures in order to create the trust of a profile (utilizing the average from obtained items or profile-level trust). While both works of Fu-Guo&Hua [122]

and O'Donovan&Smyth [123] are mentioning only "trust" notion in their work, it can be seen that the collective measures proposed in the articles are actually measuring the reputation (for comparison of trust and reputation methods see Chapter 3). Similarly, we wanted to mention also two other works that utilized the "trust" to categorize their work, however evaluating collective notion fitting "reputation" concept. Advogato was a working system²⁵ [124]. Advogato was a "*website with an online community, basing on blogs of the free software developer's advocate*" [125]. The system was assigning each user a single trust value basing on a network flow model. The computed value had three levels (apprentice, journeyer, and master). Another model, Appleseed [126], also utilized the initial seed of trusted users, that later propagated their trust further to their neighbors. The authors proposed to use the decay factor while computing inferred trust value in order to tackle the problem of trust decay with distance. Similarly to the previous works, the value computed is a global one as it is based on the information from the initial seed nodes. We discuss these works in this section, as although they use the term "trust", it can be seen that they suit better as *reputation*. We include the comparison table for these four methods in Chapter 3.

2.6.3 Reputation valuing

Not to be omitted while talking about the reputation notion is also the issue of its judgment in terms of valuing reputation as positive or negative. Contrary to *trust*, that is used as a positive term and can be contrasted with the negative term that is *distrust*, the concept of *reputation* is generally not estimated in terms of positive or negative value. This can be illustrated by real-life sentences [115] "I will buy it because this company has good reputation" and "I will not go there, they have bad reputation". When considering these simple examples, it is easy to notice that *reputation* can be either good (with a positive value) or bad (with a negative value).

Furthermore, intuitively there is no "middle stage" in the sense of zero-value *reputation* – it can be either good or bad. That also differs from null-value *reputation*, meaning there is no information about the reputation of a user. This is another difference between terms *reputation* and *trust*, where trust by default is only positive notion and having no zero-value stage, while at the same time, the opposite, negative in value is a separate concept of distrust (see Section 2.5.4).

²⁵Formerly available on: <http://advogato.org>

Table 2.7 Comparison of reputation properties in *state-of-the-art* methods

Method	Collective	Dynamicity	Long-term	Context-dependent
Arithmetic mean	yes	no	no, unless specifically considered	no, unless specifically considered
FCR [117]	yes	no	no	no, unless specifically considered
FuzzyTrust [7]	yes	no	no	no
Binomial Rep Score [118]	yes	no	partially	no
Multinomial Rep Score [119]	yes	partially	partially	no
ReMSA [120]	yes	yes	yes	no
Jha [121]	yes	no	yes	partially
<i>Fu-Guo et al.</i> [122]	yes	no	no	yes
<i>Odonovan&Smyth</i> [123]	yes	no	no	no
Advogato [124]	yes	no	no	no
Appleseed [126]	yes	no	no	no

2.6.4 Synthesis of Reputation Methods

The properties mentioned previously (in Section 2.6.2) are used to compare the discussed reputation calculation methods. The results of the analysis can be seen in Table 2.7.

In case of most works [117, 7, 118–121] the reputation is indeed considered to be collective. This goes along the intuition of reputation being a consensus of a number of people. What is more, the two works [122, 123] that, as mentioned before, use the notion of "trust" for their methods, also utilize the collective notion of the relation they focus on. Therefore, we argue that their metric also actually deals with reputation. While collectivity of reputation is broadly used, dynamicity in contrast is barely included – only in works [119, 120]. Similarly, only one work [122] by Fu-Guo et al. fully considers context-dependence of reputation. However, the authors assume the existence of the pre-defined topics taxonomy in order to achieve it. Interestingly, in methods such as arithmetic mean or FCR [117], although the authors do not consider context-dependence, there is a possibility of extending these approaches to consider the selected topics as well, which would provide a partial inclusion of context-dependency feature. Moreover, the long term aspect of reputation is also rarely considered, only in two works [120, 121].

In comparison, the method we propose in this work assumes collectivity of reputation and considers both dynamicity and long-term observation requirement. The details of our reputation approach can be found in Chapter 5.

2.7 Conclusion

In this chapter, we presented the general view of social networks analysis and then showed different existing and relevant work concerning influence, popularity, trust, and reputation. We started by reviewing existing generic terms, concepts and ideas within Social Network Analysis. We then discussed *influence* definition and properties, including attributes of influential content and influential user. We next described existing works for influence, dividing them into methods for influence evaluation and approaches for influence diffusion, and we compared the methods, stressing the position of our contributions regarding existing works. We followed up with *popularity* short review of the literature, and its differentiation from the concept of influence. Afterward, we examined the notion of *trust*, showing its properties and taxonomy, reviewing the *state-of-the-art* methods concerning this term, and summarizing the approaches in comparison tables. Finally, we presented works dealing with the concept of *reputation*, classifying the works into categories depending on the types of solutions they provided, and finishing by a comparative synthesis of the *state-of-the-art* methods with respect to our proposed method.

In the next chapters, we introduce our contributions that focus on influence modeling, but also incorporate notions of reputation, trust, and popularity. In Chapter 3, we start by proposing a typology and a hierarchy of the four notions. We also define and model the concept of influence, present a proposition linking influence and reputation, as well as investigate a novel concept of micro-influence. Then in Chapter 4, we use the established definitions to instantiate the theoretical model from Chapter 3, and propose a general purpose approach for evaluating influence. We use it to perform experiments detecting influence and micro-influence in different social networks. Then, in Chapter 5 we focus on one particular type of social networks, namely citation network, and present an instantiation of the model, focused predominantly on the time aspect of influence with the use of the properties of a citation network. Moreover, using this extension we also show the method that uses the linkage between influence and reputation, measuring reputation by basing on influence information.

Chapter 3

Social Network Interactions Modeling

3.1 Introduction

As it could be seen in Chapter 2, the interactions of users connected to influence, popularity, trust, and reputation have drawn much research attention. The roles of trusted or influential users, users with high reputation and popular users can be used in various ways. For instance, for recommender systems, the advantages of incorporating users' roles into the recommendation process vary from making the process more efficient, helping with the problem of new users (cold start problem) to having results quicker and more accurate.

However, we noticed that, along with the increasing number of measures and systems aiming to introduce better solutions for measuring *trust*, *reputation*, *popularity* or *influence*, there also has been increasing confusion of the usage of these terms. The notions are used interchangeably, and often utilized in the misleading way – contrary to their intuitional, sociological understanding.

For instance, the work described before in Chapter 2 by O'Donovan&Smyth [123], introduces a system that supposedly measures *trust*, but in one of the last sections, the authors admit that the measure they used could also be referred to as *reputation*. In another work by Chaney et al. [127], authors, while introducing a system which aimed at measuring "*influence*", pointed out that the concept they use is referred in other related to their works as *trust*, and compared their system with others that utilized *trust*. Although these are only couple of examples of usage of the notions in a confounding way, they already show the need for clarification and prioritization of influence, reputation, trust, and popularity.

In this chapter, we compare, contrast and clarify the differences between the notions of trust, reputation, influence, and popularity. We first propose an intuitive hierarchy of the terms, based on the analysis of the works showed in Chapter 2. The hierarchy shows the complexity of each notion and orders the notions from the least to the most complex. Then,

we further describe each of the terms by defining their typologies. We pair the terms into two couples which include the most similar and the most confused notions: influence and popularity, and trust and reputation. We recall some of the *state-of-the-art* works mentioned in Chapter 2 that in our opinion use incorrectly terminology that categorized what their methods actually measure. We present the comparison table, that categorizes such *state-of-the-art* methods using both terminology used in the articles themselves and the categorization we propose, in accordance to the properties and characteristics of the notions showed in our work. Finally, we propose definitions of influence and reputation. We especially focus on influence modeling by considering different aspects of influence and specifying the ones that we later use.

3.2 Hierarchy of Terms

Basing on the analysis of the terms and their usage in the literature presented in the previous chapter, we propose a general hierarchy of the terms concerning their abstract level. The idea behind such hierarchy is to clarify and order the notions with respect to complexity (according to what was presented in Chapter 2), in order to give an overall view on these terms. The hierarchy can be seen in Figure 3.1, which depicts the proposed classification – the greater the complexity of the abstraction is, the higher position the term has.

To further stress the particular differences between the notions, we show the essential information that needs to be obtained from the social network in order to measure the value of each term. In the following, we describe the details for each term:

- **Popularity** is the least complex concept. In order to evaluate user's popularity, we need to know the structure of the social network, i.e. connections between users, as the term bases on the incoming and outgoing edges. What is more, popularity can also be a desired property of influence, due to the fact that higher popularity of a user signifies more people being affected by her.
- **Trust** measurement requires not only to know the structure of the network but also to have the information about individual (person-to-person) relations between users. The network structure shows the acquaintances between users which is assumed to be the basis of any trust relation. Additional information about person-to-person relations is needed to further infer their strength. For example, in the previous chapter, we mentioned several works that used thresholding in order to limit weak-trusted users and evaluate the trusted ones, basing on to of known-to-exist relation (e.g. friendship). The indicators of trust strength are factors such as number of exchanged messages,

frequency of encounters, or even similarity of users' profiles. Indeed, the users' profile similarity is sometimes considered as an indicator of trust based on the research from sociology and social psychology literature, e.g. [128, 129], and more recently in computer science domain, where it is often considered that trust between two people is higher if they have similar taste [130].

- **Reputation** evaluation needs several pieces of information. Due to the collective characteristics of the reputation notion, it is required to have the trust relations between users. Therefore, there are two possible sets of requirements. On one hand, we can already have a trust network beforehand, i.e. the social network where the relations between users are said to be trust. On the other hand, assuming that there is no trust information to be obtained beforehand, it is needed to have both the structure of the network and additional information about person-to-person relations (as it was described in part about trust). In any case, in order to achieve a reputation score, we finally do require to have either the information about group relations between the users, which leads to obtaining group reputation of an entity or other group or assumption about the way reputation is aggregated based on trust. For instance, in Chapter 2, we described some works that utilized the average to aggregate trust.
- **Influence** is the most complex term. To measure it, similarly to the evaluation of other concepts, both the structure of the network and the general information about the particular relations between users are required. Moreover, as the measurement of influence supposes to estimate the impact of one user on another one, we also need shared information spread. By shared information spread we mean any indicators that show both influencer sharing some material (e.g. sharing post) and influencee receiving and processing this material (e.g. the post comments).

3.3 Terms Typologies

In order to summarize the concepts for which we have shown the extensive literature review in the previous chapter, we present the typologies of each of the terms: influence, reputation, trust, and popularity.

3.3.1 Influence typology

Influence assessment aims to measure the impact of somebody's opinion on a group of people. The typology of the influence is shown in Figure 3.2. The source of influence can be both:

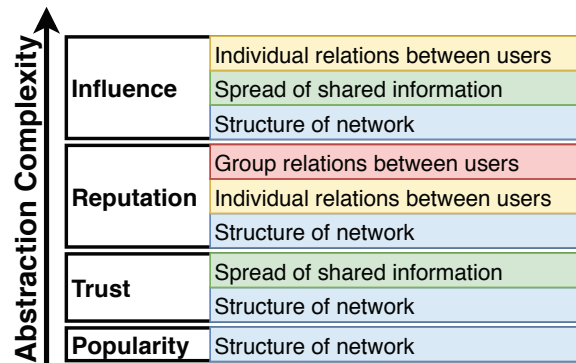


Fig. 3.1 General hierarchy of terms *influence*, *reputation*, *trust* and *popularity* with details about what information is needed to be obtained from social network in order to calculate each of the notions.

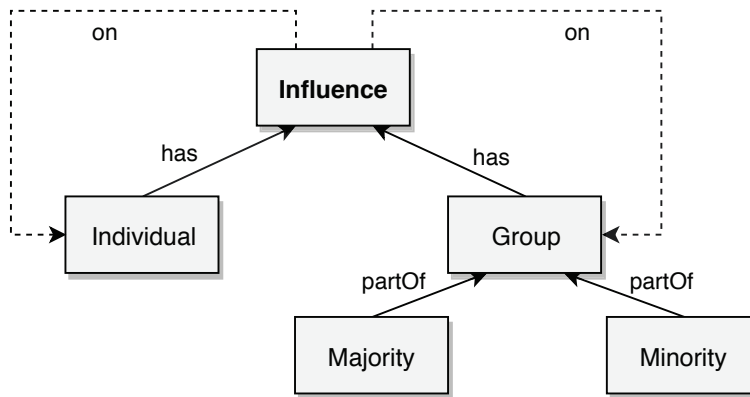
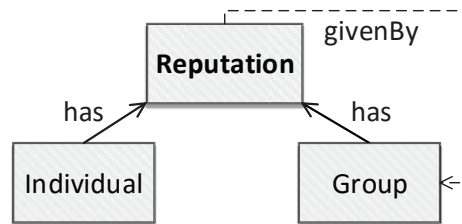


Fig. 3.2 Typology of *influence*

an individual, or a group of people [33]. For each of the sources, the influencer can have influence on either an individual or a group. In the case of an individual (subject) having an impact on another individual (object), or in other words person-to-person influence relation, we talk about *pairwise influence*.

Two types of influencing groups can be distinguished. Firstly, we can observe a majority group within the network, that holds a particular opinion or a way of behavior. Secondly, we can notice a minority group that has a tendency to change (or attempts to change) network's majority opinion. For example, a minority group of teachers changing the opinions of their students. This particular division can be seen in Figure 3.2. For instance, majority while being a part of (partOf) a group has an *influence* on another group; an individual has *influence* on a group. As an additional note, basing on sociological studies, we can also characterize the people that tend to exert the influence as either "*similar*", "*desirable*", or "*expert*" [33] towards the influenced persons.

Fig. 3.3 Typology of *reputation*

3.3.2 Reputation typology

Reputation is a collective measure given by a group of users within the network (or the whole network). Additionally, the distinction between individual and group reputation can be also observed [114] – the former being the global view on a particular member of a social network, while the latter concerns the overall opinion about some subgroup that can be observed within the network (e.g. subgroup of teachers in a social network of university employees). As shown in Figure 3.3, this division of an individual and group reputation is important because, while the first one can be calculated accumulating the individual, point-to-point *local trust* values, the group reputation is not that simple to compute. In fact, using individual connections of each pair of users belonging respectively to assessing and assessed group does not correlate with the intuitive understanding of reputation. In our view, when evaluating group reputation (obtained from another group), there has to exist a particular subgroup that plays a decision-making role in the assessment of the reputation of a group.

In our understanding, reputation always implies a computational process, since it is the overall value of opinions. To illustrate, let us consider the simplest scenario of elections, where we can say that the reputation value is measured. In the election process, each person specifies binary, local "trust" (by choosing the person – value 1 or choosing somebody else – value 0). Then, the votes are computed – summed up, and the winner is the individual with the majority of votes, which could be interpreted as having the highest reputation. Taking that into consideration, reputation is always *implicit*. An individual or group can have *reputation* that is given by another group.

3.3.3 Trust typology

Trust is a relation between two users, where the trusted user is expected to act in a particular way or perform a particular action. Figure 3.4 shows the typology of trust. For example, we can say that a user u_1 *has trust in* another user u_2 .

It can be observed that the showed typology assumes that the concept of trust is limited only to an individual. One could argue that, in common language, we sometimes acknowledge groups engaging in trust-like interactions. However, in the scope of social networks, at least to-date, the information that can be obtained from the network based on which we can evaluate interactions is limited. Hence, differentiation between trust towards the group and the group reputation would be almost impossible to distinguish and too complicated to evaluate using current available social network information. Therefore, in this work, we assume that trust is observable between individuals. Using this semantic limitation of trust, we therefore assume that trust-based interactions from the group towards an individual or from the group towards another group is simply reputation.

3.3.4 Popularity typology

Being popular is essentially related to being perceived by others. We can divide the objects of popularity gain into two entities: individuals and groups. Figure 3.5 illustrates both of these cases. For example, we can say that a user *gains* popularity, and also that a group *gains* popularity. In addition, we can distinguish a *popular group* which is a subgroup of the whole social network that has many connections.

As stated before in Chapter 2, the current usage of popularity in SNA bases only on *perceived popularity*, connected to a central position of a user or a group in the network, and being widely connected with other entities. Therefore, it can be seen that this notion is much less complex than the other concepts we discuss. Moreover, being popular is also a possible property of influence, which was discussed in Section 2.3.1.

3.4 Terms Differentiation

As could be seen in the *state-of-the-art* presented previously, one of the main problems with finding ways to evaluate users relations such as trust or influence in a social network is,

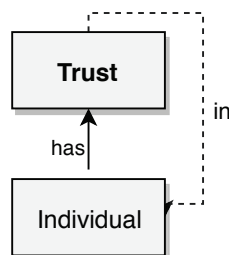
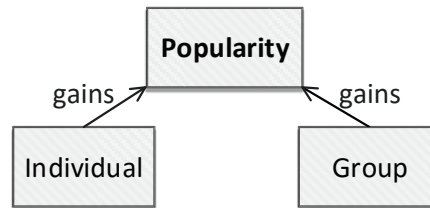


Fig. 3.4 Typology of *trust*

Fig. 3.5 Typology of *popularity*

besides the clarity of the terms, the issue of *interchangeable* user and not precise division between each of the terms.

Here, basing on the typologies and the hierarchy presented in Section 3.2 and 3.3, we present a list of *state-of-the-art* approaches (described in Chapter 2) that we find are incorrectly assigned to be measuring one of the relations, while actually measuring another. We divide all the terms (influence, popularity, trust, and reputation) into two pairs that consist of the most confused concepts, namely influence and popularity pair, and trust and the reputation one. We show the terminology used by the authors themselves, and contrast it with nomenclature that we find is more appropriate for each method, based on all the clarifications we showed in previous sections.

3.4.1 Trust versus Reputation

As mentioned before, we argue that the term *trust* refers to the particular relation between two users, thus it is limited to this, point-to-point relation. On the other hand, *reputation* describes a notion which, as a global quantity, is defined basing on overall users opinion. Moreover, the notions differ as well when we consider their other properties, which we presented in Chapter 2. While both trust and reputation are context-dependent and dynamic, trust is also transitive and directed, whereas reputation is long-term and collective.

While discussing different *state-of-the-art methods* in Chapter 2, we pointed out that some of the works that used the term trust to describe their methods are actually measuring the relation that is global, therefore fitting reputation description. What is more, we also described a method doing the opposite – utilizing the *reputation* categorization, while computing a point-to-point, asymmetric notion matching *trust* characteristic. In table 3.1 we gathered the methods in question. We included the nomenclature from literature and contrasted it with the terminology we find more appropriate considering what they actually measure and what we defined as *trust* and *reputation*.

Table 3.1 Selected *trust* and *reputation* methods from Chapter 2 for which we pointed out the inconsistency of the notion they suppose to measure judging by name and the actual notion targeted in measurements. Literature nomenclature refers to term used *state-of-the-art* and our terminology shows notion which we find is more appropriate due to methods used metric.

Method	Literature Terminology	Our Terminology
<i>O'Donovan et al.</i> [123]	Trust	Reputation
<i>Fu-Guo et al.</i> [122]	Trust	Reputation
Advocato [124]	Trust	Reputation
Appleseed [126]	Trust	Reputation

3.4.2 Influence versus Popularity

As previously mentioned, a *popular* user is a person with many connections, while an *influential* user is the individual that puts the pressure on other individuals and therefore changes, in some way, their behavior (and/or feelings in case of real-world networks). Moreover, the requirement for the influential user being well connected, as well as the fact that methods, commonly regarded as influence metrics (e.g. centrality measures [37]), focus only on this factor (connectedness) led to frequent confusion notions of popularity. In short, *popularity* is mainly centered on having lots of connections, while *influence* is the notion of changing others, where it is important to consider not only having the connections but also their quality.

These differences lead to the conclusion that the methods that measure *influence* which are relying only on the user's location in the network topology are in fact not capturing the essence of *influence* but rather *popularity* since *popularity* is strictly connected with the notion of being known. The comparison literature and our understanding of both terms classification is shown in Table 3.2.

As it was mentioned earlier, there are few works dealing with measuring popularity, when it comes to broader term definition including the *sociometric popularity*. However, in our opinion, all methods that concern user's location within the social network should only be regarded as *popularity* measures (and not as *influence*). Therefore, we claim that some measures introduced in Chapter 2, that capture only the topology of users within the network, should be classified as *popularity* methods.

3.5 Definitions

In this section, in order to model the influence, we present the proposition of definitions specifying the notions of and in the context of *influence*. We focus on different aspects of

Table 3.2 Selected *influence* and *popularity* methods from Chapter 2 for which we pointed out the inconsistency of the notion they suppose to measure judging by name and the actual notion targeted in measurements. Literature nomenclature refers to term used *state-of-the-art* and our terminology shows notion which we find is more appropriate due to methods used metric.

Method	Literature Terminology	Our Terminology
Degree Centrality [37]	Influence	Popularity
Closeness Centrality [37]	Influence	Popularity
Betweenness Centrality [37]	Influence	Popularity
FollowerRank [73]	Influence	Popularity

influence itself, as well as define two related concepts: *micro-influence* and *macro-influence*. Additionally, basing on the presented context we also discuss and define linkage from *influence* to *reputation*.

Influence

We define the influence from the perspective of Actions and Reactions on social network sites, which goes with intuitive understanding of influence, and the way we tend to evaluate influence in the real world. The simple schema of action and reaction exchange on social network sites can be seen in Fig. 3.6. We leverage the situation in which one user is performing an action by generating content (i.e. photo or post), while a second one is performing a reaction¹) to the content. We target measuring the influence between an action generated by a user – the Subject of Influence – and the reacting user – the Object of Influence. Importantly, without loss of generality, in the next sections, we refer to three most popular types of reactions due to their ubiquity, however, all definitions can be extended in order to include more or different reaction types.

As mentioned in Chapter 2, within Social Network Analysis the representation and analysis of social relations are predominantly done using graph and matrices. However, while such representation is easy to apply, it is mainly focusing on the relations structure (syntax), hence it is not suitable for usages where the stress is put on the relations meaning and semantics.

On the other hand, the ontology-based Social Network Analysis methods seem to overcome this limitation. As a matter of fact, the purpose of an ontology is to establish a conceptual model with a rich structured data, that can be shared and reused. Modelization of

¹In the Action-Reaction schema, we refer to an Action as a self-activity of user u_1 (in Fig. 3.6), while Reactions symbolize activities overtaken by other users in response to the user u_1 Action.

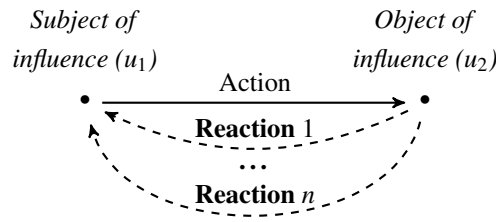


Fig. 3.6 The Action-Reaction concept showed as a simple schema. The Subject of Influence generates content visible to the Object of Influence who reacts to the content, possibly by using multiple types of reactions several times.

social relations with ontologies enables the automatic gathering of the information about not only the existence of relation but also specific relation meaning, its properties and possibly its restriction rules. Several ontologies have been used to represent social networks, the most popular ones are FOAF, SIOC, RELATIONSHIP. First ontology, FOAF (Friend Of A Friend), is used to represent people and their friendships. In comparison, SIOC (Semantically Interlinked Online Communities) represents the activities of communities (blogs, forums, mailing lists, wikis, etc.) on the Web by specifying *OnlineAccount* and *HasOnlineAccount* from FOAF. Finally, RELATIONSHIP ontology specifies *knows* property of FOAF, in order to precise the relation types, e.g. "InfluencedBy" or "Knows By Reputation". Nevertheless, it is important to notice that the representation of social relations must be fine-grained enough so that it is possible to specify in detail the relation itself and to use it for gathering the results of the analysis of the social network. In particular, the influence relation used in abovementioned ontologies is too general and insufficient for both expressing the complexity of the influence, and representing its different aspects (e.g. subject and object of influence, time dependency, recognition, activity generation, etc.). In the following, we propose a semantic-based representation of modeling influence relation for social networks.

In order to modelize the Action-Reaction concept, let us represent the social influence in a dynamic social network as an ontology $O(V, P)$ where V and P are sets of vertices and properties respectively. V is composed of classes *Entity*, *Audience*, *Action*, *Reaction* and *Time*, connected by properties *from*, *at*, *to*, *part_of*, *is_influencer*, *is_a*. The ontology is represented in Figure 3.7. The class *Action* can have the following subclasses: *PostingText*, *PostingVideo*, *PostingPhoto*, *PublishingArticle*. The class *Reaction* can have the following subclasses: *Upvoting*, *Commenting*, *Sharing*, *Citing*. The class *Entity* can have the following subclasses: *User*, *Company*, *Conference*. Let us consider A as the set of all actions, R as the set of all reactions, E as the set of all entities, and T as the time interval.

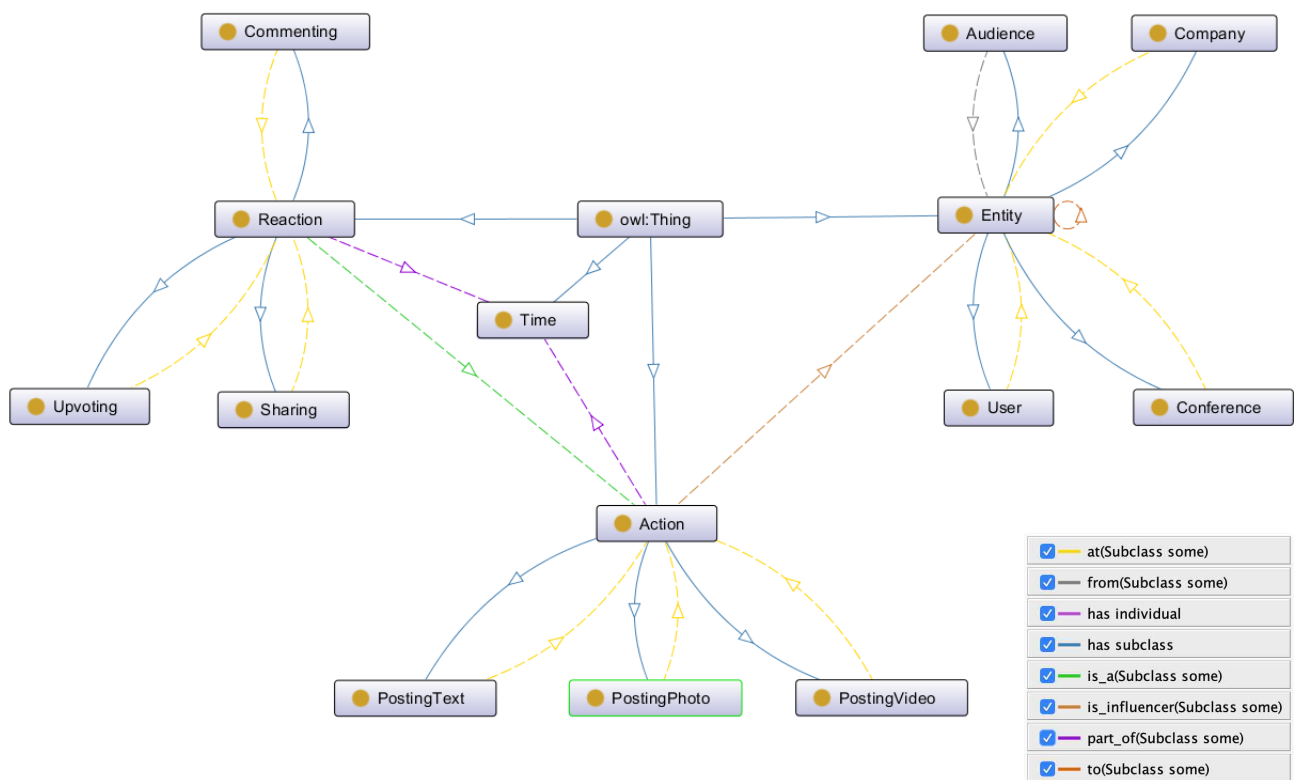


Fig. 3.7 Ontology representing Action-Reaction concept for modeling social influence in a dynamic social networks

Definition 1 Action

An action $a_i \in A$ performed by a source entity $e_i \in E$ at time $t_i \in T$ is represented as a triple $a_i = (p_i, e_i, t_i)$, where p_i is the type of the action a_i . The action a generates reactions on the other entities as an effect.

Example 1 Using the ontology from Fig. 3.7 we can say that an action a_1 (postingText) was made from user u_1 (Alice) at time t_1 (1/01/2019 19h00).

Definition 2 Reaction

A reaction $r_j \in R$ is performed by an entity $e_j \in E$ at time t_j . The reaction is after and as a response to an action $a_i = (p_i, e_i, t_i)$ ($e_i \neq e_j$), and is represented as a quadruple $r_j = (q_j, e_j, t_j, a_i)$, where q_j is type of reaction, $t_j \in T$ and $t_j > t_i$.

Example 2 Utilizing the ontology (Fig. 3.7) we can say that reaction r_1 (comment) from user u_2 (Bob) was done at time t_2 (1/01/2019 19h01) as a response to an action a_1 .

As mentioned, the type of both actions and reactions depends on the considered SN. The examples of possible types from the most common social networking sites can be seen in Table 3.3.

The entities that are reacting on an action can be considered as a subgroup of entities – an audience. Formally, we define Audience as follows:

Definition 3 Audience

An Audience is a partOf Entity class that is representing the group of entities $\{e_1, \dots, e_n\} \in E$ that reacted to a particular action of another entity $e_i \notin \{e_1, \dots, e_n\}$, $e_i \in E$, in a particular considered interval of time T . We say that the group of entities $\{e_1, \dots, e_n\}$ is the audience of entity e_i for time interval T .

Example 3 Utilizing the ontology (Fig. 3.7) and given an action a_1 of type postingText from user u_1 (Alice) at time t_1 (1/01/2019 19h00) and reaction r_1 (commenting) from user u_2 (Bob) was done at time t_2 (1/01/2019 19h01) as a response to the action a_1 . We can say that, considering time interval $T (t_1, t_2) \in T$, user u_2 (Bob) is the audience of user u_1 (Alice).

It is clear that particular entities belonging to audience depend on several considered factors: the entity, the type of considered reactions (e.g. only comments), and the time interval for which we consider both actions and reactions. An example of the difference between audience members depending on the considered time interval is showed in Example 4.

Example 4 An example using the ontology can be seen in Figure 3.8. It can be seen that, using this ontology, we can modelize the existence of multiple actions and reactions at a different

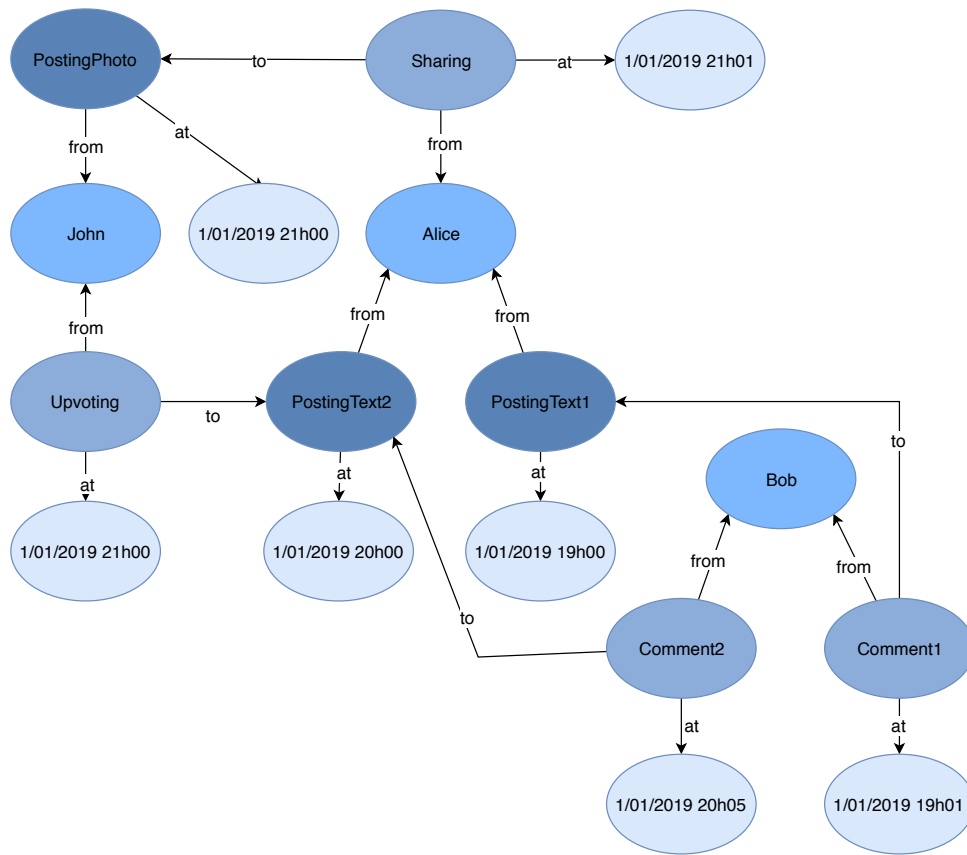


Fig. 3.8 Example of knowledge graph instantiating the concept from the presented ontology

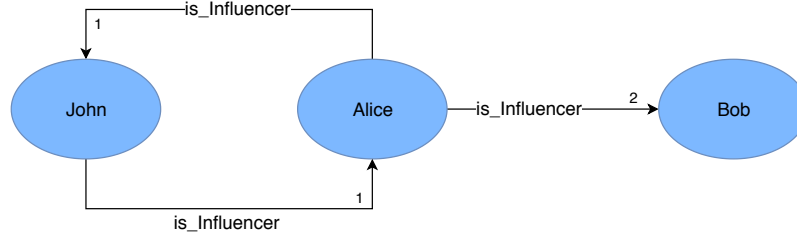


Fig. 3.9 Example of knowledge graph containing entities and isInfluencer relation between them, with numbers being exemplary numbers showing intensity

time as well as numerous entities. Alice, John and Bob are the instances of the *Entity* class, and *User* subclass. Both Alice and John perform *Actions*, using *PostingText* and *PostingPhoto* respectively. Each of the users reacts – John and Bob react to Alice posts via *Upvoting* and *Commenting*, and Alice reacts to John action by *Sharing*. Considering time interval $T_1 = [1/01/201919h00, 1/01/201921h00]$ Alice’s audience at T_1 consists of Bob and John (they reacted to two different actions *PostingText1* and *PostingText2*). In comparison, considering time interval $T_2 = [1/01/201919h00, 1/01/201920h00]$, Alice’s audience is comprised of only Bob.

Basing on the social network context and definitions of Action and Reaction given above, we can now define influence as follows:

Definition 4 Influence

The relation of influence between two entities e_s and e_t ($e_s, e_t \in E$) occurs iff e_s performed at time t_i at least one action $a \in A$, on which e_t performed one or more reactions $\{r_1, \dots, r_n\} \in R$ in a particular considered interval of time T , where the start t_j of the time interval T is after action time t_i ($t_j > t_i$). We say that e_s **influences** e_t . The entity e_s is a Subject of Influence or an **influencer**. The entity e_t is an Object of Influence, or an **influencee**. If Object of Influence is a singular entity, we can call the influence between them as **pairwise influence**.

Importantly, we do not assume that the Subject and Object of Influence have a relation between each other, i.e. follow, friendship, etc. Obviously, the actions of the Subject of Influence must be visible by the Object of Influence in order to the Object be able to react. This assumption implies only the visibility of the actions performed by the Subject and represents a more flexible approach in terms of data requirements and applicability to various social network platforms without a notion of a direct relation between users.

An example of a knowledge graph containing the entities and isInfluencer relation (based on the previously described Example 4), can be seen in Figure 3.9.

It can be observed that the presented influence definition involves the asymmetry and time-dependency of influence, and is focused on the following aspects of influential content

(mentioned previously in Chapter 2): popularity, recognition, activity generation and immediacy. In the following, we discuss and define in deep different factors of influence that are based on the above influence definition, namely: (i) intensity of influence depending on the type of reaction, (ii) influence spread and audience engagement, and (iii) influence time dependency.

(i) *Time dependency*

The first crucial factor to consider in order to precisely model influence is time. As it was mentioned in the influence definition, we acknowledge that influence is occurring in time, hence it is necessary to examine and include different aspects of time in the influence estimation process. As mentioned in Chapter 2, there are two, connected to each other important features to consider when modeling influence – dynamicity and time-dependence. As users in social networks interact with each other, the network by consequence is dynamic, having disappearing and appearing nodes, links, etc. There are two aspects to consider in order to take into account dynamicity and time.

Firstly, there is a need to decide if and how to divide the data used for the analysis of influence. The most common way in the literature (e.g. [131, 132]) is to aggregate the dynamic network, i.e. transform it into a series of snapshots of a graph. Data aggregation allows dividing the data into parts, thanks to which they can be represented as graphs, manipulated and analyzed. However, the aggregation requires (1) choosing of the time window size, appropriate for the network characteristics and (2) choosing the time window way of sequencing – the time windows can be disjoint or overlap. Depending on the required granularity of time, time window size can be either moving or constant. In case of moving time window, the time window size is not constant and can depend on either the incoming events, for instance incoming action in social network or sensor activity, or on the additional metadata, for example incoming information about real-life events for a social network such as elections, natural catastrophes, etc. In case of a constant time window, the size of the time window is constant and arbitral, e.g. a year, a week, couple of minutes, etc. Moreover, despite the abovementioned issues, considering the context of Action-Reaction concept, using time windows has some further disadvantages. As Action-Reaction concept implies the occurrence of a sequence of the first action and then reactions, the partitioning of the data into time windows causes the emergence of the issue of whether the reactions should be divided in the same snapshots as actions. To illustrate, let us assume the following example: for 7 day time snapshot, user u_1 performed action a_1 on day 1 and action a_2 on day 2. Considering reactions, the question is how to divide the reactions

time slot and then, when calculating influence, to which time the influence value should be assigned. For instance, if we assume the same time snapshot for both actions and reactions, then for action a_1 we consider much longer time for reactions (7 days for a_1 vs 1 day for a_2). In comparison, assuming the consideration of "infinite" reaction time window – from the action occurrence until the end of the data, then the problem of to what time window the influence value calculated based on those long time span of reactions should be assigned – if reactions occur much after the initial action, influence could be for instance assigned to time of action, or time of reactions.

It is also important to mention that, independently from the above-mentioned assumptions about time aggregation, we can also distinguish two possible types of analysis that can be performed for influence estimation: (1) evaluation, where based on the available data we want to measure a particular quantity and (2) prediction, where basing on data to-date we want to forecast the value of a particular quantity in the future. Looking from the context of this work, gaining influence is a long-term and continuous process. Therefore, in many cases, considering the whole available dataset when attempting to evaluate influence gives the best estimation of users influence to-date. In comparison, influence prediction usually requires partitioning the dataset into time series, thanks to which one can analyze the past trends and predict the future ones.

Secondly, within the considered data portion (while dataset or aggregated snapshot) time-dependency aspect should be taken into account as well. Here, we focus precisely on time-dependency aspects in the context of the previously introduced Action-Reaction concept (Fig. 3.7).

To illustrate, let us consider two situations, in which users u_1 and u_2 are posting content for time period $[t_1, t_{10}]$, and content is visible to the same number of users (audience). In the first situation, user u_1 is posting in each of the time points t_1, \dots, t_{10} . In the second, user u_2 has posted only two times, in t_1 and t_{10} . Additionally, both users u_1, u_2 received during this time period the same amount and type of reactions. While evaluating influence, the question is whether user u_1 posting much more ("constantly") should have equal value of the influence (as we count only the reactions that both users received), or should user u_2 indeed have higher influence? We propose to tackle this issue by introducing the component that favors lower frequency of performing actions. This is in accordance with the fact that we tend to appreciate more users with fewer posts but with higher quality and possible maximum gain for reactions.

(ii) *Intensity of influence depending on reactions*

Table 3.3 Social Network Aspects depending on the type and/or site

Social Network Type	Action	Reaction
Social Network Sites		
Facebook	posts, photos	comments, likes (\approx upvotes), shares, mentions
LinkedIn	posts, updates	comments, likes (\approx upvotes), shares
Google+	posts, photos	comments, +1 (\approx upvotes), shares
Content-sharing		
<i>Microblogging</i>		
Twitter	tweets (\approx posts)	replies (\approx comments), likes (\approx upvotes), retweets (\approx shares), mentions
Weibo	posts	replies (\approx comments), likes (\approx upvotes), retweets (\approx shares), mentions
<i> Blogging</i>		
Medium	posts	comments, claps (\approx upvotes), shares to outside platform, e.g. twitter/fb, bookmark
Politico	posts	comments, shares to outside platform, e.g. twitter/fb/g+
Creative content		
Youtube	videos	comments, likes (\approx upvotes), dislikes, shares, views
Instagram	photos, stories	comments, hearts (\approx upvotes)
Collaborative sites		
Yelp	reviews	upvote review, upvote profile

The fact that we model influence basing on the Action-Reaction schema (Fig. 3.6) implies the flexibility in terms of a number of features the model is capable to analyze, hence the type of data it can process. Obviously, by minimum, the data is required to have the users actions and reactions of one kind (e.g. comments, references). Considering the existing to-date potential sources of data, we enlisted most of the major social network sites in order to gather all the similar features categorized to Action and Reaction, following the categorization of the social network sites form Chapter 2. The results are presented in Table 3.3.

From this comparison, it can be seen that most omnipresent reactions available to the users to perform upon the generated content are *upvotes* (also named *likes*, *claps*, *hearts*, etc. – in this work, all one-click reactions that imply appreciation of the content will be called by the general name *upvote*), *comments*, and *shares* (the action of sharing the content originally posted by other users). In the following, without loss of generality, we use as an example these three reactions due to their ubiquity.

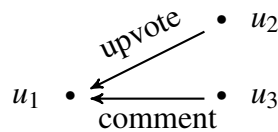


Fig. 3.10 A simple visualization of part of social network where users $\{u_2, u_3\}$ react to the content generated by user u_1 using two different reaction types

In particular, we want to focus on the implications that different types of reactions have on the influence strength. Indeed, upvotes, comments and shares have various functions and meanings within social networks. According to [133], the upvote is treated as a lightweight reaction, easy to perform to acknowledge the posted content, similar to "wordless nod". In comparison, comments are regarded as "more satisfying to receivers" [133]. Moreover, because of the quickness and easiness of upvoting, it may also be regarded as less meaningful than other reactions. Clearly, reacting using comment involves both effort (writing comment content in comparison to "default" value of upvote) and time (writing and answering versus just one-click). Furthermore, a study [134] has shown that the majority of people share content due to its value – 94% of subjects share "valuable or entertaining content with others", 84% share to support causes and issues they care about. This means that when we see content that is highly impacting we are more willing to share it. This phenomenon is much different from the "casual" upvoting. It was also observed that receiving more complex reactions from acquaintances corresponds to the increase of relationship strength and closeness, as opposed to getting upvotes where no such association was noticed [135].

Property 1 *Intensity*

Property of influence relation determining the quantity of influencer strength per a reacting entity. It combines information about the number of reactions and their type. Depending on the type, the reaction can have different degree of importance.

Taking the above into consideration, the type of reaction should implicate its degree of importance. Considering the cited literature, we assumed the hierarchy of the reactions, in which on the bottom (least importance) is upvoting, then comments, and finally the most important is sharing. To illustrate, let us consider the following example, showed in Figure 3.10: user u_1 created the post; user u_2 upvoted the post, while user u_3 commented on the post. The hierarchy aims to evaluate influence according to the importance of the reactions, in this case evaluating the influence of user u_3 higher than user u_2 . It is also important to acknowledge that for each generated influencer content,

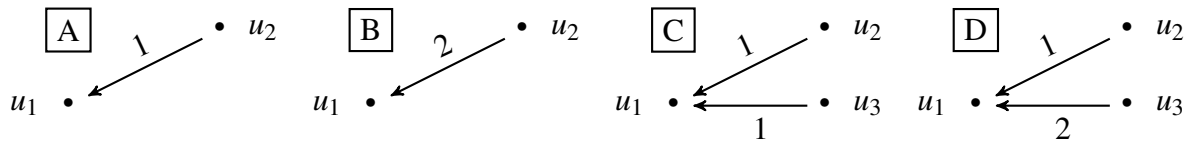


Fig. 3.11 A simple visualization of part of social network showing different scenarios of users $\{u_2, u_3\}$ reacting of the content generated by user u_1 . For simplicity, arrow symbolizes reaction of one type (e.g. comment) and the number signifies the number of reactions

we can specify several combinations of reactions of the influencee – entity can *only* upvote, comment or share the content, can upvote and comment, upvote and share, comment and share, and obviously, all three at the same time, meaning that the entity is upvoting, commenting and sharing the same content.

(iii) ***Spread and engagement***

Another important aspect of influence resulting from Action-Reaction schema involves consideration of the occurrence of multiple users' reactions to the one user's particular content.

Let us imagine a user u_1 who performs an action – creates a post, for whom we want to evaluate the influence. The users u_2, u_3 can react differently, as pictured in Figure 3.11. In two cases (Fig. 3.11 A and Fig. 3.11 B), only user u_2 reacted to the post with one and two reactions, respectively. Intuitively, the comparison of these two situations leads to the conclusion that the influence of user u_1 should be higher in Figure 3.11 B, as the user u_2 has stronger response in this case. In the other two cases (Fig. 3.11 C and Fig. 3.11 D), both users u_2, u_3 reacted. We can say that the overall influence of user u_1 in Fig. 3.11 D should be higher, because of higher number of reactions obtained. While it is fairly easy to compare these pairs of situations, A and B or C and D, the issue starts to be complicated when we want to order influence from highest to lowest in all the presented situations. Intuitively, without any particular model, we can state that influence in case A will be the lowest, while influence in case D the highest. However, it is not that obvious in the case of B and C. Is the fact that user u_1 gets a reaction from two separate users important enough to evaluate the influence of u_1 in situation C higher? Or is the strength of a particular reaction more important than the spread of the audience?

In order to tackle this problem, we propose to differentiate two components of influence, namely influence *spread* and audience *engagement*. Intuitively, in the example above, user u_1 in situation C would have higher spread (as two different users are reacting),

while in situation B would obtain higher audience engagement value (only one user reacting but with multiple reactions).

Property 2 Spread

Property of influence relation determining the number of audience members per action performed by an influencer i.e. the number of users affected by influencer action.

The idea behind the spread is to calculate the active audience (meaning users that are reacting to the considered action), in order to determine the actual overall broadcast range. We define spread as the number of users that made reaction at least once, i.e. general audience cardinality. Considering the example from Fig. 3.11, in the simplest case in situations A and B, the spread would be equal to 1, while in situations C and D it would be equal to 2.

Property 3 Engagement

Property of influence relation determining the strength of the audience reactions per action performed by an influencer.

The audience engagement notion aims to conceptualize how powerful is the user's influence, therefore evaluates the overall involvement of already active users reacting to the content. For instance, comparing situations B and C from Fig. 3.11, the engagement would be higher for situation B.

Micro-influencers and Macro-influencers

In some cases, popularity of the users and their content do not play a crucial role for one's influence – instead there is a need for approaches that target finding users less broadly known but still influential in the niche they operate in. In other words, using the nomenclature from Chapter 2, they have less popularity. Therefore, the scope of this section should be regarded as a complementary work and an extension to the task of dealing with determining the influence within social networks. In particular, we want to show the applicability of the term *influence* to users that have a very high impact despite not having an enormous audience.

Indeed, micro-influencers are starting to be a topic of very recent research. For instance, the work of Lin et al. [136], while focused in business domain, has mentioned micro-influencers as one of the important roles in a social network. To-date, the term is mainly used in marketing, where service sites are using the micro-influencer concept in order to engage

the companies and the micro-influencers together for advertising purposes. While they focus on the application of the term, their definitions are similar and non-specific, e.g. [137] describes micro-influencers on Instagram platform as “*creators on social media platforms who typically have between 1,000 and 100,000 followers*”, and the exact boundaries of the audience size vary: article [138] limits the followers number to 5 000 followers, [139] gives limits of 10,000 and 500,000 followers. Furthermore, a recent study [140] investigating the usefulness of micro-influencers has shown much higher engagement rate (likes, comments) for users with less than 10 000 followers: “*1,000 followers generally received likes on their posts 8% of the time. Users with 10 million+ followers only received likes 1.6% of the time*”. Interestingly, a very recent publication of Côté and Darling [141] dealt with the related subject of Twitter scientists’ reach of audience, especially small audiences and the property of those audiences. This study additionally characterizes the possible audiences, shows the recent interest in users with the smaller public, and discusses different prospects for scientists from different disciplines using Twitter, showing the vast differences of the properties depending on the audience size.

Using the above context and the previous definitions of Influence, Action, Reaction, etc. we can specify the notion of micro-influencer:

Definition 5 *Micro-influencer*

A micro-influencer is an influencer that has :

- 1. a limited spread value, that is Audience size that is both non-empty and greatly smaller than the maximal audience size observed in the SN,*
- 2. the highest possible engagement value.*

The limitation of the audience size is a direct implication of our focus on the impactful but not popular users. Obviously, the exact value setting the bounds for the size of the audience is a subject of the arbitrary decision. The value will be highly dependent on the properties of the analyzed social network such as size of the network, density, and average of users’ followers, etc. Therefore, the value cannot be set as an absolute but has to be relative to both the maximal and minimal observed size of the audience. Moreover, depending on the application, some additional boundaries and restrictions might be appropriate, e.g. targeting users that have no more than 1 000 followers, as we want to maintain a personal contact (via messages) with all the followers.

The problem of boundaries specification connects with the issue of inreach and outreach of audiences [141]. Particularly, depending on the use case, the interest can be put on users with outreaching audiences, that can attract users that are not directly connected to the

specific subject, or on users with their followers being dedicated to a particular niche. A good example of this can be seen on Youtube. Some users (both with bigger and smaller audiences), who brand themselves with some particular topics (e.g. gaming), are still more appealing to a various spectrum of users (not necessary computer games enthusiasts). On the contrary, many of the users' channels are much more in-depth and will only be alluring to users with a high interest in the subject. Therefore, there can be two separate cases of an advertiser searching either for highly dedicated focus group (inreach), in which case the boundaries will be smaller, or for a less dedicated, more versatile group, in which case the limits can be set larger.

The second part of this definition is high engagement. As discussed before, we focus on two components of influence: spread and engagement. Thus, as we purposely limit the spread, the influence will mainly depend on high engagement value.

Similarly, we can define the notion of macro-influencer, being the concept symmetrical to previously defined micro-influencer, as follows:

Definition 6 *Macro-influencer*

A macro-influencer is an influencer that has both:

1. *the highest possible spread value,*
2. *the highest possible engagement value.*

For macro-influencer, we aim to maximize the values of both spread and engagement, which will lead to the selection of those influencers who have both possibly the biggest and engaged audience. Importantly, the works that find and rank influencers (see Chapter 2) target exactly macro-influencers – the entities that are by far the most apprised and known within a social network, however, as the differentiation between micro- and macro-influencers is not yet popularized, they refer to those entities as *influencers*. Considering that, in the scope of this thesis, in order to be coherent with other works, we utilize term *influencers* when referring to *macro-influencers*, and the term *micro-influencers* when we particularly target entities fitting the Definition 5 (e.g. Chapter 4 Section 4.3.2).

Link from Influence to Reputation

Both *influence* and *reputation* concepts deal with interactions between people in social networks and provide insight into human behavior. However, to this date, in SNA discipline, they were studied only separately. Nevertheless, within scopes of Sociology and Psychology, different surveys [142, 143] have shown that individuals connected with high reputation – having high levels of competence and "*demonstrating superior skills and abilities*" [144] are

proved to have higher-rank (i.e. influence) within the group. Particularly interesting is the recent study [144], which provides results that lead to the conclusion of social influence being strictly connected to the notion of "*sharing of expertise or know-how to gain respect*"²[144].

Additionally, in order to aim to precisely evaluate reputation, time-dependency aspect of a network seems to be a necessary condition – as observed in [145], an entity reputation evaluated from retrospective and including its history makes the reputation value more certain and stable.

Taking the above into consideration, we propose to formalize the link from influence to reputation as follows:

Proposition 1 *Assuming an entity e is macro-influencer in a particular social network basing on long term observations during time interval T we can say that e gained high reputation in this social network after the time T . Time interval T depends on social network characteristics such as domain, dynamicity, frequency of actions, etc.*

3.6 Conclusion

The confusion and misuse of the concepts of trust, reputation, popularity and influence prevent their proper modeling. Therefore, the need for these terms clarification and differentiation is crucial. Moreover, precisising the notions is a necessary basis for the proposition of accurate measures. The use of the right metrics that capture the sociological sense of the concepts is beneficial for better observation and thorough analysis of social networks and hence it is improving their use in applications.

Taking this into consideration, in this chapter, we detailed the notions, starting from the general order and then specifying each of them. We introduced a new way of the terms hierarchical order with regard to the abstraction level complexity of the concepts. We also proposed each of the notions typology. Next, we selected several works shown in Chapter 2, and compared the terminology used to describe the methods by their authors with the nomenclature that we find more appropriate from the perspective of what they are actually measuring. Finally, we proposed a modelization of influence, by defining notion in the context and of *influence*. The model based on the Action-Reaction schema and introduced several important components of influence.

²The quote concerns notion refereed in the work [144] as *Prestige* (as authors want to avoid the confusion with other concepts from biology and psychology), however the definition given by authors strictly coincides with this of accepted meaning of *Reputation* in Social Network Analysis described in Chapter 2, therefore we treat the concept as reputation..

In the following, we use the presented, theoretical model of influence and instantiate it in order to perform influence evaluation in practical applications.

Chapter 4

Proposition of General Model of Influence

4.1 Introduction

In previous chapters, we discussed different social interactions in social networks related to the notion of influence. In Chapter 3, we showed that influence is the most abstract and complicated notion from all described in this work. In order to actually evaluate one's impact, we need to know not only the structure of the networks, but also we are required to obtain the information about individual relations between users as well as the additional knowledge about how the shared information spreads.

In the literature, many works have tackled the influence detection and estimation issues. Nevertheless, as we have shown in the synthesis of influence works in Chapter 2, there are still issues and lacks of those approaches. Firstly, many methods are typology-based. Accordingly, because of such focus on the topology aspect of the influence, users that are more connected are higher valued in many works. However, it is important to notice that the connectedness of the user signifies the possibility of her neighbor to *see* her content, but definitely does not guarantee the users *engaging* with it. Furthermore, due to the favoring of high connectedness, little focus goes to the issue of influence audience, as it is assumed that the bigger audience the better. However, this often might not hold true. To illustrate the problem, let us consider the network that consists of different users - proactive and reactive ones, having different interests, and having various numbers of connections to others. Now, assuming an exemplary application of influence evaluation for targeting the social campaign to people, while using limited resources, the question is how to select creators to share the event, which not only have an audience, but also the audience that would be involved in

the campaign. Lastly, the existing works lack consideration of the time. As mentioned previously in both Chapter 2 and Chapter 3, time is an important factor to examine for influence evaluation.

To address these problems, we created, described and discussed the theoretical model of influence in Chapter 3. This established model is based on the Action-Reaction schema, that uses both actions and reactions of users to evaluate their influence. In this chapter, we instantiate the theoretical model and present a flexible and general framework, called ARIM (Action-Reaction Influence Model), for evaluating influence between users using one – any – on-line social network platform. ARIM relies on the users proactive and reactive behaviors that can be found on any social networking site, thanks to which it incorporates both their spread and engagement. Importantly, its flexibility allows it to incorporate various types of reactions, depending on particular social network characteristics. We also focus on generality aspect of the model, so that it can be used with numerous, different datasets. Furthermore, in order to incorporate time aspects into our model, we target considering the frequency of events in time within the social network. In order to tackle the problem of how to measure, prove and sustain the influence on a different audience, we also use ARIM and defined previously, in Chapter 3, the notion of *micro-influencer*. We specify micro-influencer definition for our purposes and show experiments made with the use of ARIM influence evaluation model aiming to investigate the micro-influence issue.

The remainder of the chapter is as follows. In Section 4.2 we present the general influence model ARIM that focuses on influence aspects important for model expressiveness, namely *intensity* of users reactions, *spread*, *engagement* and *time dependency* that were defined in previous chapter. Next, Section 4.3 is dedicated to the evaluation of showed notions. We first present the performed experiments using ARIM for influence evaluation using three different real-world databases. Then, we show the experiments using micro-influence application, that utilizes two real-world databases.

4.2 Action-Reaction Model of Influence (ARIM)

In this section, we present the instantiation of the definitions presented in Chapter 3 proposing Action-Reaction Model of Influence (ARIM). ARIM is an application of the established theoretical influence model, that targets flexibility and generality. In particular, we specify the formulas used for influence calculation of ARIM model, that are compatible with the definitions given in the previous chapter.

Let $a_i = (p_i, e_s, t_i)$ be an action of type p_i , performed by entity e_s in time t_i and $r_j = (q_j, e_t, t_j, a_i)$ be a reaction of type q_j , performed by entity e_t in time t_j to action a_i , and let

T be the considered time interval, $t_i, t_j \ni T$ and $t_j > t_i$. We also define several additional functions in what follows. Function $R_{type}(e_i, T)$ is the function returning the set of reactions of one type performed by entity e_i within time interval T . As mentioned in Chapter 3, we assume type being one of $\{Upvoting, Commenting, Sharing\}$, which results in three functions – $R_u(e_i, T), R_c(e_i, T), R_s(e_i, T)$ – returning the set of all reactions performed by entity e_i of type *upvoting*, *commenting* or *sharing*, respectively. Function $Audience(e_i, a, T)$ is the function compatible with Audience definition (see Chapter 3 Definition 3) that returns the audience (i.e. set of entities) that reacted to action a performed by entity e_i within time interval T . Function $AllActions(e_i, T)$ is the function returning all actions performed by entity e_i within time interval T .

Given the above, we can specify *intensity* of influence depending on reactions, that was discussed previously in Chapter 3 Section 3.5. As mentioned before, without losing generality we assume that we encounter three types of reactions, however, if there is a need, obviously the specification of the model can be further extended to include more. Recall that the idea behind the intensity is to determine the influence strength basing on acquired reactions, with focus on different degree of importance of reaction depending on its type. Therefore, we propose the *ReactionsIntensity* function that calculates the intensity of all the reactions done by a particular reacting entity e_t to a particular action a in time interval T , differentiation the importance of occurrence of various combinations of reaction types. It can be specified using the following formula:

$$\begin{aligned}
 ReactionsIntensity(a, e_t, T) = & w_1 * |R_u(e_t, T)| + w_2 * |R_c(e_t, T)| + \\
 & w_3 * |R_s(e_t, T)| + w_4 * |R_u(e_t)| * |R_c(e_t, T)| + \\
 & w_5 * |R_u(e_t, T)| * |R_s(e_t, T)| + w_6 * |R_c(e_t, T)| * |R_s(e_t, T)| + \\
 & w_7 * |R_u(e_t, T)| * |R_c(e_t, T)| * |R_s(e_t, T)|
 \end{aligned} \tag{4.1}$$

In formula 4.1, $R_u(e_t, T), R_c(e_t, T)$, and $R_s(e_t, T)$ are sets returned by the above defined function, i.e. reactions performed by entity e_t in time interval T of type *upvoting*, *commenting*, *sharing*, respectively; weights w_1, \dots, w_7 signify the degree of the importance of each of reaction combination. The weights should be tuned to emphasize each reaction combination (lower weight – less emphasis). The number of possible reactions types can obviously be higher or lower depending on the types of reactions the dataset includes. *ReactionsIntensity* function includes the multiplication of each combination of the reactions, which increases the overall value of the measure.

We do notice that one might argue that the degree of importance for reactions combinations could be modeled just by using the linear combination of weights and vector of reactions. However, we aim to put a different importance level to each of the reactions (and their possible combinations) by not only using weights vector but also utilizing non-linear multiplications corresponding to reaction combination, so that the importance of existence of multiple reactions at the same time can be stressed, and have a greater value on final score. In order to achieve this, we opted for modeling reactions with the use of a non-linear function.

Above-mentioned *ReactionsIntensity* function returns the information about the intensity of reactions per particular reacting entity. Using this function, we can specify *ActionAvgIntensity* function which specifies how much appraisal on average the action a performed by entity e_s received, in the form of reactions, from its audience within time interval T . It is formally defined as:

$$ActionAvgIntensity(a, T) = \frac{\sum_{e_i \in Audience(e_s, a, T)} ReactionsIntensity(a, e_i, T)}{|Audience(e_s, a, T)|} \quad (4.2)$$

where $ReactionsIntensity(a, e_i, T)$ is the defined above *ReactionsIntensity* function, and $Audience(e_s, a, T)$ is the set returned by *Audience* function of all entities that reacted to action a performed by entity e_s within time interval T .

Using the above equations, we next specify the two influence components, *Engagement* and *Spread*, in accordance to their definition presented in Chapter 3.

Recall that *engagement* targets measuring the involvement of the reacting entities. Accordingly, *Engagement* of entity e_s within time interval T is defined as follows:

$$Engagement(e_s, T) = \frac{\sum_{a_i \in AllActions(e_s, T)} ActionAvgIntensity(a_i, T)}{|AllActions(e_s, T)|} \quad (4.3)$$

where $AllActions(e_s, T)$ is the set returned by the function *AllActions* of all actions performed by entity e_s within time interval T , and *ActionAvgIntensity* is function defined in Formula 4.2.

Consequently, recall that *spread* aims to measure the number of affected entities. Accordingly, *Spread* of entity e_s within time interval T is defined as follows:

$$Spread(e_s, T) = \sum_{a_i \in A} |Audience(e_s, a_i, T)| \quad (4.4)$$

where A is the set of all actions performed by entity e_s within time interval T and $Audience(e_s, A, T)$ is the set, returned by function *Audience* defined above, of entities who reacted to multiple actions (defined by set A) performed by entity e_s within time interval T .

The third influence component introduced in Chapter 3 is time-dependency. ARIM favors lower frequency of performing actions, through function *ActionFreq* specified as follows:

$$ActionFreq(e_s, T) = e^{\frac{1}{|A(e_s, T)|}} \quad (4.5)$$

where A is the set of all actions performed by entity e_s within time interval T . Using *ActionFreq* function, we penalize the entities with larger number of actions, e.g. for two entities with equal *spread* and *engagement*, we favor the entity that performs less actions. By doing so, we are ensuring that we prioritize users that have the influence but generate lower number of posts. Therefore, in our example, they should be regarded as more influential, as they indeed post less, while same amount of both engagement and spread.

It is important to notice that the aim of ARIM is to evaluate the influence based on existing data (in comparison to predicting future influence value, see Chapter 3). In order to achieve the best estimate, we decided to utilize the whole available data in the experiments, however, as could be seen, ARIM is able also to perform on snapshots of data.

Finally, the influence value of entity e_s within time interval T can be described using the formula:

$$Influence(e_s, T) = Engagement(e_s, T) \times Spread(e_s, T) \times ActionFreq(e_s, T) \quad (4.6)$$

Formula 4.6 binds all the measures presented before using the multiplication. Thanks to this, the contribution of spread and engagement to the final influence score depends on their value. Therefore, an entity with high engagement and low spread will have similar influence value to one of an entity with low engagement and high spread, assuming that they have equal amount of actions. This is important, as being the better spreader does not straightforwardly implies being more influential, as we described previously.

4.3 Evaluation of ARIM

In this section, we describe the experiments conducted using the proposed ARIM model discussed previously. We divided the experiments into two parts. Firstly, in order to validate ARIM, we conducted experiments aiming to evaluate influence and finding the most influential users. Secondly, we used ARIM for investigating the issue of micro-influencers discovery described previously in Chapter 3.

Table 4.1 Statistics about used Facebook dataset [8]

Parameter	Number
Number of acting users	1 067 026
Number of users that reacted	23 426 682
Number of posts	25 937 525
Number of comments	104 364 591
Time span of data	15/10/14 - 11/02/15

4.3.1 Application to Influence

As mentioned before, ARIM is an instantiation of the theoretical model of influence showed in Chapter 3, that focuses on generality (in terms of application to multiple social networks types) and flexibility (in terms of inclusion of multiple reaction types), simultaneously implementing influence components such as time-dependency, intensity, spread or engagement. In order to show ARIM flexibility to operate on different data, evaluation of ARIM consists of the experiments using three different real-world datasets, that have different characteristics as well as contain multiple types of actions and reactions.

The first dataset consists of data from Facebook [8]. It contains one type of action and one type of reaction, i.e. information about posts and their comments (without the text content) and, additionally, with precise information about the time of each action or reaction. Table 4.1 presents the basic statistics about the dataset. The second dataset includes data from Pinterest [9], with one type of action (posting) but two types of reactions: repins (shares) and likes (upvotes). Table 4.2 shows the basic Pinterest dataset statistics. The third dataset contains data from Microsoft Academic [146]. This data has one type of action and one type of reaction, namely scientific papers (actions) and references between them (reactions).

We conducted three sets of experiments using ARIM resulting in general influence evaluation of all users, utilizing datasets of Facebook, Pinterest and Microsoft Academic. However, we discuss here the most influential users from each of the datasets (top influentials). The implementation was done using PostgreSQL ¹ version 9.6 and R language ² version 3.3.1.

Results for Facebook database

For experiments performed on Facebook dataset, we created a social network where nodes are users and the relation available in the dataset – comments are the edges. Due to the nature of the data that contained one type of relation (comments), there was no need for weights

¹<https://www.postgresql.org/>

²<https://www.r-project.org/>

Table 4.2 Statistics about used Pinterest dataset [9]

Parameter	Number
Number of users that did action	1 307 527
Number of users that reacted	8 314 067
Number of posts	2 362 006
Number of shares	37 087 685
Number of upvotes	19 332 254
Time span of data	03/01/13 - 21/01/13

Table 4.3 Top 10 Influential users from Facebook [8]

#	Engagement	Spread	#Actions	Influence
1	1.039	66181	96	69478
2	1.216	19793	549	24116
3	1.208	18093	148	22012
4	1.204	17030	103	20701
5	1.071	17817	200	19183
6	1.097	17040	941	18717
7	1.092	16087	263	17637
8	1.413	11086	67	15899
9	1.053	14185	998	14953
10	1.066	12678	34	13924

parametrization, we used $w_1 = 1$, as all other parts of Equation 4.1 do not exist. Table 4.3 shows the Top 10 ranking of the most influential users. It can be observed that the user in the first place, while having low (relatively to other top 10 users) engagement rate, is having exceptionally high spread. At the same time, this person has created 96 posts, which is also relatively low. Despite the fact that the audience is not very reactive, i.e. commenting only once, and not entering into discussions, the user is considered very influential due to the user's huge spread for very few actions. Complementary to Table 4.3, Figure 4.1 presents a comparison of Top 3 users in terms of influence score, engagement and spread rate, and number of posts. The high spread rate of the top 1 user relative to two other top users can be easily noticed.

Another interesting case can be observed on the 8th position in the ranking, with the person having the lowest spread rate in the ranking, significantly lower than both users on 9th and 10th position. Interestingly though, this person engagement rate is very high (highest value in the ranking), with additionally small number of posts. Therefore, this user higher place can be explained with the fact that ARIM is not only focused on both engagement and spread equally, but also it favors the smaller number of posts. Hence, the user on the

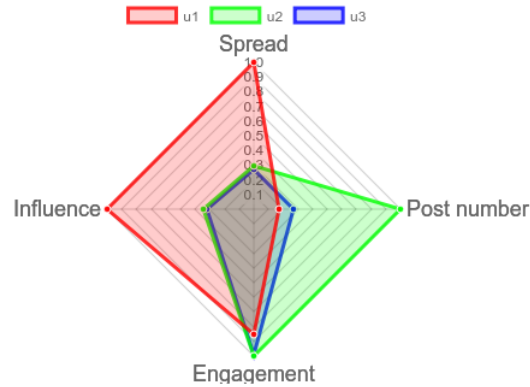


Fig. 4.1 Detailed comparison of top three users with regard to influence score using Facebook dataset

Table 4.4 Top 10 Influential users from Pinterest dataset obtained using ARIM with equal weights (all reactions considered equal)

#	UID	Engagement	Spread	#Actions	Influence
1	2777	1.314	23386	1282	30743
2	20703	1.249	19777	566	24747
3	2367	1.367	13512	1025	18487
4	5656	1.314	9843	535	12958
5	4000	1.286	9908	360	12778
6	1731	1.442	8553	328	12372
7	5074	1.389	8876	465	12358
8	820	1.262	9735	615	12304
9	4968	1.301	9013	569	11742
10	993	1.344	8580	387	11559

8th position in the ranking surpasses the next user (9th position) that, although having high spread, he/she has also lower engagement and very high (998) number of posts (the biggest number of posts in the whole ranking).

Results for Pinterest database

The second set of experiments was conducted on Pinterest database, containing two types of reactions, namely shares (called on the site "repins") and upvotes ("likes"). Here, the social network created for experiments was represented as a graph where users were symbolized by nodes and shares and upvotes by edges. In order to show the results difference when considering different degree of importance depending on reaction combinations (see Equation

Table 4.5 Top 10 Influential users from Pinterest dataset obtained using ARIM with weight emphasis on share reactions

#	UID	Engagement	Spread	#Actions	Influence
1	2777	2.263	23386	1282	52961
2	20703	1.935	19777	566	38329
3	2367	2.283	13512	1025	30877
4	820	2.224	9735	615	21690
5	4000	2.133	9908	360	21196
6	5656	2.133	9843	535	21032
7	4968	2.262	9013	569	20422
8	1731	2.360	8553	328	20245
9	5074	2.256	8876	465	20067
10	993	2.258	8580	387	19427

Table 4.6 Additional information about users gained reactions from two ranks using Pinterest dataset

UID	Shares Sum	Upvotes Sum	#Shares and Upvotes Concurrently
820	12617	4184	219
993	9251	4159	583
1731	9242	4665	829
2367	19404	9028	1203
2777	28920	10863	1358
4000	10729	5245	618
4968	10709	3621	466
5074	8897	4816	694
5656	10695	5786	885
20703	15944	11467	1066

4.1 in Section 4.2), we have chosen to put higher weight to *Sharing*, which gave us two cases for experiments:

1. equal weights for both reactions, hence the formula 4.1 includes $w_1 = 1, w_3 = 1, w_5 = 1$ giving the final form of:

$$ReactionsIntensity(a, e_t, T) = |R_u(e_t, T)| + |R_s(e_t, T)| + |R_u(e_t, T)| * |R_s(e_t, T)| \quad (4.7)$$

2. higher weight for shares, hence the formula 4.1 includes $w_1 = 1, w_3 = 1, w_2 = 2$ giving the final form of:

$$ReactionsIntensity(a, e_t, T) = |R_u(e_t, T)| + 2 * |R_s(e_t, T)| + |R_u(e_t, T)| * |R_s(e_t, T)| \quad (4.8)$$

Notice that, as there are no comments in the dataset, the weights w_2, w_4, w_6, w_7 equal 0. Tables 4.4 and 4.5 present the obtained results from runs for both cases respectively. Additionally, the complementary Table 4.6 presents the detailed information about the users, containing the aggregated sums of shares and upvotes (2nd and 3rd column respectively) and the number of times that both of the reactions occurred simultaneously (for the same post and from the same user). The information about the latter number (4th column) is important, as the Equation 4.1 (Section 4.2) for ARIM includes additional component in the formula regarding cases of simultaneous occurrence of different types of reactions.

Going back to the Top 10 rankings (Tables 4.4 and 4.5), it can be seen that, for both experiment executions, the first three positions are unchanged. This can be explained by a very high spread value of each of the users, which is the predominant component for their high influence. Figure 4.2 shows in detail the ratios of spread, engagement and post number for each of the top 3 users. Moreover, from Table 4.6 we can see that all of the top 3 users have a very high "combination" number, which means that they were appraised by other users simultaneously using upvotes and shares.

The use of the emphasis on the shares can be clearly seen by the example of user 820. In the first rank with equal weights (Table 4.4), this person position is low (8th). However, the stress by using the higher weight for share reactions (Table 4.5) results in the increase of the position of user 820 to 4th, jumping ahead of users like 5656 who, while having higher spread value, has fewer shares in total. Similarly, user 4968, who also has a high number of shares, is promoted from 9th to 7th position. Interestingly, in the case of second rank (Table 4.5), the emphasis on the shares also resulted in the top user 2777 having much higher influence score in comparison to all other users. Indeed, the gap between users 2777 (1st)

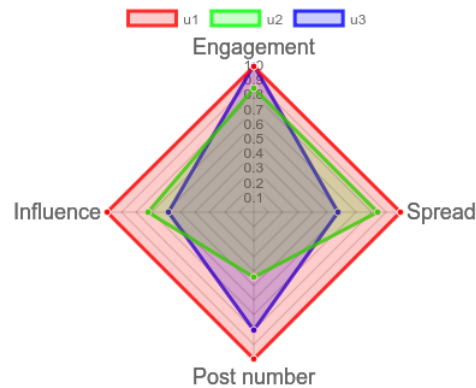


Fig. 4.2 Detailed comparison of top three users: 2777 (u1 – red), 20703 (u2 – green), 2367 (u3 – blue) with regard to both influence scores using Pinterest dataset

Table 4.7 Top 10 Influential users from Microsoft Academic dataset obtained using ARIM model

#	UID	Engagement	Spread	#Actions	Influence
1	759350BA	1.10899102687836	9643	1	29069.3071570812
2	7DA6662F	1.10899102687836	9643	1	29069.3071570812
3	7D4118DD	1.10899102687836	9643	1	29069.3071570812
4	0F360470	1.10899102687836	9643	1	29069.3071570812
5	7F5220D4	1.03349049886068	8714	3	12568.6569088798
6	7E6176D6	1.03349049886068	8714	3	12568.6569088798
7	81312479	1.03349049886068	8705	3	12555.675739247
8	04AB0CBC	1.20544059753418	9535	50	11726.0677967592
9	6F3B5422	1.19766062781924	9522	42	11678.9095413436
10	2BFF1916	1.15748445487317	9766	81	11444.4136672994

and 20703 (2nd) significantly rose (two fold), while the gap between users on the second and third positions (20703 and 2367 respectively) stayed similar. This is due to the fact that user 2777 has significantly higher share sum (28920 versus 15944 and 19404, for users 20703 and 2367 respectively), along with the high spread rate.

Results for Microsoft Academic database

The Microsoft dataset also contained one type of relation – reference between papers. Therefore, experiments performed with its use were done including one reaction – thus, weight was equal to 1. The created social network contained paper authors as nodes (entities) and references between their pages as edges.

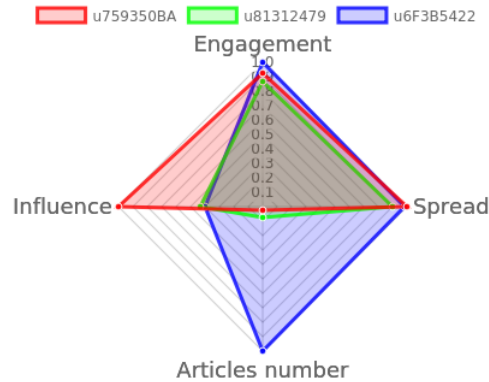


Fig. 4.3 Detailed comparison of selected top 10 users: (u1 – red), (u2 – green), (u3 – blue) with regard to Microsoft Academic dataset

Table 4.7 shows the Top 10 ranking of the most influential users. It can be observed that users on rank between 1 and 7 perform at most 3 actions. Nevertheless, they have huge influence score because their actions affect greatly other users – their value of spread is high. In comparison, users ranking in places between 8 and 10 actually performed much more actions (more than 42). However, while doing so, they still obtained a much lower influence value. Therefore, while their engagement per particular action can be similar to users on a higher place, their overall influence is lower, as they need to publish much more in order to engage the same number of people.

4.3.2 Application to Micro-Influence

The second part of the experiments involved utilizing ARIM applied to micro-influence, using definition presented in Chapter 3, in order to perform micro-influencers discovery. Recall that, in Chapter 3, the definition involved the limitation of the audience size of micro-influencer, however, the exact boundary was deliberately left to be specified precisely according to the particular social network properties. The illustration of micro-influencers placement in a social network can be seen in Figure 4.4.

Accordingly, for the experiments we have applied the definition so that we search for users using:

1. limitation of spread value, i.e. the limits of audience size L of potential micro-influencer e_m are 100 and 500 reacting entities i.e. $L \in [100, 500]$,
2. ordering max function for finding the highest possible engagement value for potential micro-influencer $max(Engagement(e_m, T))$, which orders entities by engagement value.

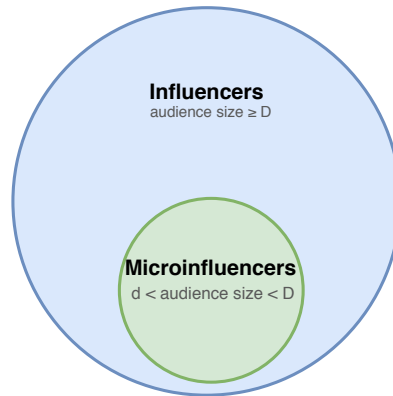


Fig. 4.4 Visualization of the placement of micro-influencers within a social network, where audience size is between D (upper limit) and d (lower limit)

The experiments were performed using two datasets of Facebook [8] and Pinterest [9] introduced in the previous subsection. The implementation was done using PostgreSQL³ version 9.6 and R language⁴ version 3.3.1.

To the best of our knowledge, no previous work dealt with micro-influencers, thus there are no comparable metrics. However, we did utilize PageRank method in order to show the key differences between the application of our idea and standard, *state-of-the-art* method applied with limits to attempt identifying micro-influencers. The choice of the PageRank is twofold: firstly, the method is one of the most popular approaches utilized for calculating influence [147], and, secondly, as PageRank targets the nodes with large audience, it should be seen that the use of only the limits (thus, only utilizing one part of the definition about audience size) is not sufficient enough to find the actual micro-influencers. We used weighted PageRank method with the reactions (comments, upvotes) as edges, directed from the user that performed the reaction, and the number of reactions (in-degree) as weights for the algorithm.

Facebook dataset

The application of the audience limit has led to the selection of 79 389 users that have the audience of that size. The results of the experiment performed on Facebook dataset are shown in Table 4.8. In this table, we can see the top twenty users in the order given utilizing the ranking from ARIM framework. In order to compare the results with the PageRank ranking, the columns *PR posit* and *PR val* present the ranking position (*PR posit*) and normalized PageRank influence value (*PR val*) respectively. Furthermore, Table 4.9 presents the results

³<https://www.postgresql.org/>

⁴<https://www.r-project.org/>

UID	ARIM posit	ARIM val	PR posit	PR val	Engagement	Audience size
11jh44w613qww	1	1	48262	0.001614	5.779887	118
15rfcd2cgpdds	2	0.502126	57692	0.001432	3.085694	133
ea43njsf6yo	3	0.49617	73208	0.001014	3.053465	150
1scz2cw2buk8	4	0.489723	13858	0.002791	5.879393	314
-1anjuucz0wiyo	5	0.489336	56051	0.001465	3.016482	110
-1dtof2rg2vcow	6	0.480393	8654	0.003296	7.751748	192
x1nb85o7nif4	7	0.477513	65560	0.001256	2.952504	153
5fb51yi0w2v4	8	0.471037	9354	0.003209	2.917462	223
6mji7114m3gg	9	0.457631	75872	0.000879	2.844917	110
-edpabk3i4q9s	10	0.456656	28941	0.002075	2.83964	119
-1raq7kohfmeww	11	0.453498	78787	0.000492	2.822553	124
cvaxiriqapds	12	0.444122	44884	0.00168	2.771816	157
-1dwoa9vr4y1hc	13	0.422427	49006	0.001599	2.654413	108
-g4gbjzx0jif4	14	0.421442	14041	0.002778	4.367602	164
10vj1m2yomneo	15	0.419198	31837	0.001987	2.636937	114
-388wc65lggao	16	0.415836	76994	0.000793	2.618747	144
j5pvdoei10cg	17	0.406018	60214	0.001379	2.565618	104
-1xx9hmnsegd1c	18	0.387517	5770	0.003745	2.465503	336
-wkei8jiqc7pc	19	0.384298	75435	0.000906	2.44808	144
-1r3rhn6jhzu0	20	0.3831	46190	0.001654	2.441597	141

Table 4.8 Top 20 Micro-influencers using ARIM method, compared with their position from PageRank for Facebook dataset

of top twenty users using PageRank, similarly compared with ARIM ranking position (*ARIM posit* and *ARIM val*). Normalized values were calculated using the minimal and maximal values for the overall rankings (including all users, not only micro-influencers).

It can be clearly observed that the top micro-influencers of ARIM have extremely low positions in the PageRank rank. All of the top twenty users have the PageRank positions placed at a couple of thousands. The reason for such vast differentiation lies in the different focus of the methods. Moreover, the opposite is also true: the high positioned users in PageRank have very low positions in ARIM ranking. It can be seen that PageRank chooses the users with high spread value (large audience), while ARIM targets engagement. This is exactly the key difference that causes that the resulting PageRank users will indeed have a lot of users that will see the content shared but will be less prone to react on it in any way. The contrary is true in the case of ARIM – the reach of the audience might be smaller, but those are the users much higher involved in the things shared to them. Notice that the main purpose behind finding micro-influencers is to find the users that, while they do not have vast spread, they highly impact their audience. Moreover, having a smaller audience can be

UID	PR posit	PR val	ARIM posit	ARIM val	Engagement	Audience size
-1jy1nmhvcdgcg	1	0.008702	33383	0.056201	1.49695	496
-qsiiojecsyyo	2	0.008427	31415	0.060834	1.150296	495
-fswnrkmo4yrk	3	0.008318	32253	0.058863	1.132718	486
198c8091cpdds	4	0.008241	44963	0.033605	1.453853	484
2gli11t588hs	5	0.008147	41057	0.039427	1.338818	484
-4kx0785szx4w	6	0.008138	40971	0.039569	1.134784	464
-scejupm7ff9c	7	0.008093	37984	0.045554	1.576255	473
5a14f85mzdds	8	0.008069	12971	0.151025	1.185753	497
yxrki09k2cjk	9	0.007982	55313	0.022991	1.31333	494
-aymifid4w54w	10	0.007972	77495	0.006454	1.077537	470
1h5n33mesf9xc	11	0.007952	52250	0.025658	1.167382	496
-736jrswr4xvk	12	0.007946	38421	0.044526	1.187037	474
-egv4x59mhm4	13	0.0079	6852	0.168751	1.281674	468
-1smwnk9u4zy80	14	0.007896	44255	0.034481	1.350198	478
-mdvxfedsgt8g	15	0.007895	71799	0.011508	1.116505	486
-15roml73v2ebk	16	0.007882	17224	0.14159	1.134692	467
o2xfdybxnthc	17	0.007865	57608	0.021221	1.27784	458
42w2131oqk74	18	0.007857	32391	0.058528	1.129727	454
-tmrw5uucvfuo	19	0.007848	62329	0.017793	1.095211	486
cuxc0d30szcw	20	0.007843	21281	0.131461	1.079881	492

Table 4.9 PageRank top 20 for users with limited audience compared with their position from ARIM method for Facebook dataset

additionally beneficial as the micro-influencer does have more time for replying and getting feedback from the audience.

Pinterest dataset

In the experiment utilizing Pinterest dataset, the data comprised of both shares and upvotes of users. As we wanted to treat both of the reactions equally, we used equal weights for them. The limitation of the audience size led to the selection of 90 438 users that meet the criteria of audience size.

The outcome of the experiment using the Pinterest dataset is presented in Table 4.10. Analogically to results from Facebook, the table comprises of the top twenty users from ARIM framework compared with their position in PageRank ranking. Furthermore, Table 4.11 shows the top twenty users according to PageRank method compared with their positions from ARIM.

The results, similarly to the ones from Facebook dataset, show the vast difference between the top twenty list from ARIM framework which considers both limitation of the audience and the high engagement assumptions, and the outcome of PageRank that fulfills only requirement

UID	ARIM posit	ARIM val	PR posit	PR val	Engagement	Audience size
4328149	1	1	24767	0.000922	4	279
6097768	2	0.816224	5767	0.000185	3.333333	123
4637141	3	0.724336	48712	0.000492	3	249
3335628	4	0.724336	43040	0.000557	3	138
791721	5	0.724336	49399	0.000486	3	108
46382	6	0.619321	31436	0.000745	2.619048	110
337355	7	0.586504	3629	0.00204	2.5	315
620508	8	0.586504	54127	0.000441	2.5	153
12913341	9	0.586504	70954	0.000319	2.5	138
2629262	10	0.586504	67553	0.000341	2.5	125
2594225	11	0.586504	910	0.00021	2.5	103
33209	12	0.586504	87241	0.000231	2.5	124
205024	13	0.586504	11101	0.000156	2.5	110
4307526	14	0.586504	82371	0.000256	2.5	156
213980	15	0.558938	71066	0.000319	2.4	145
863299	16	0.547124	35723	0.000665	2.357143	185
2729817	17	0.54056	24814	0.00092	2.333333	290
504295	18	0.54056	62105	0.000378	2.333333	289
559898	19	0.54056	56604	0.00042	2.333333	261

Table 4.10 Top 20 Micro-influencers using ARIM method, compared with their position from PageRank for Pinterest dataset

UID	PR posit	PR val	ARIM posit	ARIM val	Engagement	Audience size
7055243	1	0.000215	27004	0.241924	1.25	108
14340460	2	0.000215	40098	0.173008	1	168
6729025	3	0.000215	68993	0.120276	1.333333	155
1671014	4	0.000215	85585	0.038875	1	113
25821272	5	0.000215	48618	0.173008	1	101
15596641	6	0.000215	85630	0.038875	1	111
133874	7	0.000215	20829	0.264896	1.333333	118
3313897	8	0.000215	46661	0.173008	1	110
2925429	9	0.000215	56691	0.173008	1	117
15852983	10	0.000215	48724	0.173008	1	101
1368298	11	0.000215	45805	0.173008	1	114
2370736	12	0.002224	35196	0.173008	1	468
8517079	13	0.000215	83280	0.057082	1.333333	128
7495086	14	0.000215	47968	0.173008	1	104
21421	15	0.002224	10147	0.303586	1.473684	223
299640	16	0.000215	68407	0.127243	1.375	104
188893	17	0.000215	65674	0.173008	1	140
48052601	18	0.000215	52579	0.173008	1	183
7114546	19	0.000215	61556	0.173008	1	138
8258324	20	0.000215	64424	0.173008	1	126

Table 4.11 PageRank top 20 for users with limited audience compared with their position from ARIM method for Pinterest dataset

of the limited audience from the definition of micro-influence. All the micro-influencers that are selected by ARIM have very low positions in PageRank ranking. Similarly, the PageRank top users are at the end of the micro-influencers list from ARIM. Again, this shows the incapability of PageRank to select users with higher engagement, as the method just uses limits for audience size. In comparison, ARIM selects users lower in the audience size but having involvement of a much higher rate. This shows the importance of the two key points of the micro-influencers definition proposed in the previous section. While the limitation of the audience is definitely a necessary condition for finding micro-influencers, it is not sufficient. Indeed, the real micro-influencer can be found only with the second condition involving the high engagement rate, for a user with limited audience size. Therefore, it is highly important for micro-influencers detection methods to include both of the conditions, in order to actually perform micro-influencers discovery.

4.4 Conclusion

Our first contribution in this chapter is to introduce an instantiation of the theoretical model of influence showed in Chapter 3, called ARIM. It focuses on flexibility by considering various types of reactions and generality by being applicable to different social network types, while evaluating influence for entities in social networks basing on the proactive (actions) and reactive (reactions) behaviors of social network participants. It incorporates the different components of influence that were defined and discussed in Chapter 3. The framework includes time-dependency of influence by actions frequency component, as well as incorporates spread and engagement and measures the intensity of influence. Measurement of both spread and engagement directly corresponds to influence properties of recognition, activity generation and popularity properties, described in Chapter 2, while the intensity of influence is an attempt to measure the immediacy. Importantly, the model we presented was built flexible in terms of features that may or may not be available for a particular social network site. Moreover, it also embraces the fact that different reaction types should be differently considered and should have various significance for the final influence score of a particular user.

On top of that, we also performed experiments aiming to firstly validate ARIM framework for influence discovery and evaluation, and secondly to utilize ARIM to investigate the new concept of micro-influencers proposed in Chapter 3. The first part of the examination involving application of ARIM to influence consisted of experiments on three different real-world datasets. Data included two well-known social network sites, namely Facebook and Pinterest, and one using scientific publications by Microsoft Academic. The results of this part of experimentation present interesting discoveries about the users influence and indicate the adequacy of the proposed ARIM model. It can be also observed how datasets of different data nature can be utilized using the same model of ARIM. The results show as well how different emphasis on various types of reactions can change the overall influence rank.

Our research objectives are focused on discovering the highly influential users and evaluating their impact within social networks. ARIM is able to capture the influence, while leveraging the importance of each of the influence aspects by applying weights. As mentioned, the importance given to each influence factor will be highly dependent on the particular application. This flexibility of the approach allows us to adjust to a given context and application and use the desirable properties only. In particular, we have noticed the potential of the users that are fulfilling two of the influential user aspects, namely activity generation and immediacy, while not satisfying the requirement of having big audience size. This led to the second part of experimentation – the application of ARIM to micro-influence. This issue of finding micro-influencers is novel for the discipline of Social Network Analysis. Basing on

the definition of the notion of micro-influencer within Social Network Analysis proposed in the previous chapter, we applied it to the practical application of micro-influencers discovery in two datasets used previously. Performed experiments involved the data from online social networks of Facebook and Pinterest and utilized ARIM. We also compared the obtained results with the *state-of-the-art* method PageRank. The results show the adequacy of the proposed approach for finding micro-influencers. The experiments also affirm the necessity of the particular application to impose exact numeric conditions for micro-influencers limits of audience size, as they can vary greatly depending on the particular application.

In this chapter, we aimed to introduce our instantiation of the theoretical model presented in Chapter 3. ARIM evaluates influence using a general approach that, on one hand, is not focused on any particular social network and, on the other hand, includes multiple influence properties such as time or intensity. Consequently, the presented formulas for each of the influence components had to be easily translated between social networks of various characteristics. We achieved this, as was demonstrated by experiments using Facebook [8], Pinterest [9] and Microsoft Academic [146]. However, it could be noticed that, while components such as spread, intensity or engagement are translated between various social networks straightforwardly, time is a much more complex component. In particular, ARIM utilizes *ActionFreq* function (Equation 4.5 in order to introduce time notion. Nevertheless, to be able to focus on such complex notion as time, we find it necessary to target one type of social network in order to deepen and extend the modelization of influence with time-dependency. Accordingly, we intended to target, in the following chapter, particularly citation networks, where time is a major factor in the citation of scientific research context. Our goal is to investigate influence focusing in particular on time-dependency of influence and the causality between citations.

Chapter 5

Proposition of Time-focused Influence Adaptation

5.1 Introduction

Through Chapters 2 and 3 we have shown that there are numerous important components of influence, in order to evaluate its value in social networks. Basing on the definitions modeling influence in Chapter 3, we introduced ARIM model, that focused on the components such as influence intensity, spread, or time-dependence. Nevertheless, as we showed previously, not all components of influence that we defined are equally complex. Some aspects such as intensity, spread or engagement are straightforward to transpose from one type of social network to another. However, as we discussed in Chapter 3, time-dependency is much more difficult to translate, as it is a transverse aspect that requires specific assumptions to be taken in order to include it for influence evaluation. In particular, ARIM presented in Chapter 4 was modeled to evaluate influence utilizing the whole time interval available in the dataset, as well as including action frequency for computation. Thanks to this, we included time-dependency aspect while guaranteeing that ARIM is adaptable to a variety of social networks, independently of their particular characteristics. However, in order to deepen and extend the influence modelization aiming at the time specifically, we decided to focus on one particular social network type for which time is especially crucial. Consequently, in this chapter, we instantiate the theoretical model of influence showed in Chapter 3 for one particular type of social networks – citation networks.

Citation networks are known to have specific characteristics. For one, the dynamicity aspect of the network created using scientific citations is vastly different from what we can observe in other kinds of social networks. For instance, while micro-blogging based social

networks will have many users interactions in a short span of time (e.g. minutes or days), citation networks are drastically less dynamic, with events (papers) occurring with different frequency in terms of years (annual, biannual, etc.). While the rapid and frequent changes lead to more gradual evolution of the influence for deeply dynamic networks, social networks with decreased frequency of actions such as citation networks deal with less smooth and more sudden changes in influence. Consequently, it also leads to the conclusion that considering long spans of time for citation networks, should lead to better insights about the influence.

On top of that, while in Chapter 4, we utilized a citation network dataset to find the influential users, in this chapter, we want to focus on a different type of entities – conferences communities. In fact, in social networks such as Pinterest or Facebook, the choice of entities for influence evaluation is usually clear – they are the users participating in the actions and reactions exchange. In comparison, in the citation network, the entities for which we want to calculate influence can actually vary. Indeed, as we did in Chapter 4, we can use consider entities as influential authors, however, we can also use papers, laboratory groups or conferences and journals. In particular, in this chapter, we are defining influential entities as conference and journal communities, so that we can observe different types of interactions between those entities. Additionally, we also want to verify the pairwise influence between the conferences and journals, as it is a good basis for evaluating the influence in general.

Taking all of the above into consideration, in the first contribution of this chapter, we focus on citation networks scope in particular conferences and journals as influential entities. Our goal is twofold. Firstly, we want to study pairwise influence relations, in order to gain better knowledge about influence dependencies and possibly have more insight into influence propagation between particular entities in the network. Secondly, after gathering all the pairwise information, we aim to produce the overall ranking of conferences. We target primarily the time-dependency aspect of the network, where the impact of a particular paper is time-sensitive and insight may change during the lifetime of the network, even if it tends to slowly fade rather than rapidly disappear. The study we perform here is centered around three questions: (1) How to measure influence in a way to capture the relations dependency between nodes, in already predefined communities (i.e. conferences/journals)? (2) Does a particular conference have an impact on another conference? (3) How can we evaluate pairwise influence in order to compare conferences influence? We propose a model for determining influence during a particular time period between communities within time-dependent citation networks, called **Time Dependent Influence Estimation (TiDIE)**.

Moreover, the second part of this chapter is dedicated to utilizing TiDIE in order to investigate the linkage between influence and reputation that we described and formalized in Chapter 3. We aim to adopt the previously mentioned phenomena studied in sociology of

link between high influence and high reputation, in order to explore its potential benefits for analysis and prediction of reputation. Simultaneously, we provide a practical application for evaluating reputation using the influence information by utilizing TiDIE and citation networks scope. To best of our knowledge, our work is the first attempt at combining influence and reputation together, aiming to infer the reputation with the use of influence dependencies between the entities of the social network.

The remainder of this chapter is structured as follows. In Section 5.2, we discuss the basics connected to citation network and community-based citation networks used later on. Section 5.3 describes TiDIE – the time instantiation of the influence model. The description of TiDIE is divided into three parts: we introduce the measures evaluating the impact communities have on each other within citation networks, show the methods for measuring pairwise influence between predefined communities, and present the method for obtaining influence value. We end with the evaluation of TiDIE using the experiments performed on the scientific database of Microsoft Academic (used before in Chapter 4). In Section 5.4, we propose an approach exploiting the dependency between influence and reputation and dealing with the reputation prediction by adding the information of influence. This approach, called ReTiDIE (Reputation TiDIE), utilizes TiDIE model to evaluate the reputation in citation network scope. We evaluate it using Microsoft Academic dataset. Finally, we summarize the presented work and conclude in Section 5.5.

5.2 Citation Network Preliminaries

In this section, we introduce the notion of citation graph and a closely related community-based citation graph, that we utilize throughout this chapter.

A citation network can be depicted as a graph, where nodes symbolize papers and edges are the citations between them. In order to consider time for such *citation graph*, we can model the dynamic citation network as a sequence of directed graphs $\{G_1, \dots, G_m\}$ for time interval $T = \{t_1, \dots, t_m\}$, where G_i represents a directed citation graph at particular snapshot t_i . G_i is thus defined as a directed graph $G_i = \{V_i, E_i\}$, where V_i signifies set of papers (nodes), and E_i describes the set of citations (edges) between papers, from citing to referenced paper.

Basing on this classic citation graph, we describe a *community-based citation network*, in order to better illustrate the focus of this work. In this work, we target influence in the time-based citation networks between predefined communities. Therefore, first, we define the constant set of of-interest communities $S = \{C_1, \dots, C_n\}$, with an assigned set of papers and citations. Similarly to the above-mentioned citation graph, we model the time-based community-based citation network as a sequence of directed graphs $\{CG_1, \dots, CG_m\}$ for time

interval $T = \{t_1, \dots, t_m\}$, where CG_i represents a directed community-based citation graph (based on the citations between communities) at particular snapshot t_i . Importantly, due to the dynamic nature of the graph, while the set of of-interest communities is constant (these are the communities whose influence we study at each snapshot t_i), in each graph CG_i there can be other appearing or disappearing communities and citations between them at snapshot t_i . CG_i is thus defined as a directed graph $CG_i = \{CV_i, CE_i\}$, where CV_i represents all communities at time t_i , and CE_i signifies citations between communities from CV_i at time t_i , leading from citing community to cited community with associated weight above each edge symbolizing the number of citations at time t_i . In other words, the community-based citation graph is an aggregated version of citation graph, where papers are combined together to form nodes based on conferences, and the aggregated citations between conferences (i.e. group of papers) are the vertices. Considering the set of predefined communities $S = \{C_1, \dots, C_n\}$, $CV_i \subseteq S$ can be the result of any static community mining algorithm, in our work we assume that this set is created using the venue of each paper, therefore each community C_i corresponds to a conference (hence, set of papers published at particular conference C_i). Due to the fact that in this work we use only the community-based citation graphs, we will reference it simply as a citation graph or citation network. Additionally, in our work, as communities we utilize conferences, therefore we use those terms interchangeably. An example of such community-based citation graph is shown in Figure 5.1. It is important to notice that the graph showed there is visualizing the input data. Then, such input data are used to extract the semantics on which we base our influence evaluation.

5.3 Time Dependent Influence Estimation (TiDIE)

In this section, we describe in detail TiDIE model that aims to detect and evaluate influence for community-based citation networks defined previously in Section 5.2.

5.3.1 Specification of TiDIE

As TiDIE instantiates the model of influence from Chapter 3, it also follows the defined Action-Reaction concept described before. In this case, actions are manifested by publishing article, and reactions are modeled by citations to papers. In order to describe the model, we divided the TiDIE process of influence discovery and assessment into three steps:

1. Evaluating the effect of one conference onto another, for each pair of conferences A, B , which belong to a predefined set of of-interest communities S for each time snapshot

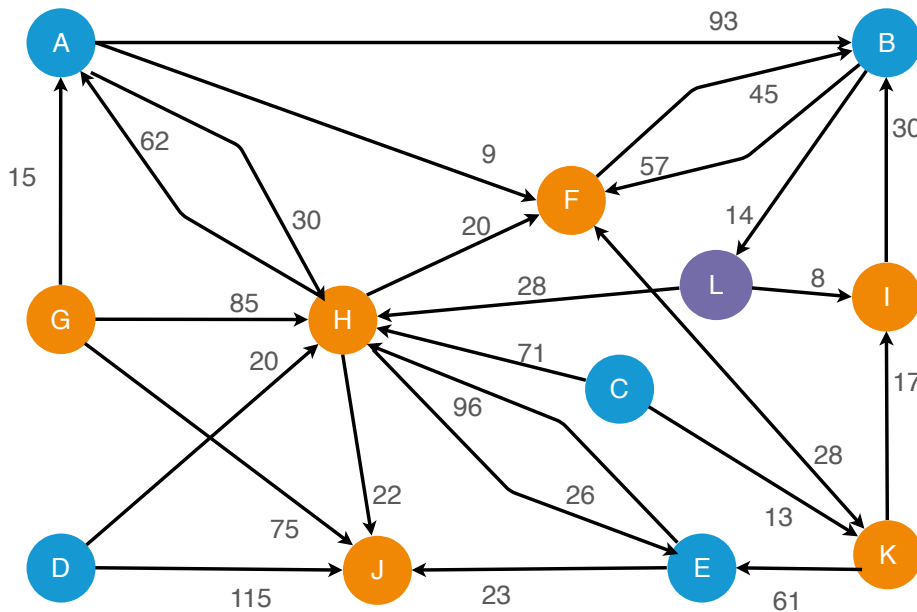


Fig. 5.1 Example of a graph containing references between conferences at time t from conference universe $U = \{A, B, C, D, E, F, G, H, I, J, K, L\}$, where each vertex symbolizes conference, each edge symbolizes reference, with the number of citations indicated above the edge, and colors indicate different conference topics.

$t_i \in T$, using one of two different measures, namely Citation Ratio, and Reference Ratio.

2. Determination of influence between pairs of conferences (communities) from set S and direction of this influence within time period T using one of the abovementioned metrics Citation or Reference Ratio.
3. Evaluating the influence of conferences from set S , using the citation ratio series at each time snapshot $t_i \in T$, with consideration to influence direction.

The first step of TiDIE is dedicated to investigating the intensity of reactions, as well as spread or engagement (depending on the selected measure). Time-dependency is included in all the steps in various ways. As we evaluate influence using snapshots, influence components are calculated per-snapshots. Moreover, we also utilize a method that, while calculating pairwise influence, focuses on causality between conference citations. We discuss each step in detail in the following.

Evaluating the effect of two communities in time snapshots

Before assessing the influence between two conferences in citation networks at a given period of time, we need to calculate the effect one community has on the other in particular snapshot t_i . Here, we show two possible measures to evaluate it. In order to investigate both spread and engagement component of the influence, discussed in Chapter 3, we decided to propose two possible measures for evaluating them. Firstly, we discuss the Citation Ratio extension, a measure based on the work [148, 52] enhanced in order to capture time-dependence of the network. Citation Ratio measures the intensity of reactions as well as engagement. Then, we introduce a second measure, Reference Ratio, which in contrast is connecting components of intensity and spread. We describe both of the measures in what follows.

(i) *Citation Ratio*

To capture the effect one community has on another in particular snapshot t_i we have used the metric based on normalized citation weight [148, 52]. This metric measures the number of citations made by one community to the other. Since this metric is based solely on the topological characteristic of the citation graph at particular time snapshot, it does not yet signify influence between two conferences, thus we will call it Citation Ratio (CR). Citation Ratio for community A towards community B at time t is defined as:

$$CR_{A \rightarrow B}(t) = \frac{|cit_{B \Rightarrow A}(t)|}{\sum_{i=1}^{|S|} |cit_{B \Rightarrow i}(t)|} \quad (5.1)$$

where $|cit_{B \Rightarrow A}(t)|$ is the number of citations at time t from conference B that reference papers of conference A (created until time t) and the denominator of the formula is the aggregate number of all the citations at time t made by conference B to any conference paper (created until time t) in the set S (including conference A). S symbolizes the group of conferences which we consider as the "general universe of conferences" to which conference B can have references while calculating Citation Ratio, which significance we will now detail. The arrow in $CR_{A \rightarrow B}$ indicates the direction of the citation influence. Contrary to previous works [51, 49], which ignore the size of the considered possible reference group, in our view, the definition and differentiation of the results of Citation Ratio metric in the sense of reference group S size lead to two completely different interpretations of the same metric. Precisely, we can distinguish two interpretations of Citation Ratio metric, namely local and global one.

For better understanding, let us consider an example in which we want to discover the influence between particular set of of-interest conferences $C = \{A, B\}$, which

gives two of-interest pairs for which we will calculate Citation Ratio, namely (A, B) and (B, A) pairs of conferences. Let us assume a universe U of all conferences that we can obtain from a general dataset containing scientific networks and $|U| > 1000$. Additionally, let us also consider a smaller subset of universe $U_S \subset U$ which is smaller in size and contains only part of the conferences, i.e. conferences $\{A, B, C, D, E\}$. Let us consider calculating Citation Ratio from conference A to B at time t using in the denominator as set S : (1) universe U and (2) subset of universe U_S . In both cases the numerator of the formula will be equal, since no matter which set of S we consider, the number of citations from conference B to conference A is constant. However, in case of denominator if we consider the first case universe U with many conferences, the number of references made by B to any other conference will be high (as there are many conferences B referenced to); on the other hand, in the second case, subset U_S contains only a small part of conferences. Thus, the value of CR in the first case will be much smaller than in the second case, indicating less impact of community A on B at time t . Taking that into consideration, we propose to differentiate the two cases, depending on the conference set used in the denominator of Formula 5.1:

- **Global Citation Ratio** – the set in the denominator is considered to include all possible communities from available data (set S equal to universe U). Assuming that we have a wide range of conferences in the dataset, the CR captures the citation dependence in a global and possibly unbiased way.
- **Local Citation Ratio** – we consider the set of the denominator a subset of all available data. The result of this metric captures the impact of one conference on another in a deliberately created subset, where the number of conferences that can be referenced is limited. It can be used in order to obtain the relative, scope measure of the impact between conferences.

The measure of Global Citation Ratio also captures one of the dynamic features of the network: over different time snapshots conferences can appear and disappear (independently from the relation between two conferences for which CR is calculated). Thus, using the maximal possible set of conferences at every snapshot leads to include this aspect of dynamicity of the network.

It can be observed that the numerator of Citation Ratio calculates the intensity of the reactions. Furthermore, CR ratio evaluates the engagement, because by utilizing all the citations (reactions) of the conference B , we actually determine the strength of the reaction relatively to all reactions the conference B made.

The selection of the subset S of universe U of all conferences can be done in any way which results in a subgroup of conferences. It is worth noticing that the selection of this subset can lead to the bias in the Local Citation Ratio in a case where the set of selected conferences will contain two smaller subsets between which there will be no citations. In this case, the Local Citation Ratio can be artificially high for a particular pair of conferences, since none of other in the set is connected to them. Some examples of possible criteria used to select subset S for the use of Local Citation Ratio are:

- Subgroup of same topic conferences - the resulting Local Citation Ratio will describe the impact between two conferences within the group of same scope conferences (which creates subgraph of closely connected communities),
- Subgroup of same committee conferences - the resulting Local Citation Ratio will show the impact of conferences having a common committee.

While Citation Ratio is calculated at each time snapshot, it is important to notice that, in the basic version, the metric (Formula 5.1) treats equally all the citations made in time t to publications published at any given time (obviously, before time t). However, citations are time-sensitive – indeed, it would be expected for more recent papers to be cited more often. On the other hand, they are not very rapidly disappearing, in comparison to, for example, tweets [149]. It is also important to notice that some of the considered pairs of conferences may not start operating at the same time (i.e. year). Let us assume two conferences A and B for which we want to calculate $CR_{A \rightarrow B}(t_i)$. At time t_i , conference B can cite papers from conference A published in the past until time t_i . In order to study the impact of time on the citations, we aim to differentiate the impact of citations of articles published in each year $\{t_j\}$ before time t_i ($t_j < t_i$) on the $CR_{A \rightarrow B}(t_i)$ value. To do so, we propose (1) a weight function pf , that prioritizes citation information for particular points in time, (2) to calculate the $CR_{A \rightarrow B}(t_i)$ value as series of the ratios, where we divide the citations made by conference B by the time of publication of the article to which the citation is made. Each such partial series is then multiplied by the weight from abovementioned weight function. The proposed method is described in Algorithm 1.

For each time t_i , Algorithm 1 calculates the number of citations of conference B made to papers of A published in time t_i , divides it by the total number of citations of conference B to any conference from subset S , and multiplies this ratio by the weight assigned according to the particular time t_i (lines 1 – 3). The priority function pf is any real-valued, well-defined function over domain $[0, 1]$. It changes the importance of historical citations over time. Since we operate on time snapshots, we convert a

Algorithm 1 Method *computeCR* for calculating Citation Ratio value $CR_{A \rightarrow B}(T)$ for a particular time T with consideration of time-dependency

Input: Conference set $S \subset U$ for which we consider influence, conferences A and B from S for which we calculate $CR_{A \rightarrow B}(T)$, max time T , t_A start of conference A , priority function pf , time step y

Output: $CR_{A \rightarrow B}(T)$ value for T prioritized according to priority function pf $CRT_series_T = 0$

1: **for** $t_i \leftarrow t_A$ to T with step y **do**

2: $CRT_series_T + = \frac{cit_{B \rightarrow A}(t_A, t_i)}{\sum_{i=1}^{|S|} |cit_{B \rightarrow C_i}(t_A, t_i)|} \times pf(t_i, t_A, T)$

3: **end for**

4: $CR_{A \rightarrow B}(T) = sum(CRT_series_T)$

point in time to $[0,1]$ domain. For example, a constant priority function emphasizes equally information in each time snapshot. Finally, the result $CR_{A \rightarrow B}(T)$ is obtained by aggregating partial results (function *sum*, line 4). In order to obtain Citation Ratio series for a particular time period, the algorithm has to be repeated for each time point within the considered time period.

(ii) *Reference Ratio*

Apart from Citation Ratio, we also introduce a second measure for capturing the effect one community has on another within particular time snapshot t_i , called Reference Ratio. Reference Ratio for community A towards community B at time t is defined as:

$$RR_{A \rightarrow B}(t) = \frac{|cit_{B \Rightarrow A}(t)|}{\sum_{i=1}^{|S|} |cit_{C_i \Rightarrow A}(t)|} \quad (5.2)$$

where $|cit_{B \Rightarrow A}(t)|$ is the number of citations at time t from conference B that reference papers of conference A (created until time t), the denominator of the formula signifies the total number of all references at time t made to papers of conference A (created until time t) by any conference in the set S . Similarly to Citation Ratio, S symbolizes the group of conferences which we consider as the "general universe of conferences" to which conference B can have references while calculating Reference Ratio. The arrow in $RR_{A \rightarrow B}$ indicates the direction of the citation influence. Comparably to Citation Ratio, depending on the considered set of communities S , we can distinguish Local and Global Reference Ratio.

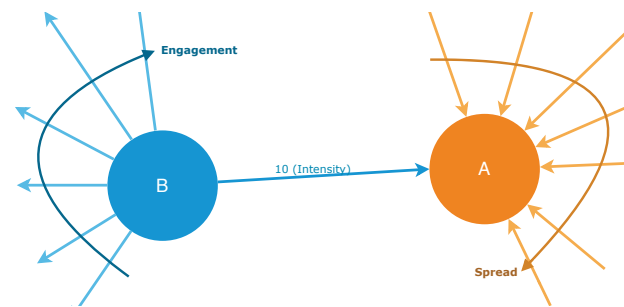


Fig. 5.2 Differentiation of CR and RR metrics in a time snapshot: CR considers in denominator all B citations including citation to A, whereas RR denominator considers all citations to A

While Citation Ratio measures the intensity and engagement, in comparison, Reference Ratio is focused on determining both intensity and spread. In particular, intensity, similarly to CR ratio, is calculated by aggregating the number of reactions of conference *B*. Moreover, by utilizing all the references citing conference *A*, we do aggregate all the audience of the conference *A*, i.e. measuring its spread.

Similarly to Citation Ratio, we consider a time-dependent version of Reference Ratio, by utilizing the priority function. Since the method is basically the same, we do not include the pseudo-code of the algorithm. Notably, the only change needed is replacing formula for Citation Ratio with the formula from Equation 5.2 of Reference Ratio. The difference between Citation Ratio and Reference Ratio can be seen in Figure 5.2. While Citation Ratio measures how much citations of conference *B* (in time t) were dominated by citation to the selected conference *A*, Reference Ratio is actually checking how much the group of citations from *B* to *A* is dominating all the references to conference *A* in time t . It can be seen that, while both ratios are measuring the impact between two conferences, the implications of those two metrics are very different.

Pairwise Influence determination

In order to determine the influence between a pair of communities and its direction, we incorporated the Granger Causality into our model, similarly to the model in [49]. Thanks to using Granger Causality on the time series of Citation Ratios, we capture the causality notion between those series. This broadens the sense of influence between two conferences, which is based not only in typology (from Citation Ratio component) but also considers dependence on actions (publishing) and reactions (citing) between conferences. Accordingly, the model is better suited for hidden knowledge discovery, as well as investigates the influence dependencies between citations from time and casual perspective. Before the specification of

pairwise influence calculation, we need to introduce the Granger Causality method that we later use, in what follows.

Granger Causality

Intuitively, Granger Causality can be explained [50] as: *Y(t) is causing X(t) if we are better able to predict X(t) using the history information of both X(t) and Y(t) than solely using the history information of only X(t)*, where X and Y are two stationary series X and Y , defined as:

$$\begin{aligned} X(t) &= \sum_{j=1}^m a_j X(t-j) + \sum_{j=1}^m b_j Y(t-j) + \zeta(t) \\ Y(t) &= \sum_{j=1}^m c_j X(t-j) + \sum_{j=1}^m d_j Y(t-j) + \eta(t) \end{aligned} \quad (5.3)$$

In the formula 5.3, m is the maximal time lag, and it is assumed to be finite and shorter than given time series; a_j and c_j are the matrices containing the coefficients of the model; ζ and η are prediction errors (uncorrelated white noise series).

In order to determine Granger Causality between two series of data, for a particular time period, Granger Causality test has to be performed. There are different Granger Causality tests proposed in the literature, such as Sims test, Wald test, Lagrange-multiplier test [150]. The test checks if the hypothesis of no Granger Causality between two series (so-called null hypothesis) is true. We say that X granger causes Y if the null hypothesis is rejected, meaning $b_j \neq 0$; otherwise, the null hypothesis holds, hence X does not Granger causes Y . Similarly, we say that Y granger causes X if $c_j \neq 0$ (null hypothesis is rejected); otherwise Y do not Granger causes X . It is important to notice that we can observe bidirectional Granger causality if both X granger causes Y and Y granger causes X . The result of the Granger Causality test is the P-value which, depending on assumed threshold ϵ , determines if the null hypothesis holds (if P-value is smaller than ϵ) or is rejected (if P-value is greater than ϵ). The ϵ value is arbitrary given, depending on how significant the results should be.

Presented above Granger Causality is used in order to determine the causal relation between two time series obtained via calculating Citation or Reference Ratio for a particular time period. In particular, we determine Granger Causality relation between a pair of conferences, e.g. A and B , using one of the two ratio metrics for obtaining time series. We calculate CR (or RR) for each time snapshot t_i from a particular time period T for which we determine the influence ($t_i \in T$), from A to B and from B to A , so that we have two separate CR (RR) time series: (1) CR (RR) series of conference A impacting B (i.e. $Y(t)$ in Formula

5.3) and (2) CR (RR) series of conference B impacting A (i.e. $X(t)$ in Formula 5.3). Next, we determine Granger Causality of A towards B accordingly to the method described above. The result of the Granger Causality test answers the question of whether conference A influences conference B , hence determines the possible direction of influence for a particular time period.

Influence of community A towards community B , indicated $I_{A \rightarrow B}$, for time period T , can be observed when Citation Ratio series for the time period T of conference A towards B granger causes Citation Ratio series for the time period T of conference B towards A , with the level of significance ε in Granger Causality test. Time period T has to start and end within a time when both conferences exist.

Algorithm 2 determines if one conference influences another. The first *for* loop (lines 1 – 4) creates CR series (or RR series depending on the formula used) for each time snapshots for the two considered conferences. Then, Granger Causality test is performed, and the final existence of influence between the two conferences (or its lack) is determined (lines 9 – 13).

Algorithm 2 Method for determining whether conference A influences conference B

Input: Two conferences A and B for which influence is determined, time period $T = [t_s, t_e]$, maximal lag number m , significance level ε , time window step y , pf priority function

Output: Influence direction (or lack of influence) from conference A to B during time period $T = [t_s, t_e]$

```

1: for  $t_i \leftarrow t_s$  to  $t_e$  with step  $y$  do
2:    $CR\_series_{A \rightarrow B} += computeCR(A, B, t_i, pf)$ 
3:    $CR\_series_{B \rightarrow A} += computeCR(B, A, t_i, pf)$ 
4: end for
5: for  $lag \leftarrow 1$  to  $m$  do
6:    $GCTest_{B \rightarrow A} += GCTest(CR\_series_{B \rightarrow A}, CR\_series_{A \rightarrow B}, lag)$ 
7: end for
8:  $minGCTest_{B \rightarrow A} \leftarrow min(GCTest_{B \rightarrow A})$ 
9: if  $minGCTest_{B \rightarrow A} < \varepsilon$  then
10:   $I_{A \rightarrow B} = true$ 
11: else
12:   $I_{A \rightarrow B} = false$ 
13: end if

```

In our experiments, we assume the value of ε equal to 0.01, in order to indicate the results being significant. Additionally, as it can be observed in Granger Causality definition, influence can be bi-directional, in the case when both considered conferences have an impact on one another in the same time period.

Influence value estimation

The method described previously allows determining the existence and direction of the influence from one conference to another within a particular time period T . However, it is not sufficient. Indeed, while just detecting pairwise influence between communities can be useful, the metric evaluating the value of the influence of a particular conference is still needed. In order to calculate the value of the influence during time period T , we propose Algorithm 3.

Algorithm 3 first calculates Citation Ratio for every snapshot of time, creating Citation Ratio series, using function *computeCR*, for each pair consisting of conference A for which the influence value is calculated and conference from subset S of which we consider influence (lines 2 – 5). Then, a set of Granger Causality tests are performed (lines 6 – 9), each with a different *lag* value, which defines how many past values should be taken into consideration. *GCTest* set as a result returns P-values, by which we can determine the existence of influence selecting the minimal P-value from the *GCTest* variable (function *min* in 9th line) and checking if it is smaller than assumed level of significance ε (lines 10 – 12). Since we iterate (line 1 and 13) over the set of conferences S (excluding conference A) performing the sequence of actions described above, we afterward obtain subset $InfSet \subset S$, which contains all conferences influenced by conference A . This process concerns determining pairwise influence from A to any other considered conference from S (pairwise influence), as explained in detail before.

Then, assuming influence is determined, we estimate its value by firstly using the exponential moving average (EMA) on Citation Ratio series $CR_series_{A \rightarrow c_j}$ from each influenced conference from set $InfSet$ (the numerator in the line 14). Secondly, we calculate the arithmetic average of values obtained from EMA (line 14). We have chosen exponential moving average with its weights adding up to 1. The choice is motivated by the fact that, in general, we believe that, especially in developing scientific areas, the "fresh" articles should be more influential hence should be considered with higher weight. Importantly, the metric for computing influence value (line 14) allows comparing conferences impact on the other ones.

5.3.2 Evaluation of TiDIE

In this section, we present the experiments conducted on Microsoft Academic database in order to validate the proposed TiDIE framework presented in the previous section.

Algorithm 3 Method for calculating influence value for conference A

Input: Conference set $S \subset U$ for which we consider influence, conference $A \in S$ for which influence value is calculated, period $T = [t_s, t_e]$, maximal lag number m , significance level ε , time window step y , pf priority function

Output: Influence value I_A for conference A during time period $[t_s, t_e]$

```

1: for all  $c_i \in S \setminus \{A\}$  do
2:   for  $t_i \leftarrow t_s$  to  $t_e$  with step  $y$  do
3:      $CR\_series_{A \rightarrow c_i} + = computeCR(A, c_i, t_i, pf)$ 
4:      $CR\_series_{c_i \rightarrow A} + = computeCR(c_i, A, t_i, pf)$ 
5:   end for
6:   for  $lag \leftarrow 1$  to  $m$  do
7:      $GCTest_{c_i \rightarrow A} + = GCTest(CR\_series_{c_i \rightarrow A}, CR\_series_{A \rightarrow c_i}, lag)$ 
8:   end for
9:    $minGCTest_{c_i \rightarrow A} \leftarrow min(GCTest_{c_i \rightarrow A})$ 
10:  if  $minGCTest_{c_i \rightarrow A} < \varepsilon$  then
11:     $InfSet + = I_{A \rightarrow c_i}$ 
12:  end if
13: end for
14:  $I_A = \frac{\sum_{j=1}^{|InfSet|} EMA(CR\_series_{A \rightarrow c_j})}{|InfSet|}$ 

```

In order to verify the proposed method, we performed experiments in the real-world dataset of Microsoft Academic consisting of the research papers [146], that was used before in Chapter 4.

In comparison to the experiments in Chapter 4, where we utilized the whole dataset without partitioning it, experiments of TiDIE involved dividing the data into citation networks snapshots for each year, containing the number of citations from and to conferences.

We also limited all available conferences and journals in the dataset to a subset, as the subject of our experiments. In order to measure influence, we intended to choose a subset of already known and recognized conferences and journals. To achieve that, we have chosen the top conferences/journals from Aminer list [151] using two groups: "Artificial Intelligence and Pattern Recognition" (AI) and "Databases and Data Mining" (DM). The Aminer rank¹ uses H5-Index [53]. The final filtered list used in the experiments consists of 45 Data Mining conferences and 77 Artificial Intelligence/Pattern Recognition conferences². The experiments involving DM and AI conferences were performed independently from each other.

¹<https://aminer.org/ranks/conf>

²Full list of all conferences and journals used in experiments is available at https://github.com/trzytematyczna/influence_csimq

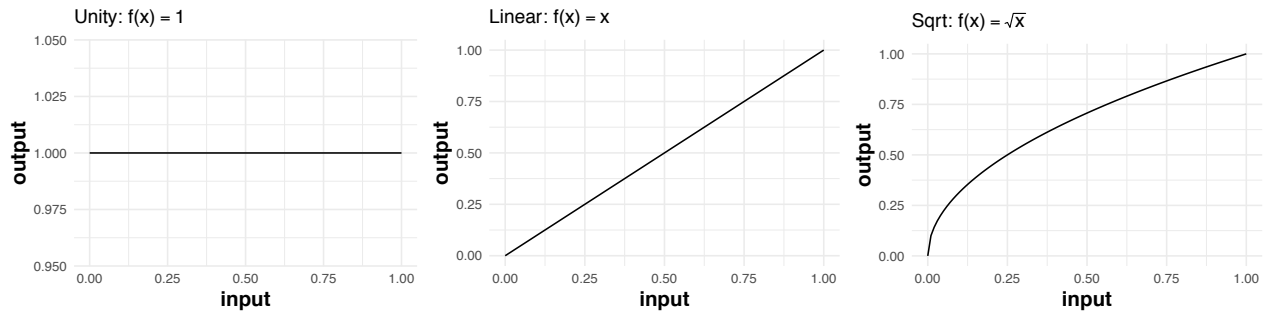
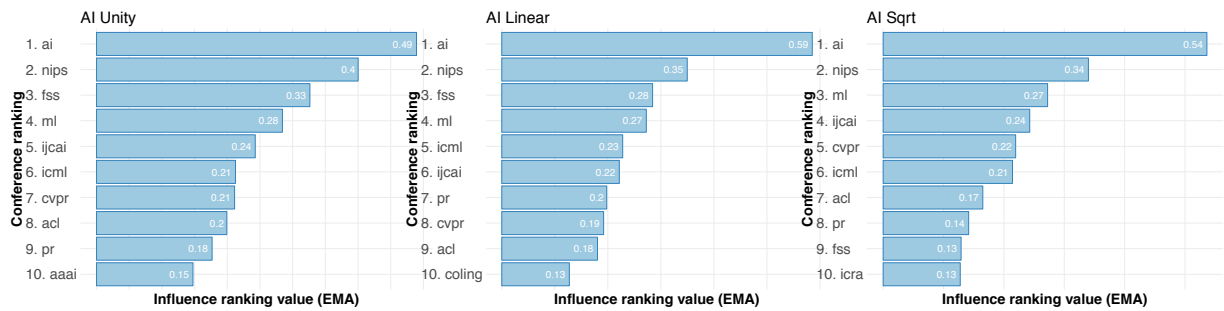


Fig. 5.3 Three functions used as priority function for calculating Citation Ratio series



(a) Citation Ratio and Unity priority function

(b) Citation Ratio and Linear priority function

(c) Citation Ratio and Sqrt priority function

Fig. 5.4 The comparison of top 10 ranking of AI conferences – the result of influence value calculation using TiDIE (Algorithm 3), using Citation Ratio and three different priority functions

The implementation and experiments were done using PostgreSQL³ version 9.6 and R language⁴ version 3.3.1 with the use of *lmtest* package⁵ for Granger Causality tests.

Results

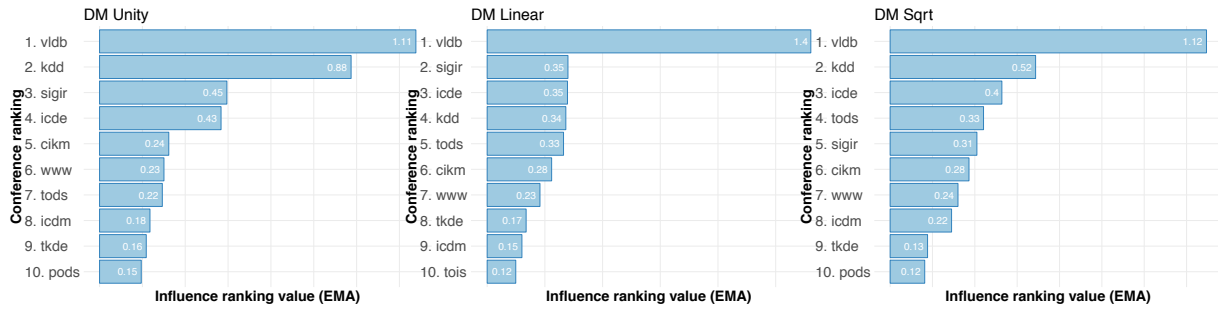
The conducted experiments, based on the described dataset, consisted of determining and estimating the influence between conference groups using the time span between 1950 and 2015. The value of influence was calculated using Algorithm 3.

To examine the model in terms of time, we have used three different priority functions: constant, linear and square root, shown in Figure 5.3. The choice of these functions was due to the fact that each of them emphasizes different time-related aspect. A constant priority function emphasizes equally information in each time snapshot. On the other hand, both linear and square root functions perform annealing of historical data. In the result, they put

³<https://www.postgresql.org/>

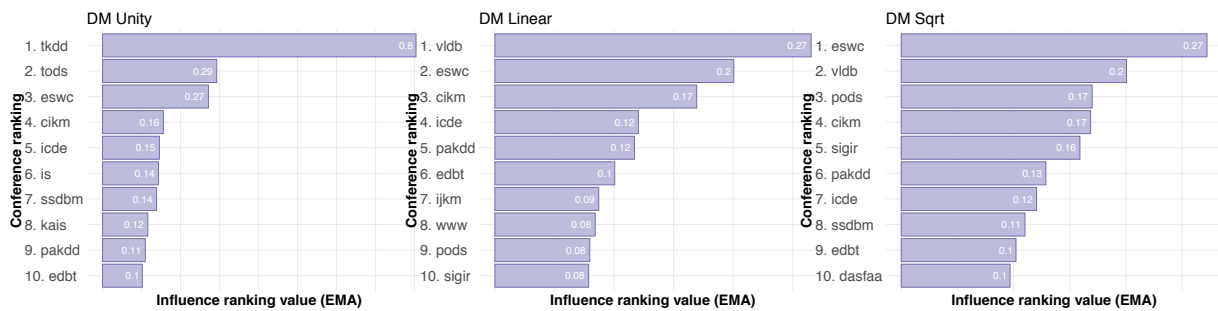
⁴<https://www.r-project.org/>

⁵<https://cran.r-project.org/web/packages/lmtest/index.html>



(a) Citation Ratio and Unity priority function (b) Citation Ratio and Linear priority function (c) Citation Ratio and Sqrt priority function

Fig. 5.5 The comparison of top 10 ranking of DM conferences – the result of influence value calculation using TiDIE (Algorithm 3), Citation Ratio and three different priority functions



(a) Reference Ratio and Unity priority function (b) Reference Ratio and Linear priority function (c) Reference Ratio and Sqrt priority function

Fig. 5.6 The comparison of top 10 ranking of DM conferences – the result of influence value calculation using TiDIE (Algorithm 3), Reference Ratio and three different priority functions

more emphasis on recent data, which is coherent with the intuitive approach of giving more priority to fresh papers.

We performed several experiments. In order to investigate the time-dependency, we used the three priority functions on both DM and AI conferences utilizing Citation Ratio. The results for each of the functions using Citation Ratio for AI conferences in the form of top 10 influential conferences can be seen in Figure 5.4. Similarly, in the case of DM conferences, the outcome utilizing Citation Ratio and three priority functions can be observed in Figure 5.5. On top of that, we also wanted to compare the methods of Citation Ratio and Reference Ratio, thus we also present the results of Reference Ratio with the use of three priority functions on the DM conferences in Figure 5.6.

In the case of ranks using Citation Ratio, the differences resulting from using three priority functions are not that drastic. For example, in AI conferences, the top two conferences – *ai* and *nips* – are that broadly cited that, no matter which priority function (that aims to

stress the time importance) is used, both of them are on top. This leads to the hypothesis that, giving the difference stress on the time importance, using Citation Ratio it is possible to test whether a particular conference is truly influential, that is influential independently of time. If there is no difference between the results from different priority functions that emphasize (or not) first or last citation years, it means that the conference is indeed uniformly influential over the years. The changes of position of conferences in the rank depending on the priority function are due to the citation differences over the years. Unit priority function does not emphasize the time in any way and treats all citations equally. In contrast, the approaches using linear and sqrt priority functions are more restrictive. This observation seems to confirm the hypothesis that considering time-dependency impacts the resulted influence dependencies.

Interesting to notice is also the vast differences between ranks for DM using Citation and Reference Ratios. Due to the difference between the two Ratios, the ranks include different sets of conferences. Along the conferences that are both in CR-based and RR-based ranks are conferences *www*, *cikm*, *vldb*, and *sigir*. It can be observed that, in the case of RR results, the change of priority function results in significant change in the ranks. For example, *tkdd*, having the 1st position in RR unity rank is not even included in results from linear and sqrt priority functions.

Moreover, to show the differences between the results of using metrics Citation Ratio and Reference Ratio, we also created the knowledge graph showing influence dependencies. Figure 5.7 presents the influence dependency graph for DM conference set, obtained using Citation Ratio with unity priority function. In comparison, the influence dependency graph for DM with the usage of Reference Ratio and unity priority function can be seen in Figure 5.8. In each graph, the size of nodes symbolizes the intensity of influence, where the biggest node being most influential in the rank, the smallest being least influential. The graphs additionally show the vast difference in the results from using the two metrics.

It is worth noticing that the influence value computed based on a number of citations does not guarantee the existence of a big number of meaningful connections (in terms of Granger Causality). For instance, conference *tkdd*, that has first place in rank created using Reference Ratio, can be seen in Fig. 5.7, created using Citation Ratio, having almost none connections. Similarly, *vldb* being in the top for CR-using rank and having a big number of edges in CR-based graph, has a significantly smaller number of connections in case of the RR-based graph.

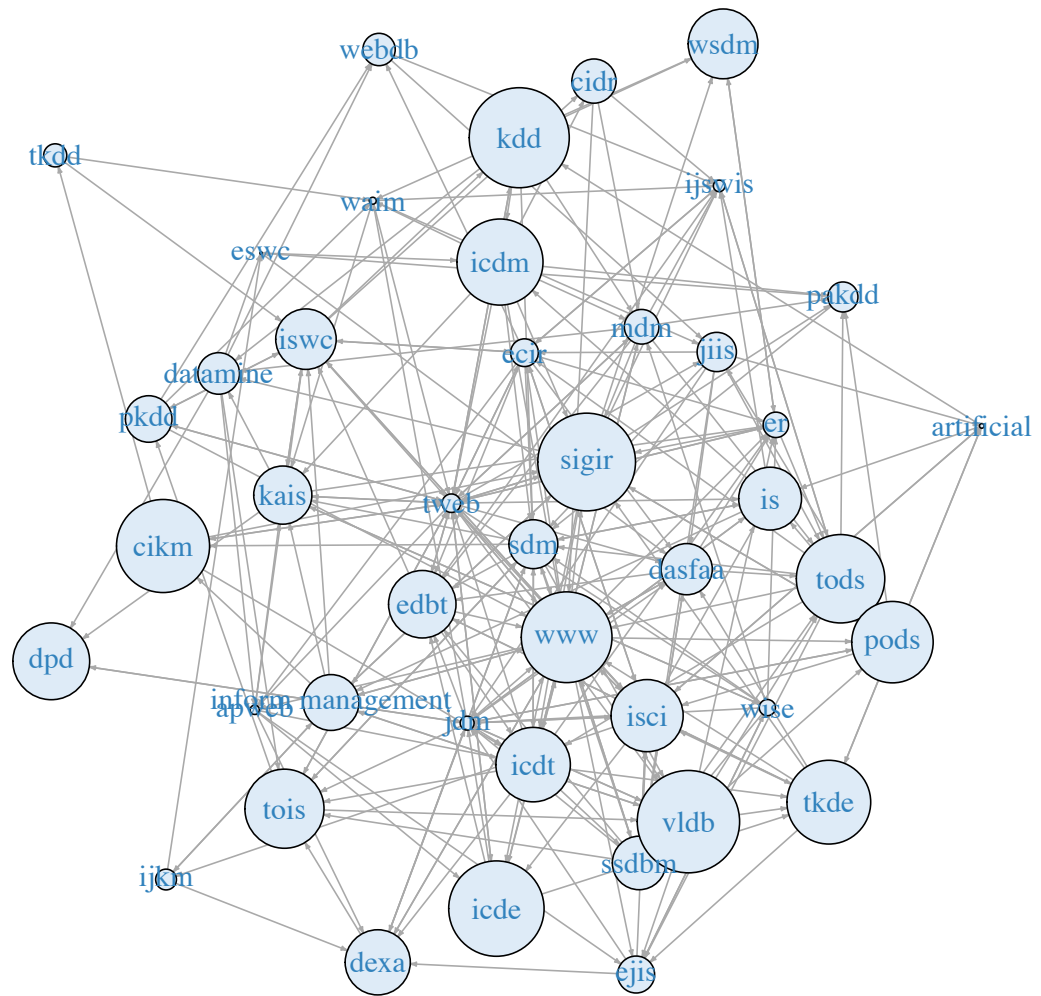


Fig. 5.7 Knowledge graph showing influence dependencies of DM conferences, using Citation Ratio and Unity priority function, where each edge represents isInfluencer relation of our ontology between conferences (Algorithm 2 using CR) for DM conference set

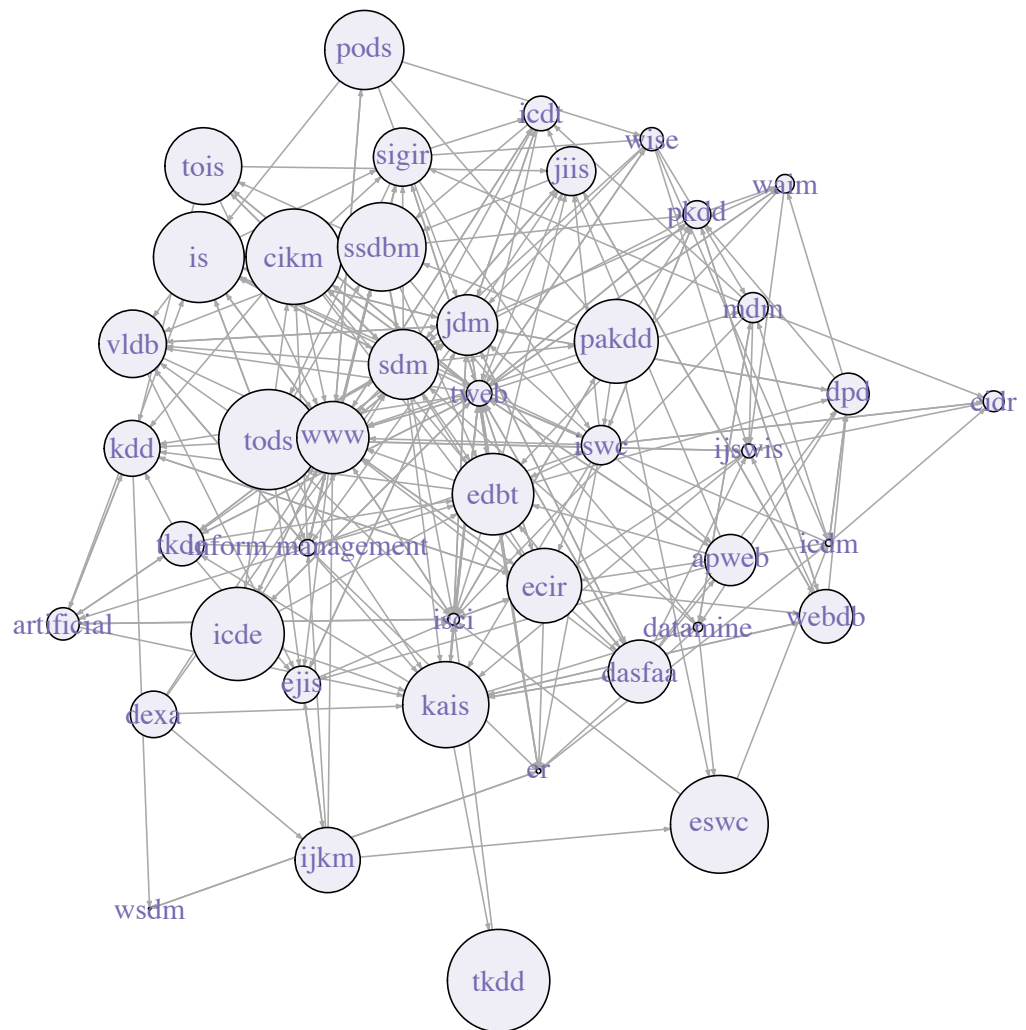


Fig. 5.8 Knowledge graph showing influence dependencies of DM conferences, using Reference Ratio and Unity priority function, where each edge represents isInfluencer relation of our ontology between conferences (Algorithm 2 using RR) for DM conference set

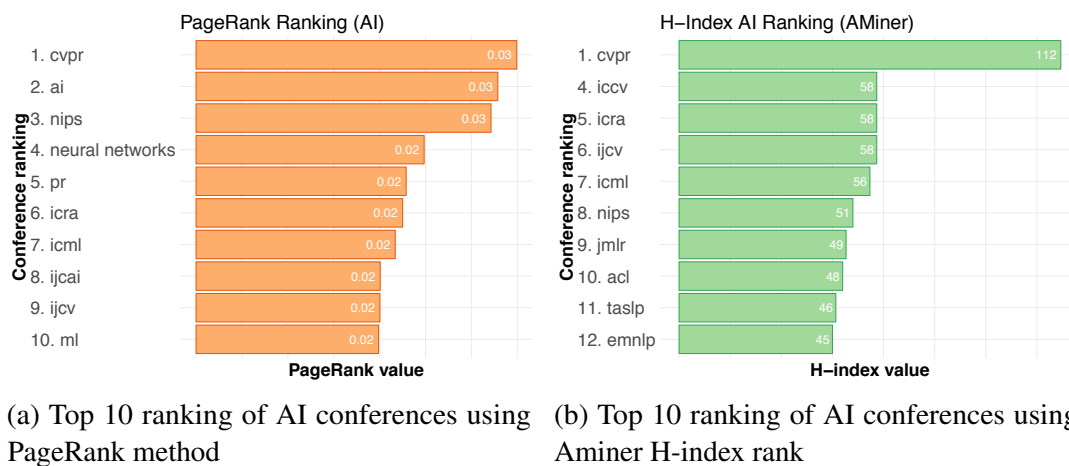


Fig. 5.9 Ranks for AI conferences using PageRank (left) and Aminer H-index (right). Our database does not include some of the conferences present in the original Aminer H-index ranking, hence some positions in H-index ranks are missing.

Comparison to Other Measures

For systems which deal with measuring relations within social networks, especially these considering influence, obtaining ground-trust knowledge is a widely known problem. Indeed, influence is actually a subjective notion, that originates in social sciences like sociology and psychology, making it ambiguous and hard to quantify. Depending on the particular system and research possibilities, each study tackles the problem of gathering the ground truth differently. In literature, in order to compare some proposed method with truth, we have observed the following trends: (1) presenting the analysis of the results containing only the proposed method (e.g. [152, 52]), (2) comparing the proposed approach to real-world rankings (e.g. [59]), (3) contrasting the presented method with another, similar-enough metrics, or (4) measuring ground-truth by utilizing or performing surveys or questionnaires (e.g. [59, 153]). In our case, in order to provide both results and comparison of our experiments, we have chosen two, more versatile ways of comparison of the proposed method to other works: (i) using real-world ranking and (ii) using a well-known influence metric – PageRank measure. The comparison is included in what follows.

(i) *Real-world Conference Ranking*

For comparing the results of our method with a real-world ranking, we have chosen the previously mentioned Aminer ranking. It consists of conference rankings, categorized by discipline, using H5-index. The rank and H5-score for DM conferences can be seen in Figure 5.10b, and for AI conferences in Figure 5.9b.

It can be seen that conferences such as *kdd*, *sigir*, or *cikm* are high in ranks both from our method and from H-index. This indicates that our approach is able to capture influence similar in a way to the assumed *state-of-the-art* method. However, while there are some similarities between the ranks of our method and H-index ranking, it is important to notice the differences between those approaches. Firstly, the H-index rank takes into consideration any citation from any journal whereas our method considers the subset of all conferences. Secondly, presented here H-index considers only the last 5 years of publication. While such information about latest trends of a conference is definitely useful, it differs from our method that takes a long term view on citations of a conference. Moreover, due to the usage of priority functions such as linear or sqrt that put different stress on the 'historical' publications, the difference is even more visible, e.g. much lower places of *www* or *tkde* conferences.

(ii) ***Weighted PageRank***

In order to compare the results from the proposed model TiDIE, we have chosen the weighted PageRank algorithm as a baseline due to two main reasons. Firstly, it is an accepted, well-established method, regarded as a *state-of-the-art* method for measuring influence [37]. Secondly, it is a well-known and popular approach, as it has been listed as one of the ten most influential data-mining algorithms, particularly focused on prestige [147]. In particular, in order for PageRank to be as close to our approach as possible, we have chosen the weighted version of PageRank, where citations are considered as weights.

Having said that, it is important to notice that PageRank and our proposed method of influence computation differ in the way they define influence. PageRank assumes to calculate rank on a network with already specified, topologically-based influence. Moreover, it does not consider time. In contrary, our method is using topological features of the network to further use it for calculating causal relations in the data. Furthermore, as mentioned, our method considers both time snapshots, and time-dependence of the citation networks.

In order to perform ranking with the use of weighted PageRank method, we have created a graph consisting of conferences as vertices and citations as edges. The lack of a notion of time for PageRank can be dealt with two-fold. Firstly, one could compute the PageRank values for each of time snapshots. However, this leads to the problem of how to compute the overall value of PageRank using those snapshot PageRank values. Secondly, there is a possibility of aggregating citations from all used time snapshots in one graph, in order to use the citation numbers as weights for PageRank.

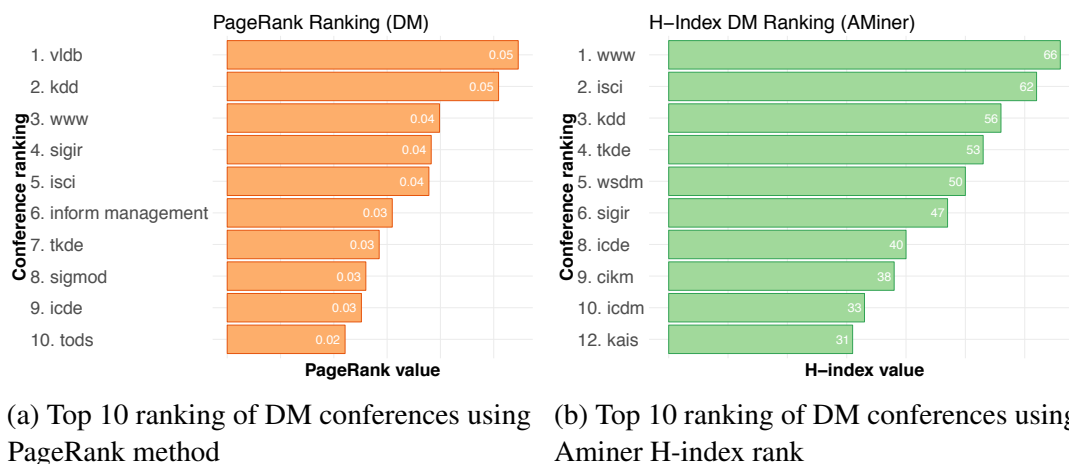


Fig. 5.10 Ranks for DM conferences using PageRank (left) and Aminer H-index (right). Our database does not include some of the conferences present in the original Aminer H-index ranking, hence some positions in H-index ranks are missing.

Due to simplicity, we have chosen the aggregation method. Since in the experiments concerning DM and AI we use Global version of both Citation and Reference Ratio for each conference, the PageRank graph contained the selected conferences, and also all conferences that ever cited or were cited by any of the selected conferences. Networks for PageRank for each topic (DM/AI) were created separately, as disjoint graphs. The result in the form of top 10 conferences of using PageRank for AI can be seen in Figure 5.9a, whereas the outcome using DM conferences is shown in Figure 5.10a.

While PageRank is focused on topological properties of network only, our method, apart from being topology-aware, is also adding additional information about the quality of a connection. In particular: Citation Ratio modified by priority functions and ranks computed basing on the number of influenced entities and the volume of influence. One of the consequences of the fact that PageRank does not consider time, and bases solely on network structure, is that any time a newer conference that might be gaining influence, but has not long history, will not be included in rank from PageRank. In comparison, as our method includes time, a newer conference that is highly cited in 'recent' time can still get a high place in the rank. The example of such situation can be seen in the case of younger conference *icdm*, that is not included in PageRank (Fig. 5.10a), however, is included in all three ranks from CR-based method (Fig. 5.5). Moreover, since H-index method takes into consideration last five years, we can say that it is not biased by the older conferences as PageRank is. Interestingly, we can observe that both H-index and our method based on CR have found some conferences not included in PageRank at all. In case of AI, conference *acl* is on 10th position

in H-index rank (Fig. 5.9b), while being position on 7th, 8th and 9th position in the rank from our method (Fig. 5.4). At the same time, *acl* is not included in PageRank. Similar situation is in the case of *cikm* conference (CR-based DM conferences, Fig. 5.5), where it is placed on 5th and 6th position and 9th in H-index (Fig. 5.10b), and not included in PageRank at all.

5.4 Reputation Prediction using TiDIE

In this section, we focus on a linkage between influence and reputation, previously defined in Chapter 3. Recall that, sociological studies [142–144] have linked the two notions. Consequently, we want to use this association from influence to reputation and propose a method to evaluate reputation basing on the influence information. In particular, we utilize citation network and TiDIE model introduced in Section 5.3, in order to calculate the influence, and, using it, we attempt to infer the reputation. In the following, we specify Reputation-TiDIE (ReTiDIE) – a model for reputation prediction that utilizes TiDIE, and present experiments performed using ReTiDIE with Microsoft Academic dataset.

5.4.1 Reputation Prediction specification

In scientific domains, maintaining long-term relations leading to both cooperation and collaboration is crucial. At the same time, reputation, while being globally available, is indeed a determining factor for decision making, e.g. for what conference to submit an article. These factors, along with the fact that scientific journals are considered as a communication system, means of research validation as well as a medium for gaining scientific recognition [145], were the reason why we focused on citation networks scope.

Recall that, in Chapter 3, we described a proposition that showed a link from influence to reputation notion. Two important parts of the proposition were firstly, the long-term observation of influence, and secondly, the assumption that being macro-influencer in such long-time observation signifies gaining a high reputation of this macro-influencer. Basing on this, we assume the following steps for ReTiDIE process of obtaining the reputation value within a time interval $T = [t_i, t_j]$ for each of the entities in a given network:

1. Calculate influence dependencies between each of the entities E and create influence dependency graph from time period T where vertices are the entities and edges symbolize influence between them;
2. Use influence dependency graph to order the entities and obtain the influence rank;

Algorithm 4 ReTiDIE method for estimation of reputation that forms a ranking, hence entities are comparable in terms of reputation

Input: Time interval T , citation network with time information for each $t_i \in T$, set of conferences

$$C = \{c_1, \dots, c_n\}$$

Output: Reputation estimate for conferences from C

```

1:  $InfSet = \emptyset$ 
2: for all distinct  $c_i, c_j \in C$  do
3:    $InfSet \leftarrow InfSet \cup determineInf(c_i, c_j, T)$ 
4: end for
5:  $IDG(T) \leftarrow CreateInfDepGraph(InfSet, T)$ 
6:  $I(T) \leftarrow CreateInfluenceRank(IDG(T))$ 
7: for all  $c_i \in C$  do
8:    $Hindex(c_i, T) \leftarrow calculateHindex(c_i, T)$ 
9:    $Reputation(c_i, T) \leftarrow I(c_i, T) \bullet Hindex(c_i, T)$ 
10: end for

```

3. For each entity e_i , calculate H-index metric for a time interval T ;
4. For each entity e_i calculate reputation for a time interval T using the formula:

$$Reputation(e_i, T) = I(e_i, T) \bullet Hindex(e_i, T) \quad (5.4)$$

where \bullet is a function that binds two magnitudes: Influence and H-index.

As mentioned, for the purpose of calculating influence, we used TiDIE model, presented in Section 5.3. Importantly, TiDIE evaluates influence with the use of time-dependency and focus on the communities within the network. The first two steps are directly related to TiDIE process of evaluation of influence. Then, in the third step, we calculate additional measure, H-index, which is one of the most popular metrics utilized in scientific papers discipline aiming at measuring productivity. In our approach, we utilize H-index [53] for conferences, in comparison to this metric usual use – for authors of papers (researchers). Thanks to the use of H-index we obtain the external information about the conference status. Finally, the fourth step binds together computed influence and H-index. As our approach produces two global rankings: influence rank and H-index rank, we model the binding function to be the method that combines the two rankings together. In particular, in our experiments we utilize two rank combining methods (see 5.4.2).

ReTiDIE is shown in Algorithm 4. First, we create influence set $InfSet$ containing the influence between each pair of conferences, using method $determineInf$ for determining pairwise influence (line 3). Then, basing on $InfSet$, we create the influence dependency graph. Next, the dependency graph is converted in order to obtain influence values I using influence rank – a total order relation (lines 1 – 6 correspond to TiDIE Algorithm 3 from

Section 5.3). Further, for each conference, we calculate the H-index for a conference in time interval T. The function *calculateHindex* utilizes the H-index method, that orders in descending order all citations *cit* from each of the publications of conference *c* and then computes, for each conference, the maximum of its citations and position, using the formula:

$$Hindex_c = \max(\min(cit_i, i)) \quad (5.5)$$

where *i* is position of *cit_i* in ordered series. Finally, the reputation value is computed by binding influence and H-index ranks for each conference (line 9). In our experiments, we have used two methods for combining multiple ranks:

- Cross-Entropy Monte Carlo algorithm
- Generic algorithm with Spearman distance metrics

Importantly, additional information about *influence network* topology could be used as emphasis, where a weight could be introduced to more regard influencing entities with higher prestige.

5.4.2 Evaluation of ReTiDIE

In order to evaluate our proposed approach, we performed the experiments using Microsoft Academic database used in previous chapters. We have chosen the set of of-interest conferences/journals containing 68 venues in total.

The implementation was done using PostgreSQL ⁶ version 9.6 and R language ⁷ version 3.3.1 with the use of *lmtest* package ⁸ and *rankagregg* package ⁹.

Conducted experiments used the maximal possible time period given in the dataset from 1950 until 2015. Firstly, for each pair of conferences/journals, we calculated influence and created influence dependency graph. Then, we calculated the overall H-index for each venue. In order to obtain the final reputation, we decided to use a method that would treat both influence and H-index importance equally. Hence, we used the methods for combining multiple ranks: (1) the Cross-Entropy Monte Carlo algorithm (CE) [154], and (2) the Genetic algorithm (GA) [154] using Spearman distance metric. The results, limited to 25 venues having the highest reputation using Cross-Entropy Monte Carlo method can be seen in Table 5.1, and 25 venues having the highest reputation using Generic algorithm can be seen in Table 5.2.

⁶<https://www.postgresql.org/>

⁷<https://www.r-project.org/>

⁸<https://cran.r-project.org/web/packages/lmtest/index.html>

⁹<https://cran.r-project.org/web/packages/RankAggreg/index.html>

Table 5.1 Reputation rank using ReTiDIE and Cross-Entropy Monte Carlo algorithm (CE) with Spearman distance.

Venue	Influence Rank	H-Index Rank	Reputation (CE)
ai	1	4	1
ijcv	10	3	2
neural netw	21	1	3
cvpr	6	13	4
ieee neural netw	8	12	5
prl	20	7	6
cviu	25	6	7
jair	17	10	8
jmlr	15	9	9
eccv	12	20	10
icpr	11	49	11
emnlp	13	21	12
acl	3	25	13
aamas	26	14	14
aim	31	15	15
paa	58	16	16
nips	2	41	17
uai	18	64	18
aaai	19	40	19
iccv	22	23	20
nc	64	19	21
coling	7	36	22
dss	54	2	23
bmvc	24	42	24
ijcai	4	38	25

Table 5.2 Reputation rank using ReTiDIE and Genetic algorithm (GA) with Spearman distance.

Venue	Influence Rank	H-index Rank	Reputation (GA)
ai	1	4	1
nips	2	41	2
ijcv	10	3	3
acl	3	24	4
neural netw	21	1	5
dss	54	2	6
kbs	51	5	7
jmlr	15	9	8
ieee neural netw	8	12	9
prl	20	7	10
cvpr	6	13	11
nca	53	8	12
cviu	25	6	13
aim	31	16	14
jair	17	10	15
icpr	11	49	16
tfs	34	17	17
eccv	12	20	18
aaai	19	39	19
uai	18	61	20
iccv	22	21	21
emnlp	13	22	22
naacl	16	45	23
coling	7	37	24
aamas	26	14	25

Results show differences between reputation ranks in Table 5.1 and Table 5.2, due to the usage of different methods that join the influence and H-index ranks. However, in both tables, strong candidates persist, such as venues: AI, Neural Networks, IJCV or IEEE Neural Networks. Important to notice is also the difference between Influence and H-index Ranks – for example, venues DSS and NCA while being at the end of Influence ranking (on positions 54 and 53 respectively), they are in the top of H-index rank (position 2 and 8). This difference is a possible result of the fact that, while influence method is focused heavily on trends over time, H-index value is putting a uniform emphasis on the whole measured period.

5.5 Conclusion

In this chapter, we proposed a further exploration of influence detection and evaluation method, instantiating the modelization of influence from Chapter 3 to investigate the properties of a particular type of social network – citation network, focusing on the transverse influence component of time-dependency. In particular, we presented two metrics for impact evaluation between communities that took into account different influence components, such as intensity, engagement, and spread. Furthermore, using the two metrics, we proposed TiDIE model for investigation and estimation of the influence for conferences in a particular time period. The model aims to both allow the comparison of the influence of two different conferences and estimate the overall influence of a conference in a particular citation network. We conducted a variety of experiments using a real-world set of scientific conferences. The results have shown that the model can identify and evaluate the influence between communities. As a comparison, we contrasted the obtained results from our approach to the baseline methods of PageRank and H-index. Furthermore, the performed tests have shown the importance of considering time-dependency within citation networks.

In addition, we used the connection between influence and reputation described in Chapter 3, in order to evaluate the latter, based on the information about the former. This application of influence method to evaluate reputation shows also the usefulness of influence modeling for social networks. In particular, we presented the ReTiDIE approach that incorporated a phenomenon of an entity high influence within the network being an indicator of the entity having high reputation levels. ReTiDIE operates in citation network scope and incorporates influence dependencies information in order to obtain reputation. The results of experiments performed using Microsoft Academic database show the possible way of including influence for calculating reputation and give a good basis for further analysis of reputation with the use of influence.

Chapter 6

Conclusion

6.1 Summary

Detecting and interpreting the behaviors of entities in social networks is definitely not an easy task. The study of involving actual users, their interactions and evaluation of their attitudes towards each other pose numerous challenges and issues. While the area of social relations is very broad, in this thesis, we particularly focused on investigation, modelization, and evaluation of interactions between users in social networks indicating primarily users influence, but also reputation, trust, and popularity.

As showed, multiple studies have been involved in researching these notions. Nevertheless, there still remain various challenges to tackle, such as: the users' notions and relations need to be clearly defined and distinguished from one another; the definitions must be modeled to capture the complexity of a relation, but also remain non-specific in order to be fully adaptive for different applications; the influence evaluation methods must consider multiple properties of influence in order to be precise; the influence models need to deal with different types of social networks and their multiple, possibly various, parameters.

To address these challenges, we first addressed the problem of distinction of the notions. We proposed a general classification of all the notions, placing it according to their complexity, and presented typologies and comparison of them. Using this distinction, we were able to focus on the modelization of influence, which led to the proposition of a theoretical model of influence. The model gave basis and notions needed for identification of influence and influential entities, while utilizing entities direct reactive activities, in order to calculate their impact. On the premise of this model lies an intuitive concept of actions and reactions in social networks. We created an ontology in order to bind all presented influence-related notions, as well as show the placement of our work in the broader perspective.

Following the establishment of the theoretical model and regarding the influence evaluation problem, we introduced two instantiations of the model. The first one, called ARIM, is general – applicable to different social networks types, and flexible – can work on various numbers of parameters. It considers type, quality, quantity and time of reactions and, as a result, assesses the influence dependencies within the social network. The experiments conducted using different real-world datasets have shown the adequacy and flexibility of the proposed model, as well as proved the adaptivity of the theoretical model on which ARIM based.

The second instantiation was a result of our particular focus on the problem of time for influence modelization. Accordingly, we targeted one, deeply time-sensitive social networks type, namely citation network. The created model, TiDIE, combined the aforementioned notions presented theoretically with the focus on causal relations of times series. The results of the experiments conducted on the scientific dataset demonstrated the suitability of our model and stressed the importance of time consideration for influence evaluation.

Finally, with the use of TiDIE, we also proposed a transition method, ReTiDIE, that utilized a phenomenon linking influence and reputation. Our approach, instantiated similarly in the citation networks context, exploited the information about the influence for reputation acquisition purposes. As demonstrated, ReTiDIE shows the proof of concept technique for obtaining reputation of scientific conferences.

Research issues

While discussing the works of this thesis, but also other works aiming to evaluate the various users relations, interactions and roles in social networks, it is important to bring to notice some issues of such research. Undoubtedly, ubiquity and quantity of content from social media in recent years enabled the rapid development of the discipline. Thanks to massive, real-world data, the research concerning and describing the users behavior and its multiple applications bloomed. It used to be fairly easy to obtain the data using APIs provided by social networking sites or by crawling the sources of the sites independently. However, currently the policies of social networking sites tend to shift, especially in the context of recent misconducts such as Cambridge Analytica one [155]. More and more sites limit drastically their APIs, so that obtaining information regarding the whole network is extremely hard. At the same time, many companies launch their own branches and partner with companies dedicated to data gathering and selling to other parties. For example, during the time of working on this thesis, the Instagram API, previously widely open, was limited to an extent that only basic information about one's own profile can be obtained [156]. Another example is Twitter – the existing free API gives very limited access to any data and the

changes in the policy of the company disabled the researchers to crawl the data independently as well as share the datasets collected in the past. At the same time, Twitter offers paid services and partnered with companies that are authorized to sell Twitter data [157].

There is no doubt about the importance of privacy of users utilizing different Internet services and sites. However, it is important to notice that the situation in which the terms of the use are created in a way that the users' data are seemingly safe, while actually they still can be sold to any company that is willing to pay, does not seem to be correct. Moreover, all this leads the research to move into the private sector, either to companies that are willing to pay for customer information or to the social networking sites companies themselves, omitting open, academic studies. As a consequence, cases of the users manipulation with the use of social network data, with the general public completely unaware of the problem, are at even higher risk than before.

On the other hand, it is also important to notice that, while some SNA connected research can benefit from using synthetic datasets, in studies involving actual users, their interactions and evaluation of their attitudes towards each other, automatically generated data can only be used for time and volume verification purposes. This is due to the fact that analysis of results evaluating influence or reputation between "artificial" users just does not lead to any fact- and data-supported conclusions about actual humans.

In the light of all the above, it is notable that our theoretical model uses the ubiquitous properties of social networks, and can be easily instantiated to a particular application needs. It could be observed by ARIM instantiation, able to work using data that can be both limited (e.g. having only one reaction type) or broad. At the same time, if needed, the notions introduced that are describing influence theoretically can be targeted on one type of social network, as it was showed in the case of TiDIE. Therefore, assuming one has a social network dataset, our work can be successfully utilized for obtaining influence evaluation.

Another, more complex and bit philosophical problem involves the issue of little to no ground truth concerning the research evaluating user relations, especially influence. Obviously, this problem already exists and concerns multiple other disciplines, including social sciences and the previous scope of SNA, when most of the ground truth was obtained by questionnaires. While the growth of social networking sites has definitely enabled data collections, it did not solve the issues when the best verification of new method results involve comparing them against the users actual real opinions. On top of that, even assuming some users would be willing to dedicate time and effort to provide some feedback, the question of whether they would be open to evaluating trust, reputation or influence of their friends remains open. This seems to be especially true for the scope of influence studies, where it is very hard to verify the results as there does not seem to be the "correct" answer. In this thesis,

we utilized the comparison to different methods in order to ensure verification. However, it is also important to note that two methods focusing on different influence aspects are expected to give non-identical results.

6.2 Future Research Directions

Our research work opens several future research directions that can be accomplished both in short and long term perspective.

Concerning the influence ontology along with the theoretical influence model showed in Chapter 3, one of the perspectives would be to combine the ontology with other ones that are connected to social networks, such as FOAF, RELATIONSHIP, or SIOC. While presented in our work ontology specifies influence from Action-Reaction perspective, the extension aiming to join the existing works with ours is an obvious next step. Moreover, we also acknowledge that, considering influence discipline so rapidly growing and developing, the new ways in which users can interact with each other will definitely be created in the future. Therefore, while the current Action-Reaction schema and, accordingly, the theoretical model of influence include all critical terms and notions for modelization of influence to-date, we are almost certain that, in long term, the extension of them will be needed.

Regarding ARIM model, presented in Chapter 4, we are currently targeting to use it as a basis for further influence discovery examination. In particular, we want to examine the short-term temporal reactions shifts, which would allow us to closely study the influence trends. In fact, we already started investigating influence trends, which led to a proposal of Interval Specific TiDIE-based model (Inic). The draft of the proposal is available in Appendix A. Furthermore, Inic that focuses on trends can also be combined with micro-influencers analysis. This combination of the two studies could lead, in a long term perspective, to two applications. Firstly, it could develop from evaluation and estimation of influence based on obtained data, which we performed in this thesis, to a prediction of the entities influence. Secondly, it could also provide a way to forecast and select the promising micro-influencers, that have the potential to grow to be macro-influencers.

At the same time, we acknowledge that the datasets used for experiments, although presenting a variety of social networks types, still remain small compared to real-world, large and complex applications. Further work on the evaluation aspects of the presented model is also planned. Moreover, another planned work is to utilize the model for further applications. In particular, as mentioned before, models and methods that enable to find influential users can also be utilized as an initial method used for influence diffusion problem. Indeed, most

works dealing with this issue assume the existence of an initial seed of users (nodes) which suppose to infect others further. Obviously, our model could be applied to this task.

Interesting development of research can also be done concerning presented in Chapter 5 TiDIE model that targeted citation networks scope, and reputation aiming ReTiDIE. While both of the studies involve a particular type of social network, the scientific papers domain remains to be yet explored. To-date, there does not exist the metric for evaluation of either influence or reputation that would be agreed upon and even somewhat close to being objective. Therefore, further extension of ReTiDIE would definitely provide further insight into the field. Targeting short term period, development of ReTiDIE would involve twofold extensions. One possibility is combining different than H-index measures with influence information. Another one is to utilize and investigate various rank-binding methods for obtaining the final reputation rank. A forward, long term improvement would be to incorporate different models that evaluate influence.

Finally, in this thesis, we regarded any influence – positive or negative. As mentioned before, the term does not imply any assessment as for being good or bad. Nevertheless, some applications, such as usage for social campaigns, could benefit from the additional information about whether or not the entity is positively influential. Therefore, another future direction of this thesis would be to combine our methods with sentiment analysis approaches, so that the methods would be able to filter reactions depending on their assessment.

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Appendix A

Draft of Proposal

A.1 Inic: Interval Specific Model

As mentioned before, time is an important aspect of influence. This draft of proposal is dedicated to examination of the short-term temporal reactions shifts, which in consequence allows us to closely study the influence trends. In particular, we propose an **Interval Specific Model (Inic)**, an extension of ARIM model presented in Chapter 4, dedicated to dealing with the influence trends within time windows. Particularly, Inic utilizes all the formulas used for ARIM described in Chapter 4 Section 4.2, while utilizing the time windows to evaluate user tendencies in time. To achieve that, Inic uses constant time windows, i.e. it will consider each time period resulting from time window separately. Therefore, we describe only the issue of dealing with time windows for Inic in what follows.

As mentioned in Chapter 3, it is important to notice that in many cases the length of the time window should be tuned to the specific portal characteristic, from which the data come. This is due to the fact that there are sites with a very rapid information exchange patterns, e.g. Twitter, where posts and reactions can be done in minutes and even couple of seconds, and there are those that have instant but more steady exchanges, e.g. Instagram. Moreover, the time window will also be highly dependent on the data granularity – data collected daily and aggregated into one snapshot will be by default unable to capture more rapid changes in the network.

It is crucial to notice that there are two time-lines of the data to consider: the action time-line and the reactions time-line. For instance, presented before ARIM model is basing on the Action-Reaction schema, hence it uses the information about the time of occurring reactions to estimate influence. As previously mentioned in Chapter 3, any influence model has to determine a time period in which it is valid to consider reactions towards particular actions (performed before those reactions). For example, if a user posts some news (performs action)

on social network portal, the impact of this post on the user's audience is not immediate. Instead, the influence on the user's audience is stretched in time, over the period from the post creation until the last audience reaction, e.g. last comment. Therefore, the question is if the entities influence connected to this action should be regarded as happening at the creation moment or when the reaction occurs? We propose to assign the influence value to time window, considering the reactions time-line (and not the time-line of action occurrence). In particular, we propose two alternative ways of assigning influence value to time window:

- Using only reaction time-line – We assess the influence value for each window in which the reactions to particular action occurred. In that way, although we do ignore the moment when the post was created, we correctly find the particular time window for which the influence (coming from reactions) have surfaced. For instance, let us assume that the action (e.g. post creation) was performed in time window 1, and reactions (e.g. comments and share) occurred in respectively time window 2 and 3. In this case, Inic would associate time windows 2 and 3 with respective influence values (and none in time window 1).
- Using point in time resulting from median of Action and Reaction times – The idea is to chose the time window according to both action time, and the time of receiving the reactions. In particular, we determine the time window according to the median of time series consisting of delay between publishing the post and publishing the reaction. The calculated influence value for this action and reactions is placed in the time window which includes this "median" time. In that way, we bind influence value to the time window in which already half of all reactions towards the action have occurred.

The choice of one of these methods depends on the time window length and the social network site characteristics¹.

A.1.1 Results of Inic

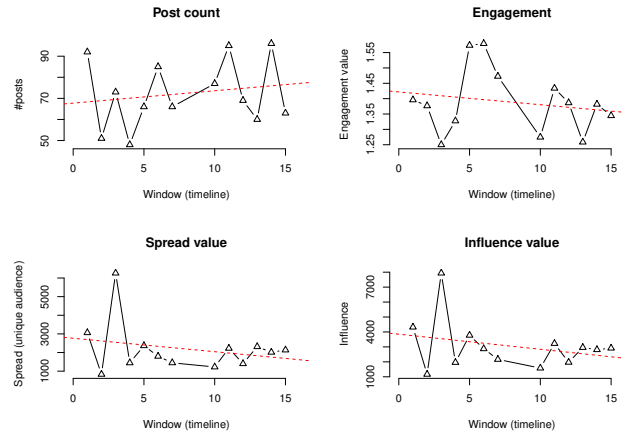
For experiments involving the trend analysis using Inic we utilized the Facebook dataset utilized before in Chapter 4. The choice of this dataset was made due to the fact that it was the only dataset that included precise time information for actions and reactions.

In previous section, we proposed two techniques for assigning influence to time, using reaction time-line and using time resulted from median of time series of action and reaction.

¹For example, the median method will be insufficient in the case in which the average reaction time for the action will be short (minutes, some hours), and the time window will be longer (as we want to consider a big enough sample for the trends, e.g. couple of days), in which case the median will be included in the time window.

#	Engagement	Spread	#Posts	Influence Score
6	1.10	17040	941	18717
89	1.19	3131	13318	3728

Table A.1 Information about two selected users for trend analysis

Fig. A.1 Falling trend of user u_6

However, after initial analysis of the Facebook data, we noticed that for the majority of users, the time to obtain comment after posting is less than 200 minutes. Such a short time is not sufficient for observing the trends and obtaining conclusions about one's influence. Therefore, in the experiments, we used only the first method, while using arbitrary chosen time window of 7 days.

As our experimentation is in the beginning phase, here, we present the trend analysis for two, interesting users, selected from the list of top 100 influentials, obtained from previous experiments with the dataset from Chapter 4. In particular, we selected user from position 6 and 89 of top 100 influentials, as those two presented interesting and distinctive to one another characteristics. The information about the two selected users can be seen in Table A.1. The results in the form of trends are presented in Figure A.1 for user from position 6 and Figure A.2 for user positioned on 89, and include the trend of post count, engagement and spread ratio trends and influence trend. The dotted line in an approximation of the trend done using Linear Regression.

It can be seen that, in case of user from 6th position, while the amount of created posts varies, both spread and the engagement decrease in time. On the contrary, user from position 89 gains not only spread for his/her posts, but also the users that are commenting are highly active - the engagement ratio equals at the beginning 4 and is rising with time. In the case of 6th user, the possible explanation for such trend is that independently from the number of posts that the user is generating, the audience is gradually losing interest. Additionally, we

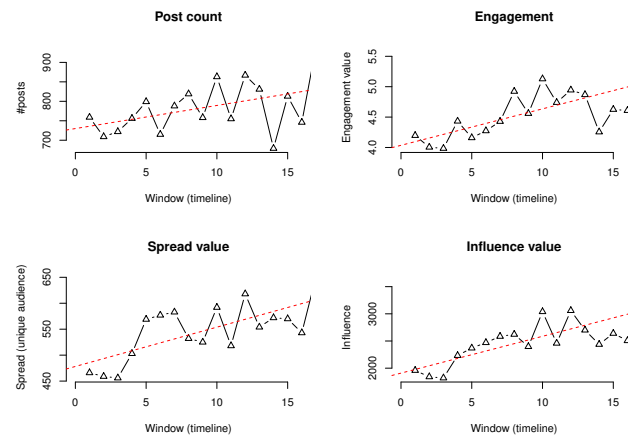


Fig. A.2 Rising trend of user u_{89}

can observe one significant peak in the spread and one time window, which suggests that the person was very popular (maybe controversial?) at one particular moment, which spiked the number of users reacting to the content. However, after that the user was not able to maintain such an audience. The case of user from 89th shows how the user is systematically gaining popularity (increasing the spread value). Moreover, observed increase of spread is simultaneous with the increase of audience engagement. This shows that Inic was able to determine influence evolution would be particularly helpful for campaigns in which the audience should be an active collaborator, for example giving feedbacks about the product.

Titre : Exploration des Interactions Humaines pour la Modélisation de l'Influence dans les Réseaux Sociaux

Mots clés : Réseaux Sociaux ; Influence ; Réputation ; Confiance ; Popularité ; Analyse de Réseaux Sociaux

Résumé : De nos jours, la popularité des réseaux sociaux (RS) est en constante progression. De plus en plus d'utilisateurs interagissent dans le monde virtuel, en exprimant des croyances, en réagissant aux avis d'autrui ou encore en échangeant des idées, en fonction de leurs qualités : influents, populaires, dignes de confiance, etc. Cependant, définir, distinguer et mesurer la force de ces relations entre les utilisateurs posent également de nombreux défis, à la fois théoriques et pratiques, qui restent à explorer.

Dans cette thèse, nous nous focalisons sur les quatre concepts qualifiant les utilisateurs : influence, réputation, confiance et popularité, pour la modélisation de l'influence. Nous mettons en avant les caractéristiques essentielles et établissons une classification globale des différentes interprétations des notions selon leur niveau d'abstraction. En conséquence, nous proposons un modèle théorique de l'influence ainsi qu'une ontologie associée décrivant ce concept. Nous présentons également une variante de l'influence, inexplorée à ce jour dans le domaine de l'Analyse des RS, la micro-influence.

Celle-ci cible un phénomène nouveau dans les RS que sont les utilisateurs avec une faible audience, mais fortement impliqués ; ils apparaissent en effet comme ayant un impact fort malgré tout. En s'appuyant sur ces définitions, nous proposons ensuite un modèle dénommé ARIM (Action-Reaction Influence Model) qui considère le type, la qualité, la quantité et la fréquence des actions réalisées par les utilisateurs, et ce en étant compatible avec différents RS. Nous abordons également la quantification de l'influence au cours du temps et la représentation de ses effets de causalité. Pour cela, nous considérons un type spécifique de RS : les réseaux de citations, particulièrement sensibles au temps. Ainsi, nous proposons un modèle, TiDIE (Time Dependent Influence Estimation), qui détermine l'influence, sur une période de temps, entre les communautés de ces réseaux. Enfin, nous combinons l'influence et la réputation avec le modèle TiDIE, afin d'étudier les dépendances entre elles. Nous proposons une méthode de transition, ReTiDIE, utilisant l'influence pour obtenir la réputation.

Title : Exploring Human Interactions for Influence Modeling in Online Social Networks

Keywords : Social Networks ; Influence ; Reputation ; Trust ; Popularity ; Social Networks Analysis ;

Abstract : Online Social Networks (SN) are constantly growing in popularity. More and more users interact in the virtual world, by expressing beliefs, reacting to opinions, or exchanging ideas, according to their qualities : influential, popular, trusted, etc. However, defining, distinguishing and measuring the strength of those relations between users are also posing numerous challenges, on theoretical and practical ground, and are yet to be explored.

In this thesis, we focus on the qualities of users connected to four concepts : influence, reputation, trust, and popularity, in the scope of SN Analysis (SNA) for influence modeling. We emphasize the most important features of these concepts and present a global classification of the notions concerning their abstract level. Consequently, we then propose a theoretical model of influence and influence-related ontology. We also present a distinction of notion not yet explored in SNA – micro-influence, which targets new

phenomena of users with a small but highly involved audience, who are observed to be still highly impactful. Basing on the definitions of the concepts, we propose a practical model, Action-Reaction Influence Model (ARIM), which considers type, quality, quantity, and frequency of actions performed by users in SN, and is adaptive to different SN types. We also focus on the quantification of influence over time and representation of influence causal effect. In order to do that, we focus on a particularly time sensitive SN type — citation network. Accordingly, we propose Time Dependent Influence Estimation (TiDIE), a model for determining influence during a particular time period between communities within citation networks. Finally, we also combine two of the abovementioned notions, influence and reputation, in order to investigate the dependencies between them. In particular, we propose a transition method, ReTiDIE, which uses influence for predicting the reputation.

