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"I visualize a time when we will be to robots what dogs are to humans, and I'm rooting for the machines"

Claude Shannon

CHAPITRE 1

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Résumé

L'Intelligence Artificielle est présente dans tous les aspects de notre vie à l'ère du Big Data. Elle a entraîné des changements révolutionnaires dans divers secteurs, dont le commerce électronique et la finance. Dans cette thèse, nous présentons quatre applications de l'IA qui améliorent les biens et services existants, permettent l'automatisation et augmentent considérablement l'efficacité de nombreuses tâches dans les deux domaines. Tout d'abord, nous améliorons le service de recherche de produits offert par la plupart des sites de commerce électronique en utilisant un nouveau système de pondération des termes pour mieux évaluer l'importance des termes dans une requête de recherche. Ensuite, nous construisons un modèle prédictif sur les ventes quotidiennes en utilisant une approche de prévision des séries temporelles et tirons parti des résultats prévus pour classer les résultats de recherche de produits afin de maximiser les revenus d'une entreprise. Ensuite, nous proposons la difficulté de la classification des produits en ligne et analysons les solutions gagnantes, consistant en des algorithmes de classification à la pointe de la technologie, sur notre ensemble de données réelles. Enfin, nous combinons les compétences acquises précédemment à partir de la prédiction et de la classification des ventes basées sur les séries temporelles pour prédire l'une des séries temporelles les plus difficiles mais aussi les plus attrayantes : le stock. Nous effectuons une étude approfondie sur chaque titre de l'indice S&P 500 en utilisant quatre algorithmes de classification à la pointe de la technologie et nous publions des résultats très prometteurs.

Abstract

Artificial Intelligence has penetrated into every aspect of our lives in this era of Big Data. It has brought revolutionary changes upon various sectors including e-commerce and finance. In this thesis, we present four applications of AI which improve existing goods and services, enables automation and greatly increase the efficiency of many tasks in both domains. Firstly, we improve the product search service offered by most e-commerce sites by using a novel term weighting scheme to better assess term importance within a search query. Then we build a predictive model on daily sales using a time series forecasting approach and leverage the predicted results to rank product search results in order to maximize the revenue of a company. Next, we present the product categorization challenge we hold online and analyze the winning solutions, consisting of the state-of-the-art classification algorithms, on our real dataset. Finally, we combine skills acquired previously from time series based sales prediction and classification to predict one of the most difficult but also the most attractive time series: stock. We perform an extensive study on every single stocks of S&P 500 index using four state-of-the-art classification algorithms and report very promising results.

Dedicated to my parents

and my wife

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CHAPTER 2

INTRODUCTION

Can machines think?

Alan Turing

2.1 Background and motivations

Artificial Intelligence promises to improve existing goods and services, and, by enabling automation of many tasks, to greatly increase the efficiency with which they are produced. Although "AI is still in its infancy" [1], there seems to be a significant amount of entry and experimentation across numerous sectors. Within the business sphere, AI is poised to have a transformational impact. Although it has already been deployed in thousands of companies around the globe, most big opportunities have not yet been tapped. According to a study conducted by International Data Corporation [2], the industries that will invest the most in AI are banking and retail. Therefore, it is of particular interest to conduct studies on AI applications in those two industries, more specifically, in finance and e-commerce which are two most technology-driven branches of both industries.

E-commerce, as a newcomer to the world, became possible only when the Internet opened to commercial use in early 90s. However it rapidly revolutionized the traditional commerce tunnel by allowing consumers to exchange goods and services with no barriers of time nor distance. Over the past decade, it has rapidly grown enabling customers to purchase any product with a click of a button. And nowadays, it has become an integral part our daily lives. In 2016, e-commerce sales reached 1.86 trillion US dollars, accounted for 8.7 percent of all retail sales worldwide and is projected to grow to 4.48 trillion US dollars in 2021, which represents 15.5 percent of all retail sales [3]. Nowadays, existing major platforms have evolved into large B2C and/or C2C marketplace having large inventories with up to tens of millions of products. Therefore, a key component for the success of such platforms is their ability to quickly and accurately retrieve the desired products for the customers within such large inventory. Product search and categorization, powered by AI, are two crucial services provided by these sites dealing with this issue.

Search engines are essential for consumers to be able to make sense of these large collections of products available online. The first stage in the consumer buying process is commonly recognized to be that of the information search. The ability to collect product information and make comparisons between the different product offerings from different providers, possibly across national and currency boundaries, is often viewed as one of the main services offered by e-commerce websites. Therefore, onsite product search engine has become a salient part for most major e-commerce companies, as show in Figure 2.1 [5]. Major e-commerce website usually provide users with a simple interface with a search bar inviting them to formulate queries using

1. https://drive.tech/en/stream-content/artificial-intelligence-is-still-in-its-infancy
2. https://www.idc.com/getdoc.jsp?containerId=prUS41878616
3. https://www.statista.com/statistics/534123/e-commerce-share-of-retail-sales-worldwide/
5. Screens captured on the 23rd June 2016

(a) Amazon's search engine

(b) Cdiscount's search engine

(c) Darty's search engine

(d) Fnac's search engine

Figure 2.1 – Some onsite product search engines in French market [4]

characteristics of the product they are interested in.

Despite of its importance to e-commerce sites, product search still has room for improvement. It has been reported that there exists a mismatch between user issued queries and seller provided product description where both use different terms to describe the same concepts (Li et al., 2014; Nurmi et al., 2008). Thus, there is an urgent need for better semantic matching methods. Moreover, product search is quite different from other entity finding task such like books, people, groups etc. First, product search engines only operate within a single domain. Second, user queries in product search consist of free-form text as opposed to the semi-structured queries with additional type or relational constraints being used. Third, products are often associated with significant amount of user data, such as purchase history and review, which could provide additional information to the search algorithm.

Furthermore, products of e-commerce are generally organized into a hierarchical taxonomy of multilevel hierarchical categories. Product classification is the task of automatically predicting a taxonomy path for a product in a predefined taxonomy hierarchy. It is a backbone for successful marketing and sale of products listed on several online stores like Amazon [6], eBay [7], Cdiscount [8] etc. Since a large number of business users list their products and expect to find buyers for their products, it is crucial that the products are listed in accurate categories. In

6. https://www.amazon.com/
7. http://www.ebay.com/
8. https://www.cdiscount.com/

addition, it also plays a vital role in customer oriented services like search and recommendation. Description, title, images etc. are all useful sources to extract relevant features to classify products. Major actors like Amazon, e-Bay, Cdiscount among others use different taxonomies to organize products making it hard and labor-intensive for sellers to categorize the products. Sometimes sellers are encouraged to find similar products to those they sell and adopt this category to their products. However, this mechanism leads to two main problems: (1) it takes a lot of time for a merchant to categorize items and (2) such taggings can be inconsistent since different sellers might categorize the same product differently. To solve these problems, ideally one would like to have an automated procedure, which can classify any product into a given product taxonomy. Such process will both alleviate human labor and further improve product categorization consistency in e-commerce websites.

As for the financial sector, it plays an important role on the economical and social organization of modern society and has existed since the dawn of human activity, much longer than e-commerce has. Since Adam Smith, it has been governed by the Efficient Market Hypothesis - "There is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis", as said by Jensen (Jensen, 1978). However, for the last decades, this concept has been challenged and the recent development of AI has irreversibly broken the balance. Numerai [9], a hedge fund created in 2015, uses artificial intelligence to make trading decisions. Instead of developing the algorithms themselves, they've outsourced the task to thousands of anonymous data scientists, who compete to create the best algorithms and win cryptocurrencies for their efforts. Many other companies like Numerai, also referred to as *FinTech*, have emerged over the past few years and are having a huge impact on the finance industry. Meanwhile, with the large amount of transactional data publicly accessible, researchers are also provided with this unique opportunity to compete with professional traders without prior knowledge nor experience in trading.

As a result, driven by the irresistible temptation of potential benefits, financial giants such as Goldman Sachs and many of the biggest hedge funds are all switching to AI-driven systems that can foresee market trends and make trades better than humans [10]. It has been reported that Goldman Sachs' US cash equities trading desk in its New York headquarters employed 600 traders in 2000, but today, only two remains with the machines doing the rest [11]. From a global scale, around 9% of all funds [12], managing $197 billion, rely now on AI models built by

9. https://numer.ai/
10. https://fr.scribd.com/document/341347760/AI-REPORT-GOLDMAN-SACHS-FT-Artificial-Intelligence
11. https://www.technologyreview.com/s/603431/as-goldman-embraces-automation-even-the-masters-of-the-universe-are-threatened/
12. https://www.wired.com/2016/01/the-rise-of-the-artificially-intelligent-hedge-fund/

data scientists. A recent study performed by investment research firm Eurekahedge [13] tracked the performance of 23 hedge funds utilizing AI from 2010-2016, finding that they outperformed those managed by more traditional quants and generalized hedge funds, as shown in Figure 2.2.

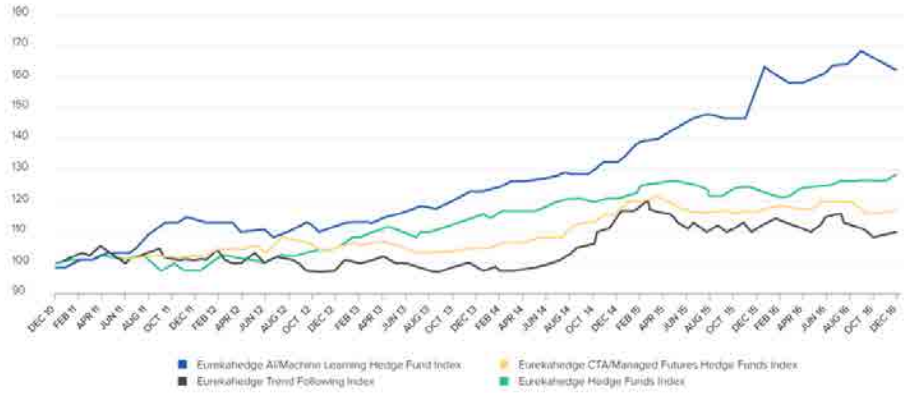


Figure 2.2 – Hedge funds performance comparison. Source: Eurekahedge

Confronted with those aforementioned challenges, driven by the increasingly demand and motivated by the power of AI, this thesis aims to reveal, in a preliminary way, the potential impact of artificial intelligence in e-commerce and finance fields through a few concrete applications and to shed some light on the future development of those fields in this era of Big Data.

2.2 Organization of this thesis

The rest of this thesis is organized as follows. Chapter 3 is focusing on reviewing related works of topics discussed in this thesis, including semantic search, search result ranking, product categorization and stock prediction. Chapter 3 - 6 present our work on addressing those aforementioned four problems. In Chapter 3, we present a novel term weighting scheme to better assess text similarity thus improve the product search accuracy. In Chapter 5, we use a time series model to predict daily sales of products and used a search result reranking algorithm based on sale prediction to increase the revenue of the company. In Chapter 6, we describe the product categorization competition we held on an online platform and present some state-of-the-art solutions regarding to our real-world problem. In Chapter 7, we follow our study on time series and present our work on predicting S&P stocks using various machine learning algorithms. Finally, Chapter 8 gives a summary of this thesis as well as discusses on directions for future work.

13. http://www.eurekahedge.com/

CHAPTER 3

LITERATURE REVIEW

A year spent in artificial intelligence
is enough to make one believe in God.

Alan Perlis

3.1 Semantic search and term weighting

Today, Google and other search engines are smarter than ever and has penetrated into every aspect of our lives. They look after tracks we leave on the Internet and use artificial intelligence to process those data and rank information to our own taste. But the Internet was not always so easy to navigate. There was a time when you had to know the exact wording of some content to be able find it. Accurately interpreting the meaning of a search query has been and still is a major topic for researchers in the field of semantic search.

Term weighting, by placing high weight on terms containing important information within a search query, is one of the techniques to improve query interpretation accuracy, which, in return, improves the over-all accuracy of a search engine. Term weighting is built upon the Vector Space Model (Salton and McGill, 1986), where each document is represented by a bag of words vector with one component in the vector for each dictionary term. The term weighting scheme *tf-idf* (Spärck Jones, 2004) is a commonly used scheme in Information Retrieval. The "idf" part of the scheme is based on the assumption that rare terms are more relevant than frequent ones. Such assumption, although relevant in a large amount of situations (Roul et al., 2014; Paik, 2013), does not always hold in the context of e-commerce. Therefore in Chapter 4, we present a novel term weighting scheme tailored to the need of e-commerce companies. Our proposed scheme is based on in-depth analysis of user purchase record. Using such user feedback information, implicit or explicit, has been commonly acknowledged to be able to boost the performance of search engines (Baeza-Yates and Maarek, 2012; Balakrishnan and Zhang, 2014). As a result, various types of user-system interactions have been incorporated to improve search experience of users (Ruthven, 2008). Query log is an important source of information as it provides signals of what people are searching for and what they have found appealing through some user interaction data. Various types of information revealing user interest can be exploited:

1. Time. The amount of time a user spend on a web page is often used to filter out irrelevant clicks. It is reasonable to incorporate the dwell into account to better interpret events like clicks (Kim et al., 2000; Kelly and Belkin, 2004; Ramachandran, 2005).

2. Click sequence. Clearly users do not click at random, but make a (somewhat) informed choice. While click-through data is typically noisy and clicks are not "perfect" relevance judgments, the clicks are likely to convey some information (Agichtein et al., 2006; Veilumuthu and Ramachandran, 2007; Craswell and Szummer, 2007).

3. Click position. Clicks often suffer from positional bias where highly ranked items get more clicks than poorly ranked ones regardless of their relevance to the given search. Click position can thus help us to better interpret the click stream registered in the log

database (Joachims, 2002; Xue et al., 2004; Agichtein et al., 2006).

4. Click through rate (CTR). Click through rate is the ratio of total clicks over total impressions. It's often used in online advertisement domain to measure the effectiveness of an ad. It's also shown to be useful in log data analysis to improve search engine performance (Ramachandran, 2005; McDonnell, 2014).

It is also worth noticing that these logs have also been shown to be useful for a multitude of applications outside of search result ranking. For example, in spelling correction (Ahmad and Kondrak, 2005), user behavior modeling (Dupret and Piwowarski, 2008; Guo et al., 2009; Wang et al., 2010).

Furthermore, eye tracking data (Buscher et al., 2012; Cutrell and Guan, 2007; Li et al., 2015; Buscher et al., 2010) and cursor movement (Chen et al., 2001; Rodden et al., 2008; White and Buscher, 2012) constitute an additional information source to improve the search query interpretation accuracy, thus user experience overall.

3.2 Search result ranking

While semantic search and term weighting are crucial for a search engine to understand user's search intention and retrieve accurately relevant information, how to rank those results to better fit the business objective of a company is another essential issue, especially in the domain of e-commerce. For example, when a user search for "Television", it is indeed important to correctly get all the televisions from our product database, but the issue of choosing which one to be placed ahead has not been tackled yet while having a significant financial implication for the business.

Some previous studies have already addressed such issue using click data and have shown promising results in improving document search (Joachims et al., 2005; Agichtein et al., 2006) and image search (Jain and Varma, 2011) performance. In Chapter 4, we exploit purchase data improve product search performance via a collaborative filtering framework. We further, In Chapter 5, propose a more sophisticated reranking strategy built upon the prediction on daily sales of a product using time series prediction. However, when click data is largely used to decide which search result to present, a particular attention needs to be paid on positional bias. The probability of an item being clicked depends not only on its relevance, but on its position in the results page. The effect of such bias has been confirmed in numerous papers (Craswell et al., 2008; Yue et al., 2010). Moreover, input search query can often be ambiguous to some extent, which makes the system even more difficult to infer the user's search intention. In fact, when the user's actual information need is uncertain, relevance estimations may be misguided,

leading to a complete retrieval failure and the abandonment of the query (Chen and Karger, 2006), which is crucial for most business. How relevant the document is in light of the multiple possible information needs underlying the search query (Spärck-Jones et al., 2007) and in light of the other retrieved documents (Clarke et al., 2009) should also be taken into account for ranking purpose. As for evaluating ranking performance, various metrics have been proposed. Some commonly used ones include *precision@k*, MAP, NDCG (Wiener, 1956; Croft et al., 2010) along with their derivatives (Liu et al., 2007; Voorhees, 2003). However they are not tailored to our e-commerce scenario where the objective is often to maximize the revenue generated through search engine. Therefore in our study, in Chapter 5 a novel metric *revenue@k* is proposed. It measures average percent revenue generated by the top k displayed products.

3.3 Product categorization

Categorization or classification is the problem of identifying to which of a set of categories, a new observation belongs, on the basis of a training set of data containing observations whose category membership is known. The problem has been widely studied in the domain of data science and artificial intelligence and has many applications already changing our daily lives, such as email spam classification (Pantel et al., 1998; Blanzieri and Bryl, 2008; Yu and Xu, 2008) and disease prediction (Cruz and Wishart, 2006; Kaundal et al., 2006; Chen et al., 2017).

On-line retailers are also interested in such technology and are attempted to automatically put their products into the correct category to increase their visibility and, in return, improve user engagement and satisfaction. In Chapter 6, we present our challenge to the data science community to use the state-of-the-art algorithms predicting the category of a product based on its textual description and image on a large dataset retrieved from Cdiscount. Text based and image based classification are subjects actively followed by researchers of related fields. In (Yang and Liu, 1999), various kinds of text classification algorithms are reviewed. Many of the classification algorithms have been implemented in different software systems and are publicly available such as BOW toolkit (McCallum, 1996), Mallet (McCallum, 2002), NLTK (Bird, 2006) and WEKA [1]. Probabilistic classifiers, such as Naive Bayes, have gained a lot of popularity recently and have shown to perform remarkably well (Joachims, 1996; Koller and Sahami, 1997; Larkey and Croft, 1996; Sahami et al., 1998) where Bayes rule is used to classify new examples and select the class that is most likely has generated the example (McCallum et al., 1998). Support Vector Machine is another family of classification algorithms that has been commonly used in text classification. Initially introduced in (Cortes and Vapnik, 1995; Vapnik and Kotz,

1. http://www.cs.waikato.ac.nz/ml/weka

1982), SVM is robust against high dimensionality which makes it popular in classifying text, indeed in text mining dimension can be as large as multiple dictionaries of languages (Hotho et al., 2005; Joachims, 1998).K-Nearest-Neighbors has also been observed in some studies to classify textual data (Han et al., 2001; Rezaeiye et al., 2014; Sebastiani, 2002). Decision tree along with its derivatives Random Forest and Boosted Trees are also commonly used in text classification and often report highest accuracy among other models (Johnson et al., 2002; Xu et al., 2012; Schapire and Singer, 2000). All of those aforementioned algorithms can be found in our top competitors solution presented in Chapter 6 and combining various models together is another way to further improve the accuracy of classification as reported in Chapter 6. Image based classification can also be beneficial for e-commerce companies and a recent classification competition launched by Cdiscount was solely based on product images [2]. With the recently development of deep learning, promising results have been reported in various studies (Chan et al., 2015; Krizhevsky et al., 2012). Particularly, in (Ciregan et al., 2012), the author built a deep neural network and was the first to achieve a near human performance of classification accuracy on the public MNIST dataset. With this recently launched competition, we are expecting to see further improvement on the state-of-the-art image classification research.

3.4 Stock prediction

Stock market has long been characterized by its dynamic, complicated, and non-stationary nature (Fama, 1965). Market movements are dependent upon various factors ranging from political events, firms policies, economic background, commodity prices, exchange rates, movements of other stock markets to psychology of investors (Gidofalvi and Elkan, 2001; Committee, 2013).

In addition, the Efficient Market Hypothesis (Peters, 1996) assumes that asset prices are fair and adjust quickly to reflect all past and present information, which implies that future stock price movements are independent from pending and past information and should therefore follow a random walk pattern. If this hypothesis were true, then any attempts to predict the market would be fruitless (Taylor, 2008). If there is to be one "father" of the EMH, this man is Eugene Fama, who remains an outspoken proponent of the hypothesis to this day (Fama, 1965; Malkiel and Fama, 1970; Fama, 1991). The hypothesis has been tested extensively across various markets. The results are, however, sometimes contradictory. Many early work support the random walk model (Alexander, 1961). "There is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis", as said by Jensen (Jensen, 1978). However, modern studies (Fama, 1991; Gallagher and Taylor, 2002)

2. https://www.kaggle.com/c/cdiscount-image-classification-challenge

on stock markets reject the random walk behavior of stock prices and a substantial number of market inefficiencies or "anomalies" has been documented (Palan, 2004).

Besides the efficient market hypothesis, there are two schools of thought regarding stock market predictions: fundamental analysis and technical analysis. Fundamental analysis (Dechow et al., 2001) consists of evaluating the *intrinsic value* of a stock by examining the financial condition of a company. However, the proponents of the EMH argue that the intrinsic value of a stock is always equal to its current price. Technical analysis, on the other hand, is a study of the market itself. Technical analysts believe market action tells everything, so price and trading volume time series are enough for prediction tasks. Since market driving forces (i.e., human psychologies) hardly change, the prices are then considered to be recurrent and predictable since history always repeats itself.

Recently development on Artificial Intelligence has drawn attention from both practitioners and researchers of stock market. Artificial neural network is one of the most promising model used by researchers to predict stock movement (Guresen et al., 2011; Bahrammirzaee, 2010; Naeini et al., 2010; Ticknor, 2013), because, theoretically ANN can approximate any nonlinear function to an arbitrary degree of accuracy with a suitable number of hidden units (Hornik et al., 1989). Other models including SVM (Lin et al., 2013; Sands et al., 2015; Kazem et al., 2013; Yuan, 2013), Random Forest (Ballings et al., 2015; Patel et al., 2015; Khaidem et al., 2016) etc. have also been extensively studied for the stock prediction tasks. Attempts combining various approaches to improve prediction accuracy have also been made (Huang et al., 2008; Lee, 2009; Żbikowski, 2015; Patel et al., 2015) resulting in promising results.

In addition, social media offers a powerful outlet for people's thoughts and feelings. It is an enormous ever-growing source of texts ranging from everyday observations to involved discussions. Using sentiment analysis to extract emotions and opinions from text will serve as another importance source of information and has been pursued actively by researchers of the field (Medhat et al., 2014; Nguyen et al., 2015; Kearney and Liu, 2014; Azar and Lo, 2016). Taking Twitter as an example, in (Skuza and Romanowski, 2015), Twitter messages are retrieved in real time using Twitter Streaming API and a classification model built on Naive Bayes algorithm is proposed to predict future stock price based on analysis of twitter data. The author in (Pagolu et al., 2016) applied sentiment analysis and various supervised machine learning algorithms to tweets extracted from twitter API and analyzed the correlation between stock market movement of company and sentiments in tweets. Both results are promising.

CHAPTER 4

AN ENTROPY-BASED TERM WEIGHTING SCHEME AND ITS APPLICATION IN E-COMMERCE SEARCH ENGINES

E-commerce search engines play a crucial role for large online retailers. Indeed, a large number of purchases are derived from searches. It is now widely acknowledged that pure content based indexation techniques are less efficient than hybrid approaches taking user feedback into account to rerank the output. Purchase data is a valuable source of feedback, arguably less noisy than other sources, such as clicks: the fact that money is spent, is interpreted as a strong signal of interest for the purchased object. Unfortunately, a large portion of queries, which we refer to as "rare queries", have unavailable or insufficient associated purchase information. In that case, following ideas from neighborhood-based collaborative filtering, we introduce a similarity function between queries. The main contribution of this paper consists in defining a new weighting scheme based on entropy that seems to work well in practice. This claim is backed up by numerical experiments where the proposed entropy based approach outperforms tf-idf weighting on real e-commerce purchase data.

4.1 Introduction

The majority of e-retailers rely on a search engine for the customers' sake to find the most relevant products. Therefore search engines have become a vital tool for the e-commerce industry. A now widely acknowledged procedure to boost the performance of a search engine consists in incorporating users feedback information in its design (Baeza-Yates and Maarek, 2012; Balakrishnan and Zhang, 2014). In particular, in the context of e-commerce, purchase data is a useful feedback. They are a collection of pairs having the form $\langle \texttt{query}, \texttt{product} \rangle$, where `product` corresponds a purchase made just after `query` has been submitted, if any. It is indeed arguably less noisy than other feedback sources, such as clicks because it involves monetary transactions (Parikh and Sundaresan, 2008). However, purchase data can be challenging to exploit, for mainly two reasons. Firstly, the vast majority of queries are unique, *i.e.* they do not appear elsewhere in the database. Secondly, a given user at a given time rarely buys many products: purchase data are extremely sparse (a few products among millions are associated to a given query).

In order to deal with such highly valuable but sparse data, a certain amount of *regularization* is needed. A popular way of performing such regularization is the so-called "collaborative filtering" (Herlocker et al., 1999). Roughly speaking, it consists in suggesting products not only associated with the given query, but also associated with other *similar* queries. The starting point is therefore a similarity function between two queries. There are basically two ways of comparing queries. The first way is to compare queries *via* the products purchased after them. For instance, `query` "Apple tablet" and `query` "Ipad" are similar in the sense that they usually yield the same purchases; although their content, *i.e.* the terms they are made of, are not similar. The second way is to compare their constituting terms. In this line of thoughts, it is important not to give the same weight to each term. Indeed, some terms are more informative than others. For instance query "sony black ps4" is closer to `query` "promo ps4" than to `query` "sony black smartphone", even though the it is not the order implied by the number of common words. In this example, giving more weight to the term "ps4" than to the term "sony" or "black" can solve the problem. This weighting is meaningful, as the term "ps4" is arguably more informative than the term "sony", as it, alone, can limit considerably the relevant products range while "black" and "sony" can be used to describe a wide range of other products.

The weighting scheme *tf-idf* (Rajaraman and Ullman, 2011) is a commonly used scheme in Information Retrieval. The "idf" part of the scheme is based on the assumption that rare terms are more relevant than frequent ones. Our claim is that the tf-idf scheme, although relevant in a large amount of situations (Roul et al., 2014; Paik, 2013), is not relevant in the context we

are interested in. In the tf-idf scheme, *rare* terms mean terms that do not appear frequently in the database, *whatever the purchases associated to them.* For instance, the term "ps4", that appears relatively frequently in the database, because the product "Playstation 4" is popular, is not considered as important as the term "color", which appears a little bit less in our database. We are interested in exact figures at this stage but more on conceptual matters. Let us argue that "color" is less informative than "ps4". Should one recommend a product based on the sole query "color" it would be a daunting task to make a good guess of what the user has in mind; whereas for "ps4", there is a good chance that the user is interested in a product related to "Playstation 4". In our proposed method, contrarily to the tf-idf weighting, we believe that the importance of a term should not solely be based on its number of occurrences, but should be mainly based on the diversity of purchases it has lead to. More precisely, we advocate that when the same term used in a large variety of purchases, it is less important than another term which is systematically associated to the very same purchase. Shannon entropy is a quantitative way to measure how much diverse a given term is. This is the reason why our proposed weighting scheme is based on entropy. We claim that this entropy-based weighting scheme gives interesting results in practice, compared to tf-idf; at least on our database. Notice that both methods are distinct not only on the exact formula used to compute the weights but also and more importantly on a conceptual ground, since tf-idf only uses the `query` database, while the entropy weighting scheme uses both `query` and `product`.

The main contribution of this paper is to present a novel term weighting scheme suitable for e-commerce context and to the best of our knowledge, no such term weighting scheme has ever been proposed.

The rest of this paper is organized as follows. We first present the problem framework in Section 4.2. Then in Section 4.3, we introduce our entropy based term weighting scheme with its mathematical framework. Its application in e-commerce is described in Section 4.4 based on real-world data. Finally, in Section 7.8 we provide conclusions and directions of our future work.

4.2 Problem framework

4.2.1 Purchase data description

E-commerce purchase data is a valuable source of feedback information. Our purchase data is use consists of a set of $\langle q, p \rangle$ pairs where q is the last searched query before purchasing the product p. The entire data is further split into two sets: $\mathcal{D}$ as training set with cardinality D and $\mathcal{T}$ as test set with cardinality T. In addition, the product catalog of our database is denoted by $\mathcal{P}$.

Along with search query log, purchase data is capable of revealing the purchase intention of searchers. It is thus logical to re-rank the items that searchers really want to buy at top positions. However, a few challenges come along with purchase and need to be addressed.

1. Sparsity. Every query is related to a very small percentage of the product catalog. Indeed, the frequency of the queries is very small in comparison with the size of the product catalog.
2. Power-law distribution of query frequency. Very few distinct queries are very commonly seen and explain a large amount of purchases while a large number of very rare queries still account for a significant amount of purchases. This power law distribution of e-commerce query frequency has also been reported in (Parikh and Sundaresan, 2008). Furthermore, those rare or so called *long tail* queries are not less important than the frequent or so called *short head* ones for an e-commerce company (Goel et al., 2010).
3. New query. Queries without historical purchase data occur in a daily basis. Studies an anther e-commerce company show that a query-log of one day contains over 20% of new queries relative to a 4-months query log (Hasan et al., 2011). This observation is also confirmed on our data set.

In order to deal with these challenges, we used a *collaborative filtering* (Herlocker et al., 1999) based framework, commonly used in product recommendation systems, that we shall describe in the sequel.

4.2.2 Ranking with purchase data using similar queries

In our context of product searching, the idea of collaborative filtering is quite simple: if two queries are similar, we can use the purchases of one query to improve the product ranking of the other query. The ranking function we use is formulated in equation (4.1).

$$r(q,p) = \alpha \log s(q,p) + (1-\alpha) \sum_{q'} \mathrm{sim}(q,q') \log s(q',p) \tag{4.1}$$

where $s(q,p)$ denotes the number of purchases on product p using q as the last search query and the parameter α can be further tuned on training set. In order to apply this formula, one has to come up with a quantitative way to measure query similarity.

For frequent queries, the component $ps(q,p)$ in (4.1) is usually sufficient to generate high quality rankings, without the aid of similar queries. Moreover the Pearson coefficient on purchase data can further be applied to measure similarity between two frequent queries and two queries are similar if they share many common purchases. It can, indeed, identify similar queries with no terms in common, like “ipad” and “apple tablet”, but it is not applicable on new queries since no previous knowledge is available for those queries.

Lexical similarity, also called *term matching*, is commonly used in the field of information retrieval. By regarding each query as a *bag of words*, a straightforward way to compute query similarity is to normalize the number of terms that occur in both queries. Let $\{q\}$ denote the set of terms composing the query q. Some commonly used similarity metrics are listed as follows.

1. $\text{sim}_{\text{Dice}}(q, q') = 2|\{q\} \cap \{q'\}|/(|\{q\}| + |\{q'\}|)$
2. $\text{sim}_{\text{Jaccard}}(q, q') = |\{q\} \cap \{q'\}|/|\{q\} \cup \{q'\}|$
3. $\text{sim}_{\text{Overlap}}(q, q') = |\{q\} \cap \{q'\}|/\min(|\{q\}|, |\{q'\}|)$
4. $\text{sim}_{\text{Cosine}}(q, q') = |\{q\} \cap \{q'\}|/\sqrt{|\{q\}| \times |\{q'\}|}$

However those similarity metrics work poorly for short text segments (Metzler et al., 2007) which is the our case since e-commerce search query length is around three in average. We will describe in the next section our proposed term weighting scheme to improve those lexical similarity metrics.

4.3 Our entropy based term weighting scheme

4.3.1 Importance of a term

Consider the search query "apple ipad" was just entered. The term "ipad" clearly carries most of the information contained in this query, as it alone can tell us what product is expected while the term "apple" can almost be considered as superfluous. When computing query similarities, we should consider queries sharing the term "ipad" be more similar to the query than those sharing the term "apple". Therefore "apple ipad" should be more similar to "ipad 128g" than "apple fuji". Notice that all three queries occur commonly on large e-retailers.

A convenient way to assess the importance of a term is to use the so-called *tf-idf* (Term Frequency - Inverse Document Frequency) term weighting scheme (Rajaraman and Ullman, 2011), which is universally applied in document retrieval. It is generally based on two assumptions.

1. *idf assumption*: rare terms are more relevant than frequent terms.
2. *tf assumption*: multiple occurrences of a term in a document are more relevant than single occurrence.

This scheme is perfectly relevant for large size documents, however, it is less relevant for e-commerce queries which are composed of three terms in average. Moreover, it is quite clear already that the "tf" component, *i.e.* the frequency within document/query, is nearly useless for e-commerce queries: a user rarely repeat a term in a query. Thus a term importance is solely based on its frequency in database. However in e-commerce query log, the best-seller products are highly demanded which makes the terms describing those product very frequent in database,

such like “ps4”, “fifa” etc. Those terms are thus heavily penalized by *tf-idf* weighting scheme while they still carry valuable information on what products are expected.

In the context of e-commerce, search engine users usually have a purchase intention in mind. The term importance could be related to its ability of telling us the searcher's purchase intention. Terms used in purchasing very various range of products should be less important than those used in purchasing a very narrow range of products. Therefore our basic idea is not to judge the importance of a term by its number of occurrences in the database, but by how dispersed are the purchases associated to it.

To turn this idea into a quantitative way, we employ the notion of Shannon's Entropy of a discrete random variable (Cover and Thomas, 1991), which we shall explicitly describe in the sequel.

4.3.2 Mathematical framework of entropy based term weighting

Recall the notion of Shannon's Entropy of a discrete probability distribution (Cover and Thomas, 1991). Given a probability distribution π on a finite set I, the Shannon Entropy is defined as:

$$H(\pi) \stackrel{def}{=} -\sum_{i \in I} \pi_i \log \pi_i \tag{4.2}$$

Now, to each term t, associate the following probability distribution, referred to as *term purchase distribution*:

$$\pi_t = \frac{1}{Z_t} \sum_{\langle q,p \rangle \in \mathcal{D}_N} \mathbb{I}\{t \in q\} \delta_p \tag{4.3}$$

where δ_p denotes the probability distribution with all its mass on product p and Z_t, corresponding to the number of purchases associated to t is a normalization term such that π_t be a probability distribution over $\mathcal{P}$.

For a term t, its entropy $H(t)$ is then defined as

$$H(t) \stackrel{def}{=} H(\pi_t) \tag{4.4}$$

As a specific example, table 4.1 shows a small sample of purchase log and the table 4.2 describes purchase distributions of the related terms.

Query	Product
hp printer	p_1
hp printer	p_2
hp 3050a	p_1
hp pc	p_3

Table 4.1 – A sample of purchase data log

	p_1	p_2	p_3
hp	$\frac{1}{2}$	$\frac{1}{4}$	$\frac{1}{4}$
printer	$\frac{1}{2}$	$\frac{1}{2}$	0
3050a	1	0	0
pc	0	0	1

Table 4.2 – Purchase distributions of terms

The entropy of terms in the previous sample can be calculated as follows.

$$\begin{aligned} H(hp) &= -\tfrac{1}{2}\log(\tfrac{1}{2}) - 2 \times \tfrac{1}{4}\log(\tfrac{1}{4}) = \tfrac{3}{2} \times \log 2 \\ H(printer) &= -2 \times \tfrac{1}{2}\log\tfrac{1}{2} = \log 2 \\ H(3050a) &= -\log 1 = 0 \\ H(pc) &= -\log 1 = 0 \end{aligned} \tag{4.5}$$

In average, frequent terms have higher entropy values than rare ones since the maximum entropy of a term is the logarithm of its frequency. Nevertheless, term frequency is not the determinant factor of its entropy. In fact, among frequent terms, those with dispersed purchase distribution have higher entropy values than those with concentrated one. For instance, purchase distribution of "hp" and "3050a" generated using our training set are presented in figure 4.1 with pie chart. We can clearly see that the purchase distribution of "hp" is extremely dispersed while that of "3050a" is relatively concentrated, which explains the higher entropy value of the former.

(a)$H(hp) = 5.79$ (b) $H(3050a) = 1.05$

Figure 4.1 – Term purchase distributions of 'hp' and "3050a".
On the one hand, the purchase distribution of "hp" is extremely dispersed, which is indicated by the diversity of colors in the pie chart (a). Hence a high entropy is assigned to "hp". "3050a", on the other hand, has a relatively concentrated purchase distribution (b), which explains its low entropy value.

So far, we have seen that term importance is inversely related to its entropy. We further apply an exponential transformation on entropy to quantify importance of a term with the following term weighting scheme.

$$w_{entropy}(t) = \exp(-\lambda \times H(t)) \tag{4.6}$$

The smoothing parameter λ can be further tuned by cross validation on training set. It is worth noticing that our weighting scheme takes values in $(0, 1]$. The lowest weight occurs on terms

with extremely dispersed purchase distribution. In our data set, "femme" and "homme", *i.e.* "woman" and "man" in English, have the lowest weights since a very large range of diverse products are associated to them.

In what follows, we shall show our our proposed term weighting can be used to improve query similarity metric and to be applied in e-commerce product search.

4.4 Application of the proposed scheme and experimental evaluation

4.4.1 Entropy-based query similarity metrics

Query similarity metric is the key element of our collaborative filtering framework employed in (4.1). It is well acknowledged that lexical similarity metrics performs poorly when queries in question are extremely short (Metzler et al., 2007), which is precisely our case where the average length of a search query in e-commerce is around three. Techniques based on query reformulation are proposed in various papers (Yang et al., 2014; Parikh et al., 2013) to rewrite a query into a more meaningful form before any further processing. Our proposed approach keeps the original form of a query and assigns different weights to different terms based on their term entropy defined previously in order to highlight the most important ones in a query so that query similarity relies mainly on the most important terms. Roughly speaking, for a given pair of queries q and q', our entropy based weighting consists in normalizing $\sum_{t\in q\cap q'} w_{entropy}(t)$ instead of $|\{q\}\cap\{q'\}|$ in lexical similarity metrics. For example, recall that Jaccard similarity metric is $\text{sim}_{\text{Jaccard}}(q,q') = |\{q\}\cap\{q'\}|/|\{q\}\cup\{q'\}|$, then the corresponding entropy weighted Dice similarity metric is defined as

$$\underset{\text{EntJaccard}}{\text{sim}}(q,q') \overset{def}{=} \frac{\sum_{t\in q\cap q'} w_{entropy}(t)}{\sum_{t\in q\cup q'} w_{entropy}(t)}$$

Similarly, computation of entropy weighted similarity metrics of Dice, Overlap and Cosine is straightforward.

In our numerical experiments, we implemented all those four entropy weighted similarity metrics into our ranking function (4.1).

In order to demonstrate the effectiveness of our entropy based term weighting scheme, we conducted numerical experiments on real e-commerce data. We shall begin by presenting our experiment setting, then follow by introducing the evaluation metric we use to compare different algorithms. Experiment results will also be analyzed in detail latter in this section.

4.4.2 Experiment setting

We extracted purchase data from a major e-commerce company for a given period. The entire purchase set was further split into a training set of 1,000,000 samples and a test set of 100,000 samples. Each sample consists of a $\langle q, p\rangle$ pair, where q is the last searched query before purchasing the product p. As we worked on a French corpus, each query was passed through a query pre-processing procedure. It consists of French accent removal, stop-words removal, special character replacement by space, lower-casing and stemming. We used Porter's stemmer (Porter, 2001) to aggregate syntactically similar queries. It allows to alleviate term plurality and French gender mismatching issue. For example the term "chères" is stemmed to "cher" and "tables" is stemmed to "tabl". It helped to reduce about 5% of our term dictionary size and thus increased the accuracy of our term weighting scheme.

4.4.3 Evaluation metric

We employed our ranking function (4.1) to rank all the products for each query in the test data after tuning the parameters α using training set. In our experiments, the optimal α is found at 0.8.

In order to compare performance of different ranking functions, there are several well known metrics (Croft et al., 2010): MAP, NDCG, or simply the Precision@r metric which is the one we use. In our context where a test set $\mathcal{T}$ consisting of pairs "query/product", $\langle q, p\rangle$ is given, the metric is defined by:

$$\text{Precision@}r(f_r) = \frac{1}{T} \sum_{\langle q,p\rangle \in \mathcal{T}} \sum_{i=1}^{r} \mathbb{I}\{f_r(q)_i = p\} \tag{4.7}$$

where f_r is a function returning the top ranked r products by ranking function (4.1) for each input query q. Notice that Precision@r depends on r. Consequently, it may happen that a given search engine performs better at a given r but worse at another r'. In that case, using integrated metrics such as MAP can help. However, it is going to turn out in our experiments that such a sophistication is not needed.

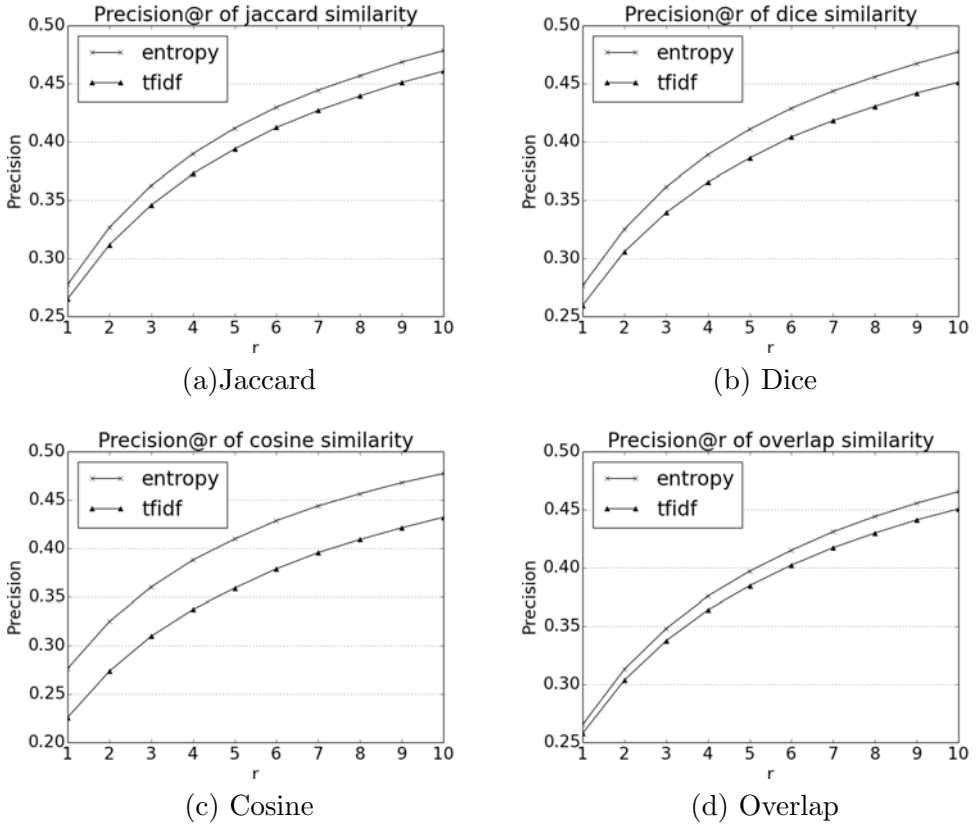
4.4.4 Results and analysis

We implemented four similarity metrics, Jaccard, Cosine, Dice and Overlap using two term weighting schemes: *tf-idf* and our proposed entropy based in ranking function (4.1). Notice that the *tf* term, i.e. the term frequency within query, is nearly useless for e-commerce queries: a user rarely repeat a term in a query. In consequence, the *tf-idf* term weighting scheme takes the

following form.

$$w_{tfidf}(t) = \log(\frac{D}{|\{(q,p) \in \mathcal{D} : t \in q\}|})$$

Experimental results using Precision@r metric with different values of r are presented in figure 4.2. We observe that entropy-based term weighting outperforms *tf-idf* on all similarity metrics implemented at all values of r.



(a)Jaccard (b) Dice

(c) Cosine (d) Overlap

Figure 4.2 – Performance comparison of entropy-based weighting and tf-idf weighting using different basic similarity metrics. X-axis is the number of allowed recommendations, corresponding to the parameter r of (4.7). Y-axis is the Precision@r value.

Some detailed analysis are conducted. Comparing to *tf-idf* which assigns constantly higher weight to rare terms and lower weight to frequent terms, our entropy based term weighting scheme share some common points but also differs in some others. Rare terms have, in average, a low entropy value thus high importance since the maximum entropy value of a term positively depends on term frequency. But if a frequent term has a relatively concentrated distribution such like "galaxy3", it can still have a relatively low entropy value, thus high importance. Only terms with high frequency *and* dispersed purchases are considered not important. Some examples are presented in table 4.3.

Moreover since terms describing best-sellers occur quite often, high frequency terms could be more important than less frequent ones. For example, the term "ps4" is more frequent than the

Term	Entropy	Explanation
hp	5.8	high freq., dispersed purchases
galaxy3	0.69	high freq., concentrated purchases
cn046a	0.5	Low frequency

Table 4.3 – Examples of term entropy

term "black" in our query log, however the former is clearly more informative than the latter about what products the user is looking for, see table 4.4.

term: t	$w_{entropy}(t)$	$w_{tfidf}(t)$
term: sony	1	1
term: ps4	840	1.25
term: black	8.05	1.30
term: promo	4.95	1.57
term: smartphone	8.2	1.4

Table 4.4 – Examples of entropy-based term weighting with $\lambda = 2$ and tf-idf term weighting. Both schemes are normalized on the weight of "sony" in order to have a relative view of term importance.

sony black ps4	Jaccard	tf-idf	entropy
sony black smartphone	0.5	0.46	0.01
promo ps4	0.25	0.24	0.98

Table 4.5 – Similarities with "sony black ps4" on different metrics

Let us take the query "sony black ps4" as an example. It is more similar to "sony black smartphone" than to "promo ps4" using tf-idf, in accordance to table 4.5, which is controversy to our intuition. Entropy-based weighting reveals that "ps4" is far more informative than others as most queries containing "ps4" end up with purchasing a play station 4. Thus "promo ps4" is considered as very similar to "sony black ps4" regardless of the number of terms in common.

4.5 Conclusion and future work

We have seen in this paper that the measuring similarities between queries was an important issue, at the core of higher level tools, such as collaborative filtering. After having reviewed a popular weighting scheme, namely tf-idf, which is based on the idea that corpus-wise rarest terms are the most important, we introduced a brand new weighting scheme. This novel weighting scheme is based on the idea that the importance of a term cannot be decided on its number of occurrences in the database alone. Rather, term importance, as we defined it, is based on how concentrated were the purchases it lead to. This notion was implemented through the

computation of term entropy that we defined in this paper. Numerical experiments, performed on real-world purchase data, showed encouraging results of our entropy-based term weighting over *tf-idf*. Detailed analysis were also conducted to explain the obtained results. Many questions still remain open. The term weighting scheme we defined in this paper is indifferent to the containing query, such that the same term has the same importance in different queries. Therefore we may consider it as a global term weighting scheme. By weighting each term conditionally to its containing query, a local term weighting scheme could be envisaged in the aid of the notion: conditional entropy. This idea will be carried on in our future work.

CHAPTER 5

RERANKING STRATEGIES BASED ON FINE-GRAINED BUSINESS USER EVENTS BENCHMARKED ON A LARGE E-COMMERCE DATA SET

As traditional search engines based on the text content often fail to efficiently display the products that the customers really desire, web companies commonly resort to reranking techniques in order to improve the products' relevance given a user query. For that matter, one may take advantage of fine-grained past user events it is now feasible to collect and process, such as the clicks, add-to-basket or purchases. We use a real-world data set of such events collected over a five-month period on a leading e-commerce company in order to benchmark reranking algorithms. A simple strategy consists in reordering products according to the clicks they gather. We also propose a more sophisticated method, based on an autoregressive model to predict the number of purchases from past events. Since we work with retail data, we assert that the most relevant and objective performance metric is the percent revenue generated by the top reranked products, rather than subjective criteria based on relevance scores assigned manually. By evaluating in this way the algorithms against our database of purchase events, we find that the top four products displayed by a state-of-the-art search engine capture on average about 25% of the revenue; reordering products according to the clicks they gather increases this percentage to about 48%; the autoregressive method reaches approximately 55%. An analysis of the coefficients of the autoregressive model shows that the past user events lose most of their predicting power after 2–3 days.

5.1 Introduction

The recent growth of on-line retail industry has made on-site product search engine a salient part of e-commerce companies. Product search is not only a problem of significant commercial importance, it also raises fundamental research questions at the intersection of natural language processing, machine learning and information retrieval. The catalog of products of the largest companies can reach millions – if not tens of millions – of items, while user queries are typically made of very few words carrying limited semantic content. This greatly hampers the performance of traditional search engines based on text retrieval, in terms of conversion of the displayed results to purchases. Many companies thus opt for strategies to rerank the products using additional sources of information, in order to achieve better user satisfaction and larger revenue.

Fortunately, sophisticated tracking systems and 'big data' technologies now make it feasible to collect, store and process all user paths of the form:

$$\text{query} \rightarrow \text{click on product} \rightarrow \text{add-to-basket} \rightarrow \text{purchase},$$

over the whole site. It is then straightforward to build indicators with a granularity at the product level following a user query: e.g., number of clicks, add-to-basket and purchases per date. These numbers can directly serve the reranking purpose, if one argues that relevant products are simply those most likely to be viewed or purchased. This purely user behavior-based point of view leads to simple and objective reranking strategies, but it is not exempt from criticism. For instance, some products (such as erotic items) are likely to attract many curiosity clicks, and could therefore end up polluting many otherwise unrelated queries. Nevertheless, we believe that the use of past user events has the potential to improve conversion rates on e-commerce websites.

Previous studies discussed reranking strategies based on click data to improve retrieval of relevant web documents (Joachims et al., 2005; Agichtein et al., 2006) or images (Jain and Varma, 2011). Jiao et al. (2015) exploited purchase data to improve product search performance via a collaborative filtering framework. In the present work we had access to a real-world data set of click, add-to-basket and purchase events collected over a five-month period from Cdiscount, a leading French e-commerce company. Based on this, our objective is to quantify the improvements brought by reranking strategies on top of a state-of-the-art semantic search engine using the BM25 statistics (Robertson et al., 1995). The most straightforward strategy consists in re-ordering products according to the clicks they gather over a fixed period after a user query: this follows the philosophy of previous works, applied to different contexts (Joachims et al., 2005; Agichtein et al., 2006; Jain and Varma, 2011). We further propose a more sophisticated

method that combines the three aforementioned types of event within an autoregressive model to predict the number of purchases. To the best of our knowledge, this work represents the first effort to benchmark reranking algorithms on real-world data set within an e-commerce context, and that exploits all the major types of implicit user feedback for that matter.

As for the performance metric on which the algorithms shall be evaluated, we believe that it is unnecessary for it to rely on subjective, human assigned relevance scores (as in, eg, Liu et al., 2007; Voorhees, 2003) Since we work with retail data, we argue that the most relevant and objective performance metric is the average percent revenue generated by the top k displayed products, or *revenue@k*, which can be seen as a natural extension of the widely used *precision@k* (Wiener, 1956). The data large e-commerce companies have at their disposal are largely sufficient to compute meaningful estimates of *revenue@k*.

The rest of this paper is organized as follows. Section 5.2 describes the data set used in this study. Section 5.3 introduces reranking strategies, which include BM25 similarity (Robertson et al., 1995), crude methods based on collected clicks, purchases or revenue, and our proposed autoregressive model fitted on all types of event. Section 5.4 deals with the evaluation metric, *revenue@k*. Section 5.5 gives the results and discussion related to the benchmarking of reranking methods on the data set.

5.2 Data set

The raw data set was provided by Cdiscount, a leading online retailer in the French market: it consists of navigation logs and sale records over a period of 150 days from July 1st, 2015 to November 27, 2015, and contains several millions of distinct user queries per month. As can be expected, purchases are extremely unevenly distributed amongst the queries: Fig. 5.1a shows a long tail of queries concentrating a large number of purchases approximately following a power law. We focus this work on the top 1000 queries, which generate a significant part of all purchases made through the search engine (Fig. 5.1b).

The raw data contain a large amount of information related to user navigation through the website. We pruned and simplified the data structure in the following way. First, we only considered three types of event related to a product following a typed query: click, add-to-basket and purchase. "Negative" feedback events such as remove-from-basket or purchase abandon could also provide useful information, but we believe they would only marginally improve the reranking strategies. Second, we processed navigation sessions containing multiple searches by assigning the last typed query to each observed event: we thus obtained a list of more than 21 million pairs $\{\text{query}, \text{product}\}$ labeled with a time stamp and an event tag: click, add-to-

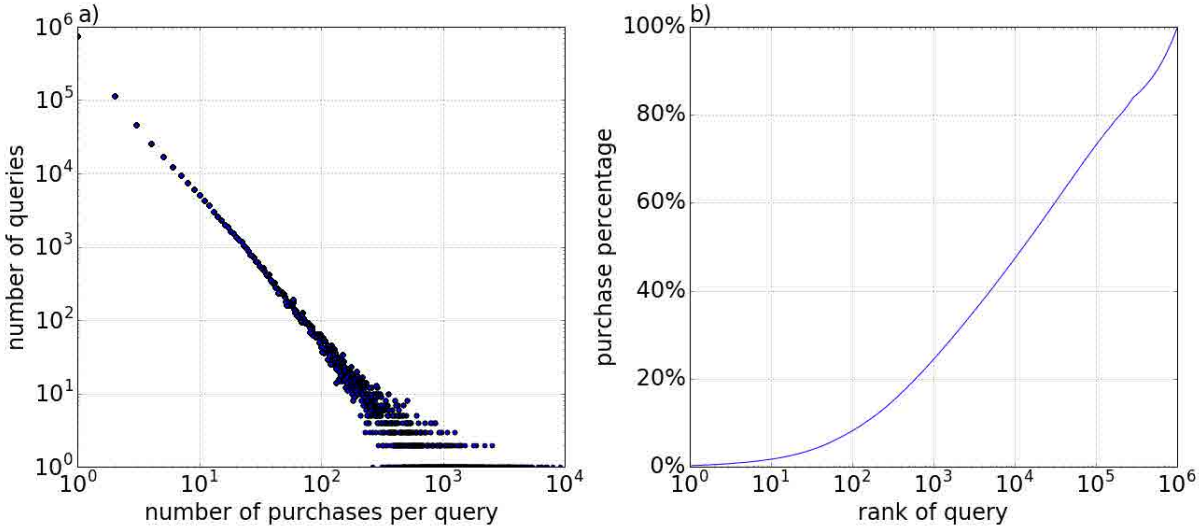


Figure 5.1 – (a) Distribution of the purchases by query; (b) cumulative percentage of purchases associated with queries (queries generating most purchases first).

Table 5.1 – Summary of the final data used in this study

150	days
1000	distinct queries
746,884	distinct products
21,450,377	user events[1]

[1]clicks, add-to-basket, purchases

basket or purchase (see Table 5.1 for a summary of the final data set). It is then straightforward to count the number of each type of event associated with a given query and product at the desired temporal granularity: an example is given in Fig. 5.2.

5.3 Reranking strategies

Queries typed by users in e-commerce search engines are typically extremely short and carry little semantic content (Singh et al., 2012). Traditional engines looking for products whose description best match the queries' keywords often fail to display the relevant products, i.e. those most likely to be purchased, because there are too many matches. For example, it is difficult to distinguish semantically amongst *iPhone 4*, *iPhone 5* and *iPhone 6* with respect to the query 'iPhone'. This is a particularly salient point, because customers are less and less inclined to crawl through pages of results until they reach the product they desire (Spink et al., 2002b) and, given the number of e-commerce actors, may simply turn to a competitor.

Many web companies thus resort to *reranking* strategies, wherein additional information (such as popularity, price or sales) is integrated to reorder the displayed items. The ecommerce-specific data presented in section 5.2 prove of valuable help for that matter: as mentioned in the

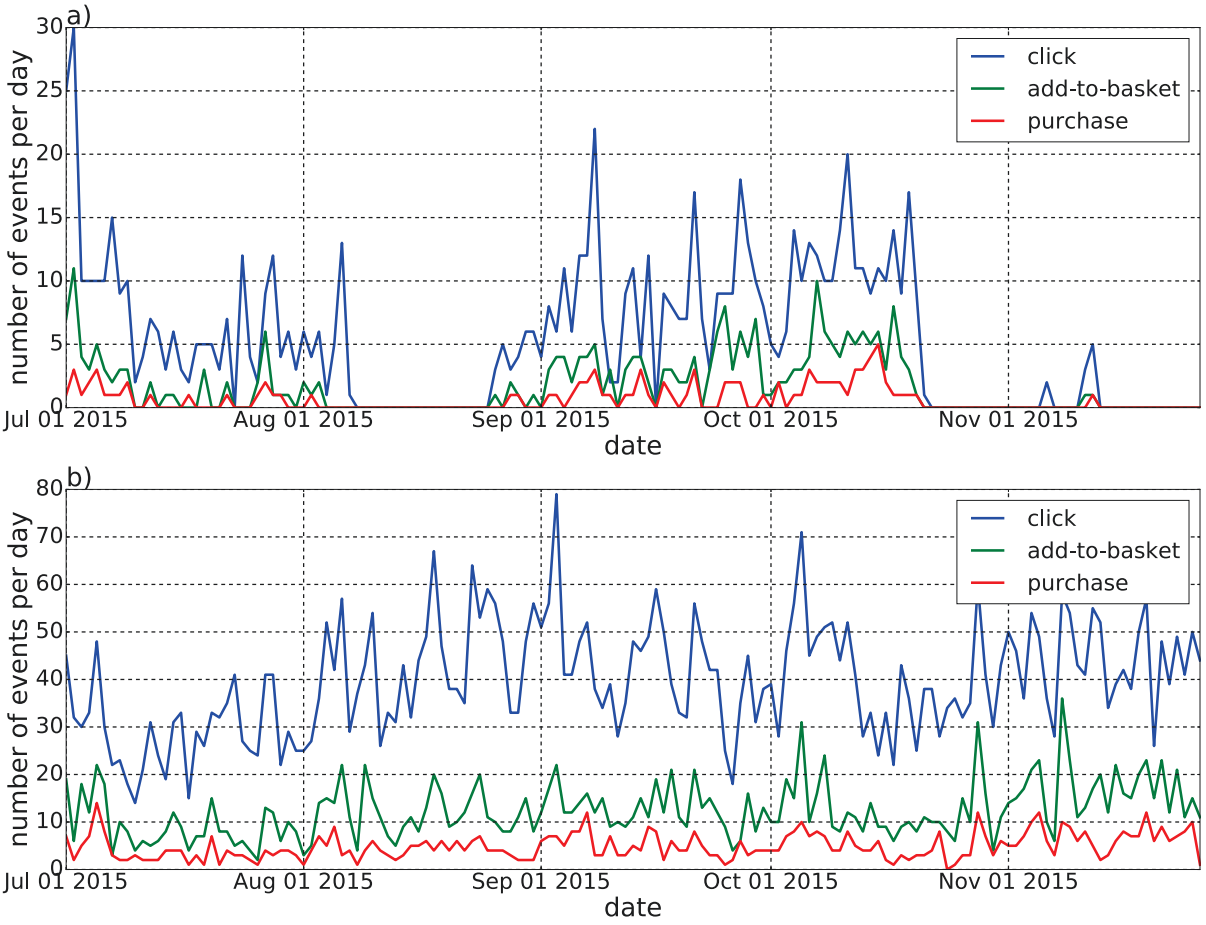


Figure 5.2 – Examples of times series of number of clicks, add-to-basket and purchases per day related to two different products following the user query 'printer'.

introduction, one can follow previous works (Joachims et al., 2005; Agichtein et al., 2006; Jain and Varma, 2011) and simply use clicks gathered by products. We also included for comparison a random and a BM25 (Robertson et al., 1995) ordering, and we finally implemented a more sophisticated method based on an autoregressive model.

Specifically, for a given user query, we started with the list of top 28 products returned by Cdiscount internal search engine. We then defined the following strategies to reorder these products:

1. *random reordering*, which any method should outperform.
2. *BM25*: BM25 (Robertson et al., 1995) is considered as a state-of-the-art similarity metric, so we used it as reference text-based ranking technique.
3. *reranking by click*: products are ordered by decreasing number of views collected after the query over a recent period. Previous works used user clicks to better retrieve relevant web documents or images (Joachims et al., 2005; Agichtein et al., 2006; Jain and Varma, 2011), so it is natural to extend this approach to the e-commerce context.
4. *reranking by multivariate auto-regression*: products are ordered by decreasing revenue, deduced from an autoregressive model fitted on the three types of event described in section 5.2. The model is described in detail in the next section.

5.3.1 Reranking by multivariate auto-regression

Several points should be raised to justify the choice of a more sophisticated reranking model. First, since e-commerce business is more interested in maximizing the revenue than the number of views, the former quantity should guide the reranking strategy. However, the number of purchases is a weak signal (Fig. 5.2 and Table 5.1) so it is not optimal to use it as a sole predictor for the revenue; it is desirable to make use of the number of clicks and add-to-basket as well, as these signals are much stronger and highly correlated to the purchases (Fig. 5.2). Finally, one may apply a temporal weighting scheme to penalize old signal rather than define a fixed period window; such a weighting scheme should ideally reflect the autocorrelation structure of the data, and not *a priori* subjective choices.

These considerations led us to select the vector autoregression (VAR) model (Hamilton, 1994) in order to predict the number of purchases of a product following a given query from past time-series of clicks, add-to-basket and purchases. Specifically, we start with the following

multivariate time-series:

$$\mathbf{N}(t) = \begin{bmatrix} n_{\mathrm{c}}(t) \\ n_{\mathrm{a}}(t) \\ n_{\mathrm{p}}(t) \end{bmatrix}, \tag{5.1}$$

where t represents the date and $n_{\mathrm{c}}(t), n_{\mathrm{a}}(t), n_{\mathrm{p}}(t)$ the number of clicks, add-to-basket and purchases related to some product after a query, respectively. The VAR model then describes the evolution of $\mathbf{N}(t)$ as a linear function of its past values:

$$\mathbf{N}(t) = \sum_{i=1}^{P} \mathbf{A}_i \mathbf{N}(t-i) + \mathbf{E}(t), \tag{5.2}$$

where $\mathbf{A}_i$ is a time-invariant matrix containing the coefficients of the linear relation between the signal and itself for a time lag of i, and $\mathbf{E}(t)$ represents Gaussian noise. The maximum time lag, P, is called the order of the process.

The matrices $\mathbf{A}_i$ can be estimated from a least square fit on the observed signal including a ℓ_1 (or Lasso) regularization which seeks to minimize:

$$\sum_t \left\| \mathbf{N}(t) - \sum_i \mathbf{A}_i \mathbf{N}(t-i) \right\|_2^2 + \lambda \sum_i \|\mathbf{A}_i\|_1 ., \tag{5.3}$$

where $\|.\|_2$ denotes the Euclidean norm and $\|.\|_1$ the $\ell 1$-norm. The parameter λ, which controls the regularization strength, is optimized using a three-fold cross-validation procedure, and takes typical values between 0.2 and 2. In the present work we estimated best-fitting matrices $\mathbf{A}_i$ for each pair $\{\mathrm{query}, \mathrm{product}\}$, but one may alternatively choose to aggregate signals by making one fit per query, or even one single global fit on all available pairs. This can be of interest in a production environment to save computational time and rerank queries associated with few events.

It is straightforward to use the VAR model for the reranking purpose. First, the products' number of purchases after a given query is predicted from past series from Eq. (5.2). The price is then taken into account to reorder the products associated with the query by decreasing predicted revenue.

5.3.2 Granger causality test

Before we proceed with the evaluation metric, it is worth verifying whether the time series we included in the VAR model are really able to forecast future purchase. Granger causality test (Granger, 1969) is a statistical hypothesis test that can help answer this question. A time series $X(t)$ is said to Granger-cause $Y(t)$ if $Y(t)$ can be better predicted using the histories of

both $X(t)$ and $Y(t)$ than it can by using the history of $Y(t)$ alone.

Explicitly speaking, one can test for the absence of Granger causality by estimating the following VAR model:

$$Y(t) = \alpha_0 + \sum_i \alpha_i Y(t-i) + \sum_i \beta_i X(t-i) + \mu(t) \tag{5.4}$$

We define the following null hypothesis:

$$H_0 : \beta_1 = \beta_2 = \cdots = \beta_p = 0. \tag{5.5}$$

A rejection of H_0 implies there is Granger causality.

We selected at random 1000 pairs of $\{\text{query}, \text{product}\}$ from our data set and performed Granger causality tests on both click and add-to-basket signals against purchase signal. The null hypothesis was rejected on over 98% of the pairs examined. Most of the unrejected cases correspond to less popular queries and products with negligible signals and accordingly large confidence intervals.

5.4 Evaluation metric

Ranking algorithms are often evaluated with the *precision@k* metric, which is the average proportion of relevant items amongst the top k results. This metric relies on the availability of a labeled test data set wherein human annotators decide which items are relevant with respect to a user search (e.g. Liu et al., 2007; Voorhees, 2003). However, there is no such data set publicly available in the e-commerce area, and manually assigning relevance scores on our data would be prohibitively time-consuming. Besides, human scores may suffer from severe inconsistencies, as annotators can have different relevance judgment with respect to the same item (Agrawal et al., 2009). Finally, relevance in the e-commerce context is highly volatile, as the desired products after a given query can vary from a period to another. For example, the relevance of the *iPhone 5* product with respect to the query 'iPhone' is likely to collapse when the *iPhone 6* is released.

We therefore argue that a better metric in the e-commerce context should be guided by the increase in revenue generated by the reranked items. After all, it is better to adopt a customer-oriented relevance score, directly related to the probability of purchase. Specifically, as a natural extension of the *precision@k* metric, we propose the *revenue@k* metric, which measures the percent revenue generated by the top k items of the search results, relative to the list of 28 products:

Table 5.2 – Evaluation scores of the reranking algorithms according to the *revenue@k* metric.

	Estimated revenue generated by:	
	top 4 products	top 8 products
Random	14.6%	29.3%
Solr/BM25	24.8%	39.2%
Reranking by click[1]	48.4%	67.8%
VAR model	54.7%	76.1%
Upper limit	88.3%	98.8%

[1]aggregated over the 30 days preceding the test date

$$revenue@k = \frac{\sum_{\text{queries}} \text{revenue of the top } k \text{ products}}{\text{total revenue}}. \tag{5.6}$$

In the present work, the *revenue@k* metric serves to evaluate the reranking strategies outlined in section 5.3.

5.5 Results and discussion

We benchmarked the reranking strategies described in section 5.3 over a 7-day test period, from November 21th to November 27th, 2015. The reranking-by–click strategy aggregated the number of click events over a 30-day interval ending at the day before each test date, and reordered accordingly the list of products associated with each query. The VAR model described in section 5.3.1 was fitted on all available time series, i.e. number of clicks, add-to-basket and purchases per day, from the first available day (July 1st, 2015) until the day before each test date. This allowed making a prediction for the number of purchases at the test date and, together with the products' price, to reorder them by decreasing predicted revenue.

The algorithms were then evaluated using the *revenue@k* metric (section 5.4), which calculates the percent revenue generated by the top k reranked products relative to the list of 28 products, averaged over the queries and over the testing dates, using the data set of purchase events (section 5.2). Fig. 5.3 and Table 5.2 show the performance of the reranking strategies according to that metric; they also display the upper limit of the revenue, which would be reached if one knew in advance the purchase events of the testing dates.

As is to be expected, the revenue is on average uniformly distributed amongst randomly ordered products, as shown by the linear trend in Fig. 5.3. A purely text-based strategy significantly improves the share of top ranked products: reordering the items according to their BM25 similarity (Robertson et al., 1995) with the query allows the the top 4 and 8 products to increase their share of the estimated revenue by about 70% and 30%, respectively, compared to a random ordering (Table 5.2). Logically, products best matching the search terms are more

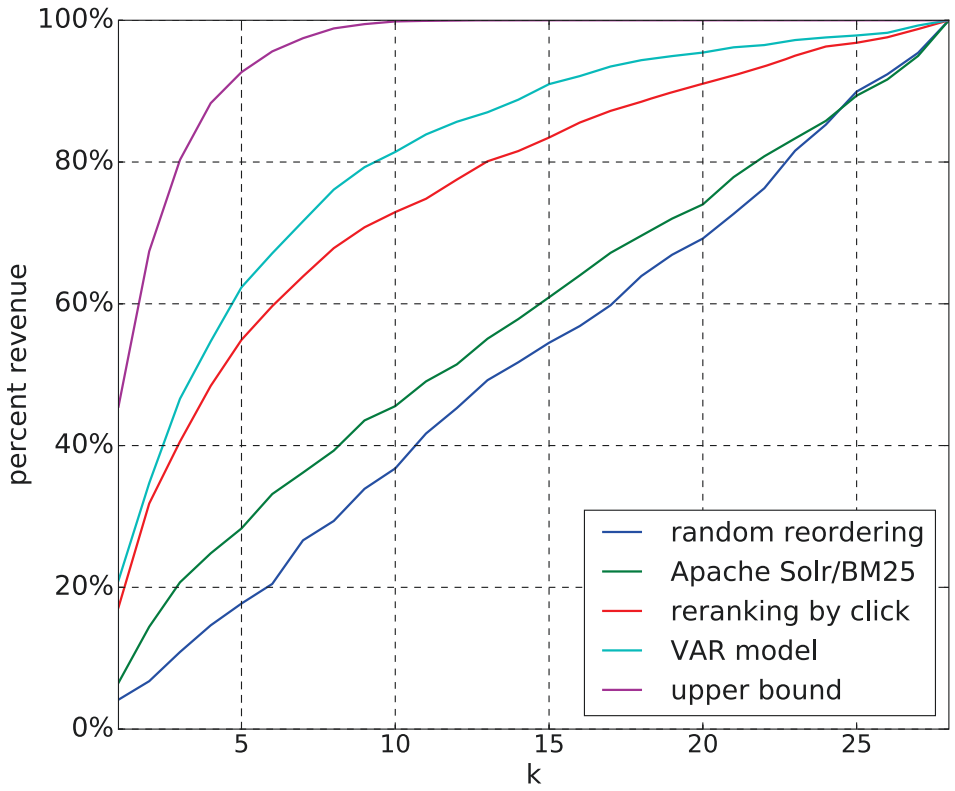


Figure 5.3 – Average percent revenue generated by the top k products (relative to the list of 28 products) of each reranking algorithm.

likely to end up purchased. However, a much stronger enhancement is achieved using past user events: crudely reordering according to the clicks aggregated over the last 30 days raises the estimated revenue of the top 4 and 8 products to approximately 48% and 68% of the total, respectively.

The VAR model achieves better results than all other strategies. Although the leap is not as impressive as that performed by the simple, click-based algorithm compared to the BM25, the improvement should not be overlooked: it increases the estimated share of the top 4 and 8 products by about 12–13%, thus reaching 62% and 77% of the upper limit (Table 5.2). Such a gain is likely to translate into significantly larger conversion rate and revenue in most e-commerce companies.

5.5.1 Analysis of the coefficients of the VAR model

Before we conclude, it is interesting to analyze the coefficients of the VAR model in order to better understand how the different types of events are related to the number of purchases, and how their predicting power decay with time. We are interested in the elements of the third line of the matrices $\mathbf{A}_i$, which correspond to the coefficients of the linear relation between (1) the daily number of purchases and (2) the daily number of clicks, add-to-basket and purchases

time-lagged by i (Eqs 5.1-5.2). Fig. 5.4 shows these coefficients, obtained by applying the VAR model to normalized time series, i.e. with zero mean and unit variance, and averaged over pairs of $\{\text{query}, \text{product}\}$ and testing days. The normalization procedure ensures that the differences between the values of the coefficients do not reflect the systematic differences in amplitude between the time series (e.g., Fig. 5.2).

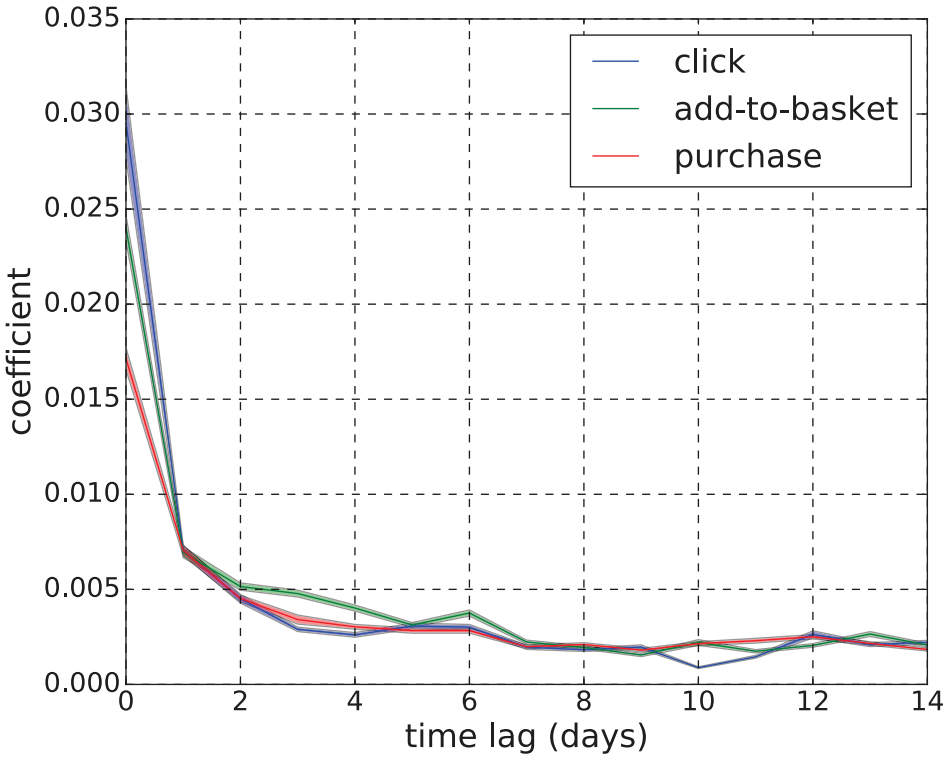


Figure 5.4 – Normalized coefficients of the VAR model related to the number of purchases, averaged over pairs of $\{\text{query}, \text{product}\}$ and testing days, function of time lag. Shaded areas show one standard error around the mean.

Interestingly, Fig. 5.4 suggests that clicks and (to a less extent) add-to-basket possess a stronger predictive power than purchases to forecast the latter time series. We believe that this is explained by the larger amplitude of the former time series which, together with their strong correlation with the latter signal, allow to anticipate finer tendencies of the purchases to come: a close inspection of Fig. 5.2a reveals that clicks without purchases sometimes precede a wave of purchase events.

As can be expected, events lose their predicting power as time lag increases. The typical decay time may seem rather short: fitting an exponentially decaying function show that the 99% of the decrease of the average coefficient associated with the number of clicks is achieved in about 2.8 days. This value is approximately 3.3 days and 4.5 days for the add-to-basket and purchases events, respectively. So, purchases retain predictive power over a longer time, probably because they are not as volatile as other events.

5.6 Conclusion

For the first time in the e-commerce context (to the best of our knowledge), several reranking strategies were benchmarked on a real-world data set of user events provided by a leading online retail company. We used an evaluation metric adapted to e-commerce data, which measures the percent revenue generated by the top k items of the search results.

A text-based reordering according to the BM25 similarity (Robertson et al., 1995) between the products' description and the query's keywords allows the top four products to capture on average about 25% of the query's revenue. This is much less than reranking products according to the clicks they gathered following the query over the last 30 days, which increases this percentage to about 48%. A linear autoregressive method forecasting the number of purchases from past time-series of daily clicks, add-to-basket and purchases further reaches about 55%. The strength of the latter approach lies in its implicit exploiting of correlation of all major user events with purchases, and of their decay in predictive power as time lag increases.

The present work thus showed how crucial to the business model reranking algorithms guided by past user events are. As future lines of improvement, one may suggest the use of nonlinear predictive model and/or the integration of additional types of event such as remove-from-basket or purchase abandon.

CHAPTER 6

THE CDISCOUNT 2015 DATASCIENCE.NET CHALLENGE: A LARGE E-COMMERCE DATA SET RELEASED TO BENCHMARK CLASSIFICATION METHODS

In 2015, Cdiscount challenged the community to predict the correct category of its products from some of their attributes such as their title, description, price or associated image. The candidates had access to the whole catalogue of active products as of May 2015, which accounts for about 15.8 millions items distributed over 5,789 categories, a subset of which served as testing set. The data suffers from inconsistencies typical of large, real-world databases and the distribution of categories is extremely uneven, thereby complicating the classification task. The five winning algorithms, selected amongst more than 3,500 contributions, are able to predict the correct category of 66–68% of the testing set's products. Most of them are based on simple linear models such as logistic regressions, which suggests that preliminary steps such as text preprocessing, vectorization and data set rebalancing are more crucial than resorting to complex, non-linear models. In particular, the winning contributions all carefully cope with the strong imbalance of the categories, either through random sampling or sample weighting. A distinguishing feature of the two highest-scoring algorithms is their blending of large ensemble of models trained on random subsets of the data. The data set is released to the public, as we hope it will prove of valuable help to improve text and image-based classification algorithms in a context of very large number of classes.

6.1 Introduction

E-commerce companies have become major actors of the retail business over the past decade (Turban et al., 2015). As the product catalog of the largest companies now routinely exceeds several millions of distinct items, a large part of which from third-party sellers, and users are less inclined to crawl through pages of results (Spink et al., 2002a), a salient yet increasingly tough need consists in filling correctly the products' characteristics in order to efficiently guide the customers towards the products they desire. It is clear that purely manual procedures are precluded, so one must rely on algorithms based on the description or image of the products.

In 2015, the leading French e-commerce company Cdiscount challenged the community on the datascience.net platform on a simple, real-word question: how can one guess the category of a product from its description, its image and other available attributes? The participants had access to Cdiscount's catalogue of active products, a subset of which had their category hidden to serve as testing set and evaluate the candidates' algorithms, thus turning the problem into one of supervised classification. Cdiscount released the data set to the public to be used as a practical benchmark and encourage improvements over text and image-based classification algorithms.

The contest was held between May–August 2015 and attracted over 800 participants. In the present paper we describe the underlying data set (Section 6.2), the challenge and evaluation criteria (Section 6.3) and the solutions proposed by the winning candidates (Section 6.4).

6.2 Data set

The data set consists of about 15.8 millions of products, which represents virtually the whole catalogue of Cdiscount as of May 2015. Each product is associated with a unique identifier, a three-level category, a title, a description, a brand, a seller (Cdiscount or third party) and a price (Table 6.1). Some products, owned and sold directly by Cdiscount itself, are also provided with a representative image in jpeg format as additional information. The total volume of text and image data is about 4 Gb and 1 Gb, respectively. As described hereafter, the data suffers from flaws and inconsistencies typical of large databases involving strong user interaction. Products do not necessarily have a brand, and their description is sometimes cut off, ending in this case with an ellipsis. The price is set to -1 for out of stock products, and can take unrealistically large values. More importantly, the category filled by third-party sellers is not as reliable as that of Cdiscount's products.

As a consequence, the vast majority of the populated categories are not strongly reliable, third-party sellers accounting for almost 95% of the database (Table 6.2). As can be expected,

Table 6.1 – Fields of the data set and examples of products (with associated image). Note that the description can end with an ellipsis.

Field		Examples	
Id		13110226	15572267
Title		Samsung LE32C450	Whirlpool AWOD2850 Lave-linge frontal
Category	level 1	1000010900 – TV - vidéo - son	1000003564 – Electroménager
	level 2	1000011032 – TV	1000003786 – Gros appareil lavage-séchage
	level 3	1000011035 – Téléviseur LCD	1000003789 – Lave-linge
Description		Téléviseur LCD 32" (82 cm) HD TV - Triple HDMI - Port USB multimédia - Résolution: 1366 x 768 - Contraste dynamique - Sublimateur de couleur - Dolb...	Lave-Linge 8.5 kg - Classe énergétique : A++ - Consommation d'énergie : 240 kWh/an - Consommation d'eau : 10800 Litres/an - Classe d'efficacité à l'essorage: B - 1200 tours/min.
Brand		Samsung	Whirlpool
Seller		Third party	Cdiscount
Price		389.99€	306.49€
Associated image		–	

Table 6.2 – Key numbers on the data set.

15,821,950	products
791,453	products sold by Cdiscount
15,030,497	products sold by third-parties
5,789	distinct categories
27,982	distinct brands

the ∼5,800 available categories are strongly unevenly distributed amongst the products: the distribution of the number of products per category approximately follows a power law, which exhibits a long tail of categories containing a large number of products (Fig. 6.1a). As a matter of fact, about 700 categories hold 90% of the products (Fig. 6.1b) and the largest one – smartphone covers – contains more than two millions items. Similar trends are observed for the distribution of the ∼28,000 brands (Fig. 6.1c) and of the descriptions' vocabulary (Fig. 6.1d) amongst the products.

It is interesting to focus on the distribution of the attributes amongst the categories (rather than the products), since the former shall be used to predict the latter. Fig. 6.2 shows that the distribution of the brands and of the vocabulary amongst the categories again approximately follow power laws. In other words, the distributions are characterized by long tails of brands

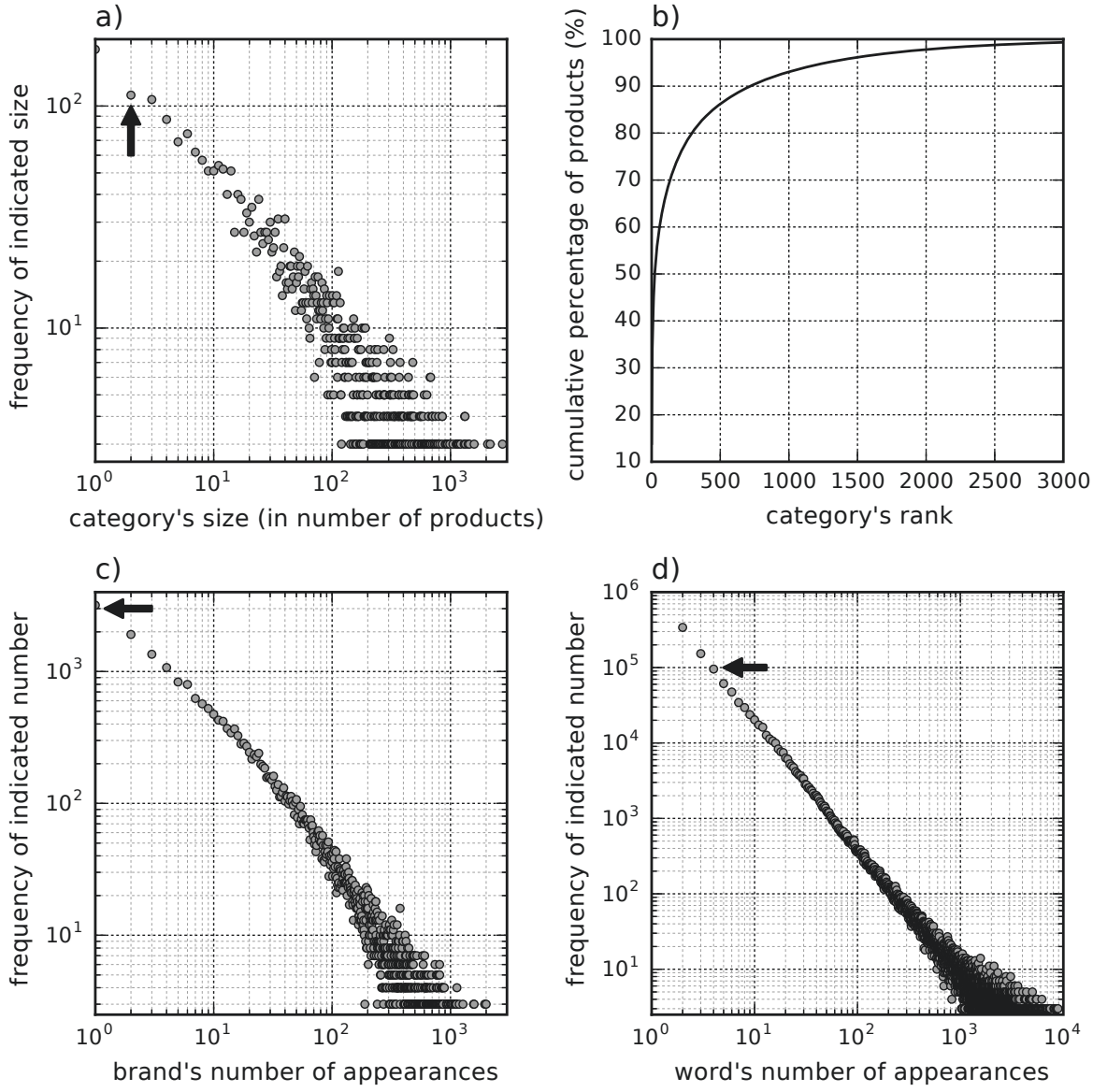


Figure 6.1 – (a) Size distribution of the categories: size corresponds to the number of products belonging to a category (e.g., the point shown by an arrow indicates that there are slightly more than 100 categories which contain only 2 products). (b) Cumulative percentage of products held by the categories, sorted by the number of products they contain. (c) Recurrence distribution of the brands: recurrence corresponds to the number of products associated with a brand (e.g., the point shown by an arrow indicates that more than 3,000 brands are represented by a single product in the catalogue). (d) Recurrence distribution of the words of the vocabulary used in descriptions: recurrence corresponds to the number of products wherein a word of the vocabulary appears (e.g., the point shown by an arrow indicates that about 10^5 words of the vocabulary appear in exactly 4 distinct products).

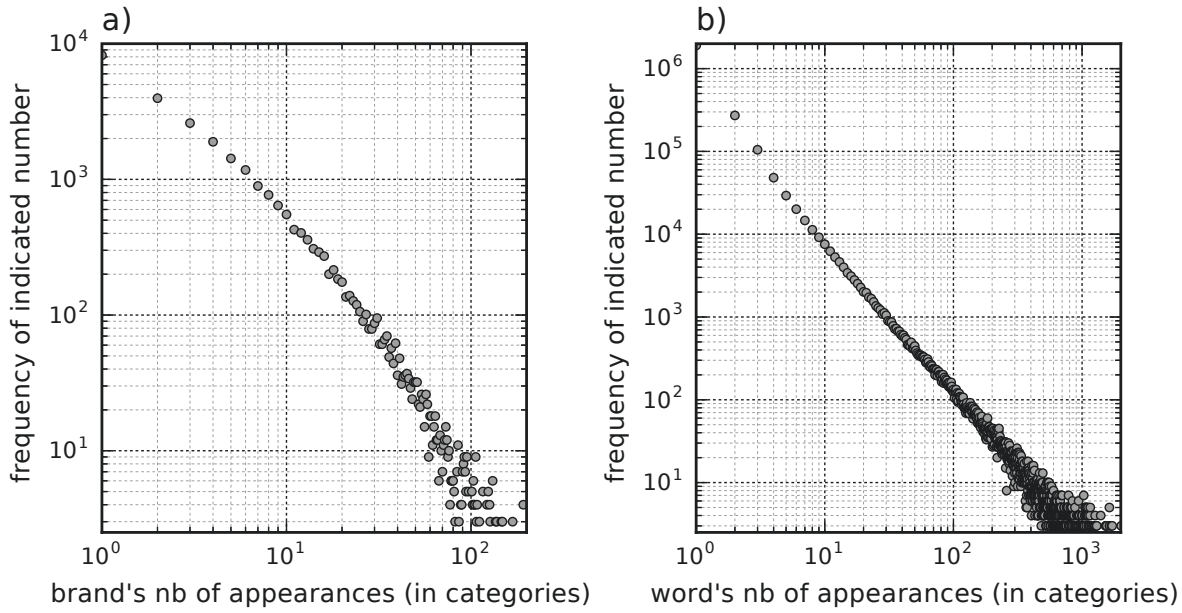


Figure 6.2 – (a) Recurrence distribution of the brands: recurrence corresponds to the number of distinct categories containing at least one product associated with a given brand. (b) Recurrence distribution of the words of the vocabulary used in product descriptions: recurrence corresponds to the number of distinct categories containing at least one product wherein a given word of the vocabulary appears.

and words that appear in many different categories: unsurprisingly, when taken individually, most of them are uninformative with respect to the product's category.

This section thus illustrates the kind of pitfalls and difficulties encountered when dealing with a large, real-world e-commerce data set of products. In particular, algorithms designed to predict the category have to cope with the strong unevenness of the distribution of the attributes amongst the products and categories as illustrated in Figs 6.1-6.2.

6.3 Description of the challenge

In 2015, Cdiscount offered a simple challenge on the datascience.net platform based on the data set described in the previous section: given a list of product attributes (title, description, brand, seller and price, see Table 6.1), what is its correct category? A subset of 35,065 products, the category of which was hidden, served to evaluate the prediction algorithms proposed by the candidates. We built this testing set by selecting exclusively products sold by Cdiscount, as the category filled by third-party sellers is considered not as reliable. As an evaluation metric, we

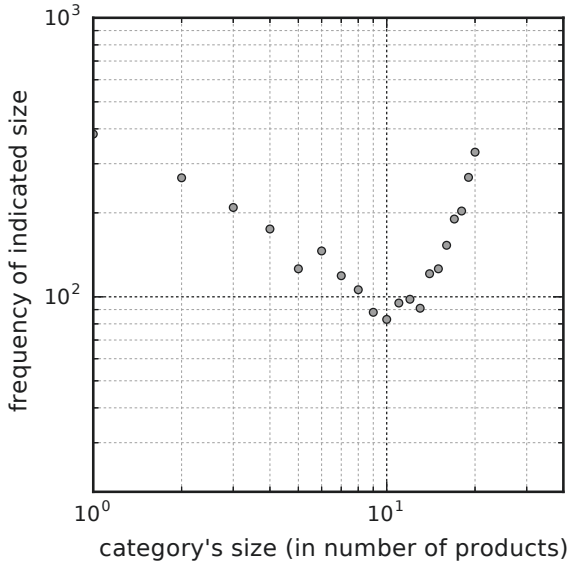


Figure 6.3 – Size distribution of the categories in the testing set: size corresponds to the number of products belonging to a category.

simply used the proportion of correct predictions:

$$\text{score} = \frac{1}{N}\sum_{i=1}^{N}\begin{cases}1 & \text{if } \hat{c}_i = c_i \\ 0 & \text{else}\end{cases}, \tag{6.1}$$

with N the size of the testing set and $\hat{c}_i, c_i$ the predicted and correct category of product i, respectively. Note that, in order to build up a testing set not too biased towards the most popular categories, no more than 20 products may belong to the same category. The resulting distribution of categories amongst the products (Fig. 6.3) consequently strongly differs from that of the whole data set (Fig. 6.1a).

The challenge attracted 838 participants who submitted 3,533 contributions. The five highest-scoring contributions were sent to a jury, which made the final ranking based on the score, quality and originality of the proposed solutions. The following section briefly describes the winning contributions, which received money prizes between 500€ and 9,000€.

6.4 Analysis of the winning contributions

The winning algorithms, mostly coded in Python or R, are able to predict the correct category of 66–68% of the products in the testing set (Table 6.3). The four best algorithms use linear models, mostly with a logistic loss function (Walker and Duncan, 1967). Interestingly, the

Table 6.3 – Summary of the winning contributions.

Rank	Score	Language/library	Method(s)
#1	68.3%	Python/scikit-learn	Logistic regression with stochastic gradient descent + multinomial naive Bayes + passive aggressive classifier
#2	68.0%	Python/scikit-learn	Two-stage logistic regression
#3	66.9%	Python, R, Vowpal Wabbit	Linear classifier with square loss function
#4	66.3%	Python/PIL, C++, Dataiku	Logistic regression
#5	66.3%	R/ConText	Three-stage convolutional neural network

square loss function also gives good results (contribution #3), although it is known to lack robustness against outliers. Two other linear classifiers appear in the winning contribution, namely, the passive aggressive classifier (Crammer et al., 2006) and the naive Bayes method (Zhang, 2004) with multinomial distribution of the features. The only non-linear model is the convolutional neural network (Johnson and Zhang, 2015a,b), which is used by candidate #5.

All the candidates concatenate at least the title, brand and description of the products to build input features. Candidate #2 applies larger weights to the title and the brand. Because of the large range of values it takes and the errors it contains, the price seems more delicate to include, but it nevertheless appears as input in two contributions (#1 and #3). In order to tackle the above-mentioned issues, the winner assumes that values above 10,000 actually correspond to thousandths of euros and uses as input the interval to which the price belongs, which takes a limited number of values. Only one candidate (#4) fully integrates the images, by associating with each product the category of the three nearest neighbours of its image, weighted by their inverse distance, as an additional input feature. Curiously, candidate #1 finds that simply appending a piece of text describing the image's geometry (rectangular or not rectangular) significantly improves the categorization of books.

As can be expected when dealing with large chunks of text data with potential inconsistencies, the candidates have to apply a variety of preprocessing techniques before the vectorization step. These usually include lower-casing, removal of stop words, conversion to plain ASCII text and word stemming. Some candidates additionally remove numbers, or replace them with generic strings such as —NUMBER— or —DIGIT—. Candidate #1 also prepends the preposition "for" (in French, "pour") to every following word in sentences where this preposition appears, in order to better differentiate accessories from the products to which they are associated. For example, for the product #1963634 whose title starts with BASEUS CABLE LIGHTNING FORMAT CLE USB POUR IPHONE IPAD IPOD, the tokens POUR_IPHONE, POUR_IPAD and POUR_IPOD are

appended to the text. Candidate #4 applies the same technique to a wider set of prepositions for the same reason, and adds the token START_BY_<WORD> to the text, where <WORD> is the first meaningful word of the title or of the description (i.e. not the brand, not a number...): the rationale behind this processing is that the beginning of the text often allows guessing the product's category. For example, for the product #5360298 whose title starts with DRONE X46 2,4GHz, the token START_BY_DRONE is appended to the text.

The vectorization step is then most often realized with the tf-idf statistic (Spärck Jones, 1972), wherein the concatenated text associated with a product is converted to a vector whose i^{th} element is proportional to the number of appearances of the i^{th} token of the corpus within the product's text, and offset by the frequency of the token in the corpus. Depending on the algorithms, tokens can be words (unigrams) or sequences of two consecutive words (bigrams). A simple word count is also applied to some of the models in contribution #1. Candidate #5 takes on a different approach that partly preserves the order of the words, wherein the text is split in successive regions of 15–20 contiguous words, and a word count is applied to each region.

In order to cope with the unevenness of the distribution of the categories outlined in section 6.2, most of the candidates resort to some form of stratified sampling (Cochran, 1953): in other words, subsets of the catalogue are randomly selected as training sets, with a limit of a few hundreds products per category and with replacement oversampling for underrepresented categories. Candidates #1 and #2 repeat this subsetting procedure several thousands of times and blend the predictions from the resulting ensemble of models, which we assume to be a key ingredient to their success. The winning algorithm actually goes a step further by (1) random parametrising several processing steps applied to the subsets (e.g., tf-idf or word count, word stemming or not, unigrams or bigrams...) and (2) including three families of classifiers in the ensemble of models (Table 6.3). Only candidate #3 chooses not to re-sample the catalog of products, but rather assigns them weights inversely proportional to the frequency of appearance of their categories.

As for the better reliability of the category of Cdiscount products (section 6.2), it is an information only two candidates take advantage of (#1 and #5): the former candidate specifically trains models on Cdiscount or third-party products and assigns them different weights in the final blend; the latter candidate explicitly gives priority to Cdiscount products in the stratified sampling step described in the previous paragraph.

Finally, candidates #2 and #5 use the three-level hierarchical structure of the categorization (see Table 6.1) to reduce ambiguity between categories belonging to different branches, by performing classifications by stage. The idea is to successively predict the category across the levels of the hierarchical tree from top to bottom. Candidate #2 trains logistic classifiers to get the

probabilities of belonging to the first-level categories, $P\left(\text{product} \in \text{cat}_1\right)$, and the conditional probabilities of belonging to the third-level ones, $P\left(\text{product} \in \text{cat}_3 \mid \text{product} \in \text{cat}_1\right)$, then applies the classical chain rule to estimate the desired marginal probabilities $P\left(\text{product} \in \text{cat}_3\right)$ as:

$$P\left(\text{product} \in \text{cat}_3 \mid \text{product} \in \text{cat}_1\right) \cdot P\left(\text{product} \in \text{cat}_1\right). \tag{6.2}$$

Candidate #5 goes through the three levels of categories and trains one neural network per category of a given level to predict the category of the next level.

6.5 Teaching materials

The shortage of data scientists has become a serious constraint across various sectors recently. Such explosion in demand results in an increasing amount of data science courses both through online platforms and in traditional schools. In those courses, it is often attempting for instructors to focus on the theoretical part of data science, therefore the data in use is often simulated or well prepared in advance. However, as we have seen through this challenge, data pre-processing and cleansing is one the most distinguished factors of the winning solutions. Higher data quality often brings more improvement in terms of prediction accuracy than more complicated modeling. We hope that our data could serve as a field training material for students after completion of related courses. They will not only have a chance of acquiring a deeper understanding of previously learned models but also be better prepared for solving real-world problems after graduation.

6.6 Conclusion

In this paper we gave statistical insights into the catalog of products of Cdiscount in order to highlight the kind of pitfalls and difficulties a classification algorithm applied to a real-world data set has to cope with. Specifically, the potential inconsistencies of the products' attributes, the varying reliability of the data, the large number of categories and the extreme imbalance of their distribution obviously complicate the classification task.

The five winning contributions of the datascience.net challenge are able to predict the correct category of 66–68% of the products in the testing set. Most of the algorithms are based on simple linear classifiers; in particular, the logistic regression appears in three contributions. When dealing with noisy, imperfect data, the preliminary processing steps thus appear to be more crucial than the choice of a complex, non-linear classifier. Another factor could be the bad scalability of such algorithms with respect to the number of classes, which is extremely large in our case. Preprocessing steps include text processing, vectorization and rebalancing of the

training data. The last point is particularly salient and was tackled by all the winning candidates, either through random stratified sampling to set up balanced training sets or by weighting training samples by the inverse of their categories' frequency of appearance. A distinguishing feature of the two most accurate algorithms is their training of ensemble of thousands of models on random subsets of the data, whose predictions are then averaged to get the final predicted category: we thus assume this to be a key ingredient to their success.

The whole data set is released to the public. The availability of a large, real-world catalogue of products with associated images and text attributes, together with benchmark results from the most accurate models to date, should prove of valuable help to the scientific community in order to improve over existing text and image-based classification algorithms in a context of very large number of classes.

Supplementary material

The data set described in this article is released to the public and can be obtained by contacting any of the authors affiliated with Cdiscount. Alternatively, the following mailing list may be used: datascience@cdiscount.com.

Acknowledgements

We thank the datascience.net team for hosting and helping us organize the 2015 categorization challenge.

CHAPTER 7

PREDICTING STOCK MOVEMENT DIRECTION WITH MACHINE LEARNING: AN EXTENSIVE STUDY ON S&P 500 STOCKS

Stocks movement direction forecasting has received a lot of attention. Indeed, being able to make accurate forecasts has strong implications on trading strategies. Surprisingly enough little has been published, relatively to the importance of the topic. In this paper, we reviewed how well four classic classification algorithms: random forest, gradient boosted trees, artificial neural network and logistic regression perform in predicting 463 stocks of the S&P 500. Several experiments were conduced to thoroughly study the predictability of these stocks. To validate each prediction algorithm, three schemes we compared: standard cross validation, sequential validation and single validation. As expected, we were not able to predict stocks future prices from their past. However, unexpectedly, we were able to show that taking into account recent information – such as recently closed European and Asian indexes – to predict S&P 500 can lead to a vast increase in predictability. Moreover, we also found out that, among various sectors, financial sector stocks are comparatively more easy to predict than others.

7.1 Introduction

Stock market has long been characterized by its dynamic, complicated, and non-stationary nature (Fama, 1965). Market movements are dependent upon various factors ranging from political events, firms policies, economic background, commodity prices, exchange rates, movements of other stock markets to psychology of investors (Gidofalvi and Elkan, 2001; Committee, 2013). In addition, the Efficient Market Hypothesis (Peters, 1996) assumes that asset prices are fair and adjust quickly to reflect all past and present information, which implies that future stock price movements are independent from pending and past information and should therefore follow a random walk pattern. If this hypothesis were true, then any attempts to predict the market would be fruitless (Taylor, 2008).

The EMH hypothesis has been tested extensively across various markets. The results are, however, sometimes contradictory. Many early work support the random walk model (Alexander, 1961). "There is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis", as said by Jensen (Jensen, 1978). However, modern studies (Fama, 1991; Gallagher and Taylor, 2002) on stock markets reject the random walk behavior of stock prices.

Besides the efficient market hypothesis, there are two schools of thought regarding stock market predictions: fundamental analysis and technical analysis. Fundamental analysis (Dechow et al., 2001) consists of evaluating the *intrinsic value* of a stock by examining the financial condition of a company. However, the proponents of the EMH argue that the intrinsic value of a stock is always equal to its current price. Technical analysis, on the other hand, is a study of the market itself. Technical analysts believe market action tells everything, so price and trading volume time series are enough for prediction tasks. Since market driving forces (i.e., human psychologies) hardly change, the prices are then considered to be recurrent and predictable since history always repeats itself.

In this paper, we took the technical analysis viewpoint and tried to predict stock market movements using historical stock prices and modern tools from machine learning and artificial intelligence. In other terms, we asked the following question: to what extent are market stock prices self predictable?

Technical analysts traditionally build compound features from historical data, called *technical indicators*, representing various aspects of a stock in order to exploit recurring patterns. Some commonly seen technical indicators include MA (moving average), RSI (Relative Strength Index), MACD (Moving Average Convergence/Divergence Oscillator), CCI (Commodity channel index) etc. In our study we regard the movement of each stock price as a time series and

perform extensive feature extraction to obtain over 200 features for each stock on a given time window. Similar to traditional technical indicators, our newly extracted features aim to capture different aspects of a stock thus reveal potential predictive power to stock movement.

We studied 463 stocks, which are constituents of S&P 500 index, with over 7 years of trading history. We examined several classification models: logistic regression, artificial neural network, random forest, and gradient boosted trees to predict the direction of tomorrow based on the information of today. We also evaluated the usefulness of 8 global market index, including 3 Asian index (Nikkei 225, Hang Seng, and All Ords), 2 Europe index (DAX, FTSE 100) and 3 US index (NYSE Composite, Dow Jones Industrial Average, S&P 500). It is worth noticing that Asian and Europe Markets close before US markets, therefore they can be used to provide additional information to predict stocks of US markets. In our numerical experiments, we first performed detailed feature selection revealing features with the most predictive power. Next we fine tuned 4 state of the art classification algorithms and compared their prediction performance on all of 463 stocks. Then we compared three different validation schemes for model selection and parameter tuning and confirmed the usefulness of time-aware cross-validation. Further on, we analyzed the predictability of stocks within different sectors and compared the prediction performance on stocks per sector, which could provide useful advise on stock investment. Last, we compared models with the one proposed in a recent and popular study on predicting S&P 500 index movements direction and verified the efficiency of our models.

In summary, our main contributions are the following:

1. The scope of our study is unprecedented in the existing literature, to the best of our knowledge. With 463 stocks and 8 index across the globe being analyzed, more than 200 technical indicators used as features, 4 state-of-the-art classification models involved, we conduct an extensive analysis and comparison of different prediction approaches.
2. We provide a publicly available notebook to make our study easily reproducible [1]. The data used in this paper is also provided in the project folder.
3. We highlight that data and feature selection play a key role in such prediction task whereas prediction performance improvement due to fine tuning remain insignificant.
4. We demonstrate that, for stock market price movement prediction, immediate past contains most of the signal.
5. We find that stocks within financial sectors are the most predictable ones with more than 10 point of prediction accuracy above the overall average.

The rest of this paper is organized as follows. In Section 7.2, we review some related works

1. https://github.com/skyjiao/stock_prediction_sp500

of our study. In Section 7.4, we formulate the stock movement direction prediction problem into a classic binary classification problem. In Section 7.5, we elaborate the time series features we create for each stock. In Section 7.6, we present our experiment design. We then follow by the result and analysis in Section 7.7. We finally conclude our study in Section 7.8.

7.2 Related Works

In recent years, there have been a growing number of studies looking at the direction of movements of various kinds of financial instruments. Both academia and practitioners have made tremendous efforts to predict future movements of stock market prices and devise financial trading strategies to translate forecasts into profits (Chen et al., 2003).

The emergence of machine learning and artificial intelligence algorithms has made it possible to tackle computationally demanding models for stock price movement direction prediction. In (Bahrammirzaee, 2010), the author shows that AI outperformed traditional statistical methods in dealing with various financial problems including credit evaluation, portfolio management and financial prediction/planning. In our study, we are interested in forecasting the direction of stock price movement. Naturally, an associated trading strategy takes a short position when direction is predicted to go down and a long position when the predicted direction is up. In (Lin et al., 2013), the author used 53 technical indicators to predict direction of three stocks and one index of Taiwan stock market with a SVM based approach and a prediction accuracy between 55% and 65%. In (Qian and Rasheed, 2007), the author tried to predict Dow Jones Industrial Average index using three models including DT, KNN, and NN. After selecting the most predicable period using Hurst exponent, the author restrained the scope of the study to this period and then performed a voting based ensemble methods to combine the result of those three models to achieve a better accuracy than any single classifier. In (Kara et al., 2011), the author used 10 technical indicators to predict Istanbul Stock Exchange National 100 Index (ISE) and reported an over 75% accuracy using neural network. In (Patel et al., 2015), the author tried to predict with 10 technical indicators the direction of stock movement for Indian stock market by using two stocks and two index as samples. Attempts of predicting stock movement without the use of technical indicators have also been made recently. In (Wang, 2014), the author tried to predict Korean and Hong Kong market using price data alone with SVM based approach preceded by a PCA to reduce the dimension of input features. In (Khaidem et al., 2016), the authors used Random Forest to predict stock direction of three stocks: Apple, Samsung and GE.

A recent survey (Zhang et al., 2017) compares 11 classification algorithms on 71 different

Stock group	S&P 500
Stock number	463
Start	Jan 2, 2009
End	Jun 30, 2017
Trading days	2139

Table 7.1 – Data summary

datasets and shows that Gradient Boosted Decision Tree (GBDT), followed by Support Vector Machine (SVM) and Random Forest (RF) are the most accurate among their competitors. It is also worth noticing that GBDT are rarely used in previous studies on stock direction prediction however the model shows its superior prediction capacity against other models in many recent Kaggle competitions [2]. Therefore, in our study, we include GBDT into our candidate list along with other most commonly used methods such as RF, ANN and Logistic Regression. SVM is excluded in our study because of its lack of capacity to naturally provide probability estimation of its prediction.

7.3 Data Description

This study focuses on US market consisting S&P 500 component stocks. Up to date, the S&P 500 stock market index, maintained by S&P Dow Jones Indices, comprises 505 common stocks issued by 500 large-cap companies and traded on American stock exchanges, and covers about 80 percent of the American equity market by capitalization.

All the data used in this study is publicly available from yahoo finance [3]. As shown in table 7.1, the whole dataset covers the period from Jan 2, 2009 to Jun 30, 2017, a total of 2139 observations recored at each trading day.

Only 463 among 505 stocks in S&P 500 have a complete trading history on the period and will thus be used in this study. The complete list of those 463 stocks are presented in Annex **??**.

Besides those stocks, we also use 8 global index as additional source of information. There are 3 Asian, 2 European and 3 American indices, as shown in Table 7.2. It is worth noticing that Asian markets and European markets close earlier than US markets. Therefore index of those foreign markets can be used to predict S&P 500 stocks of the same day, which is obviously not the case for index of US market.

For each asset i, stock or index, let r_t^i denote its daily log return at day t which is defined as:

$$r_t^i = \log \frac{c_t^i}{c_{t-1}^i}, \tag{7.1}$$

2. www.kaggle.com
3. https://finance.yahoo.com/

Index Name	Country	Closing Time (EST)	Hours Before S&P Close
All Ordinaries	Australia	0100	15
Nikkei 225	Japan	0200	14
Hang Seng	Hong Kong	0400	12
DAX	Germany	1130	4.5
FTSE 100	UK	1130	4.5
NYSE Composite	US	1600	0
Dow Jones Industrial Average	US	1600	0
S&P 500	US	1600	0

Table 7.2 – 8 global market index used as environment indicators

where c_t^i denote the close price of asset i at day t. Notice that r_t^i is positive when $c_{t-1}^i > c_t^i$ and nonpositive otherwise. Figure 7.1 shows the daily return of Apple, Amazon and Microsoft on our dataset.

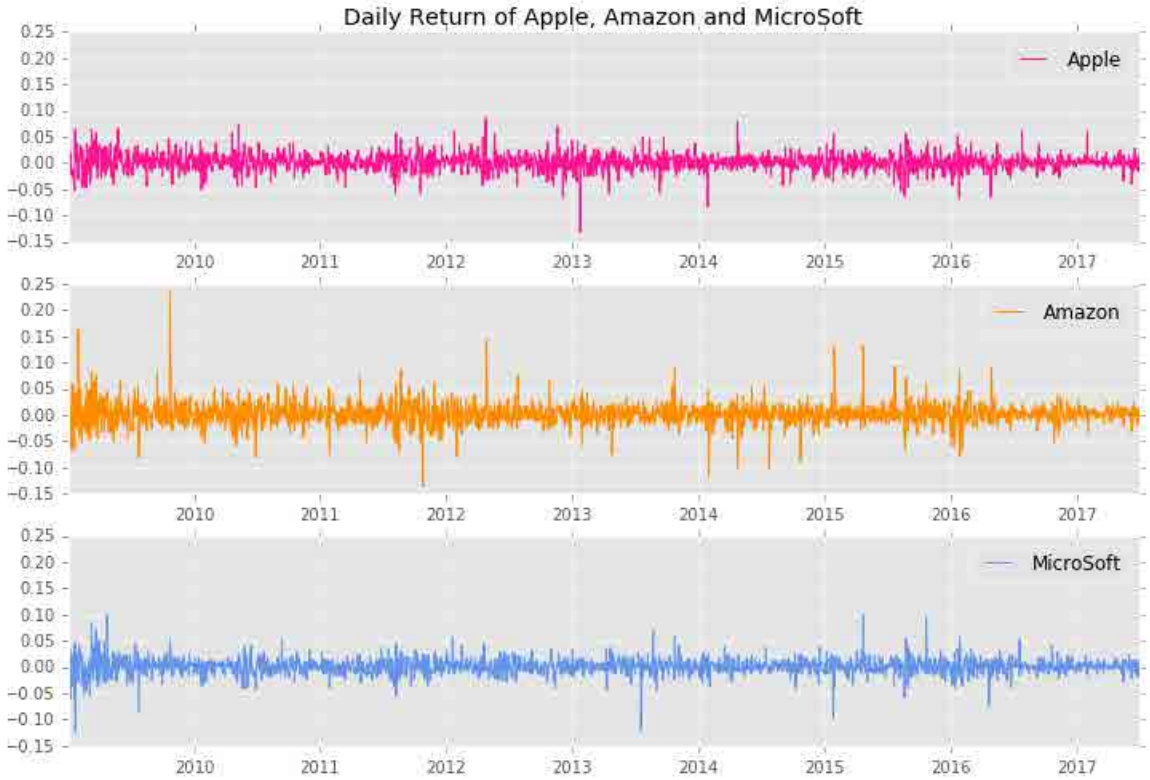


Figure 7.1 – Daily return of Apple, Amazon and Microsoft

7.4 Problem Formulation

In the current study, we are interested in predicting the direction of stock movement on a daily basis, *i.e.* the sign of r_t^i (please see Eq (7.1) for a definition).

Time series prediction is different from classic supervised machine learning where samples are assumed independent and identically distributed. Time series adds an explicit order dependence

between observations: time. This additional dimension is both a constraint and a structure that provides a source of additional information. An important aspect is that the future is always completely unavailable to make predictions.

Fortunately, time series prediction can be framed as a supervised learning problem, allowing standard linear or non-linear machine learning algorithms to be applied on it. And in our case, predicting the stock movement direction can be framed into a binary classification problem. We describe in the next section the features we use and the target we predict.

The task of a binary classification problem consists in deciding class membership y_u of an unknown data item x_u based on a data set of N samples $D = (x_1, y_1), \cdots, (x_N, y_N)$ of data items x_i with known class memberships y_i where $y_i \in \{0, 1\}$. The x_i are usually multidimensional vectors.

In most problem domains, there is no deterministic functional relationship $y = f(x)$ between y and x. In this case, the relationship between x and y has to be described more generally by a probability distribution $\Pr(x, y)$. From statistical decision theory, it is well known that the optimal decision is to choose the so-called *Bayes classifier* that maximizes the posterior distribution $\Pr(y|x)$ (Friedman et al., 2001).

For each given asset i, the response variable y_t^i is defined as follows:

$$y_t^i = \begin{cases} 1 & \text{if } r_t^i > 0 \\ 0 & \text{else,} \end{cases} \tag{7.2}$$

where r_t^i is the log return of the asset i at date t defined in Equation (7.1).

The multivariate input features x_t^i for each asset i at date t can be computed using any information available before the prediction moment. Different approaches for extracting input features x_t^i will be discussed in the next Section.

7.5 Time Series Feature Engineering

In general, the goal of feature engineering is to provide strong and ideally simple relationships between input features and the output variable for the machine learning algorithm to model.

Since our goal is to predict the next value to come based on previous values. In Section 7.4, we explained how stock movement direction prediction could be seen as a binary classification problem. Let us now explain what input features can be extracted to feed classification models.

One of the most natural time series features are the so-called *lag features*, which are values at prior time steps. For example, a simple approach to predict the value at the next time $t + 1$ is to built a model on its value at time $t, t - 1, t - 2, \cdots$.

Date	$\mathbf{r^t_{AAPL}}$	lag 1 feature	Lag 2 feature	Lag 3 feature
2009-01-02	0.061348			
2009-01-05	0.041338	0.061348		
2009-01-06	-0.016632	0.041338	0.061348	
2009-01-07	-0.021845	-0.016632	0.041338	0.061348
2009-01-08	0.018399	-0.021845	-0.016632	0.041338
2009-01-09	-0.023135	0.018399	-0.021845	-0.016632

Table 7.3 – Apple (APPL)'s lag features with step 1 to 3

The table 7.3 gives an example of lag features with step 1 to 3 on Apple (AAPL)'s daily return time series. It is worth noticing that the very first samples do not have lag features. This is a boundary effect. Such samples could either be dropped dealt with padding or imputing techniques. In our study, we use the former approach since the number of neglected samples are not significant enough to impact the modeling performance.

Another family of time series features are the so-called *window features*, which are extracted over a fixed window of prior time steps. Technical indicators are a special case of window features. For example, the commonly used k days moving average is nothing but the mean of prior values on a windows size of k. We go beyond those traditional technical indicators and compute more than 200 features for each given time window on a time series. Those features can be grouped into the following 12 families.

1. Entropy and energy
2. Autocorrelation with different lags
3. Coefficients of Continuous Wavelet Transform
4. Coefficients of Fourier Transform
5. Friedrich Coefficients
6. Auto-regression coefficients
7. Quantiles of different measures
8. Symmetry related
9. Cross power spectral density at different frequencies
10. Counting related
11. Location related
12. Others (30 features), including augmented Dickey Fuller test, skewness, kurtosis, min, max, std etc.

Window features analyzed in this study are generated using the `tsfresh` package. Detailed explanation about those features can be found in the documentation of `tsfresh` package [4].

Feature engineering is important since models cannot do any miracle without good input features. We might try to lean on the capability of sophisticated models to decipher the problem complexity. However, if we can better expose the inherent relationship between inputs and outputs in the data, models should perform better. The main difficulty is the fact that underlying inherent functional relationship between inputs and outputs is often unknown. The only feedback we have is model performance. In effect, a default strategy is to use all available knowledge.

7.6 Experiment Setup

We refer to (Friedman et al., 2001) for details on models we use throughout the rest of this paper: logistic regression, artificial neural network, random forest, and gradient boosted trees.

7.6.1 Data Pipeline

The experiments were performed with Python and three machine learning packages `scikit-learn` for logistic regression and random forest, `xgboost` for gradient boosted trees and `keras` for neural network.

The data pipeline of our numerical experiments is presented in 7.2.

After extracting and preprocessing data from Yahoo Finance, we performed feature extraction as described in Section 7.5 and transformed our market direction prediction task into a standard binary classification problem as described in Section 7.4.

7.6.2 Validation Scheme

As for the numerical experiment part, in order to guarantee the accuracy and generalization of our prediction models, we followed the standard cross-validation methodology (Friedman et al., 2001), and divided our entire dataset into three main parts: a training set, a validation set and a test set. The training set is used to fit the models; the validation set is used to estimated prediction error for model selection; the test set is used for assessment of the generalization error of the final chosen model. In our experiments, a test set of 252 samples, equivalent to data of a trading year, is kept in a "vault" and is used only at the end of the data analysis to prevent overfitting. Furthermore, in order to reduce the variance of the validation error, we employ a sequential split scheme described in Figure 7.3. Instead of using a single train-validation pair,

4. https://github.com/blue-yonder/tsfresh

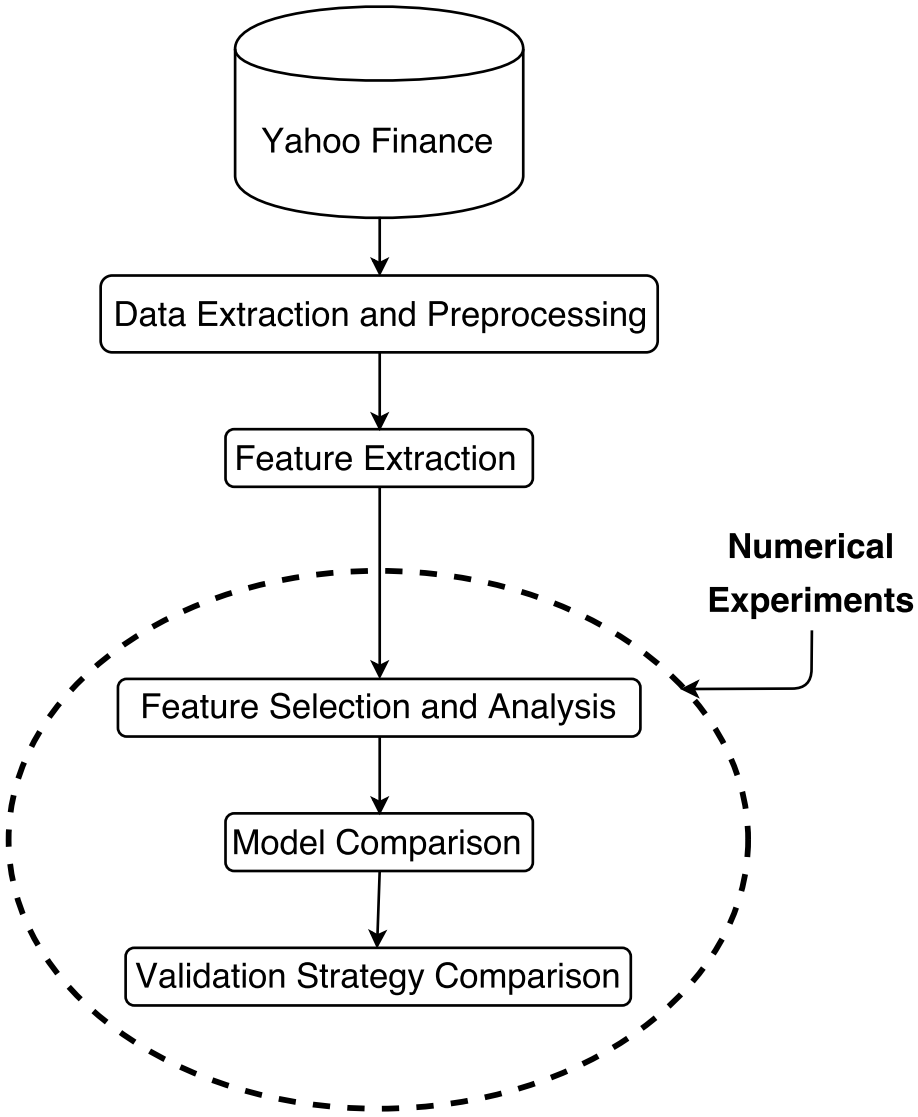


Figure 7.2 – Data pipeline

the overall validation score is the average score on 5 disjoint validation sets trained on 5 training sets. It is also worth noticing that the data is split into consecutive folds with respect to the time dimension. Because of time dimension in the data, only the past should be used to predict the future. We will show in numerical experiments the interest of the sequential split scheme rather than classic cross validation, where one would split the folds at random without taking into account time (please see Figure 7.4).

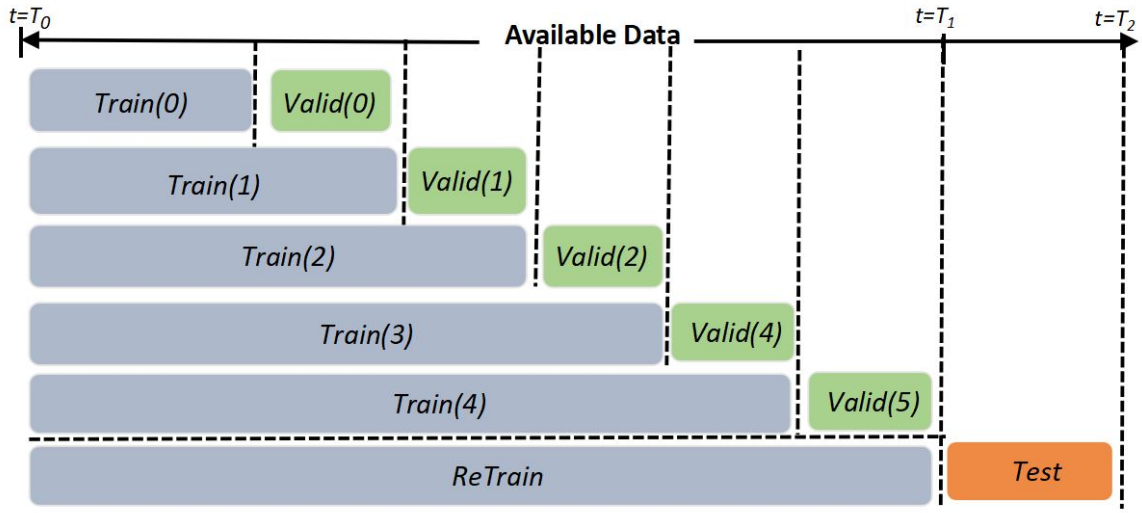


Figure 7.3 – Sequential split scheme.

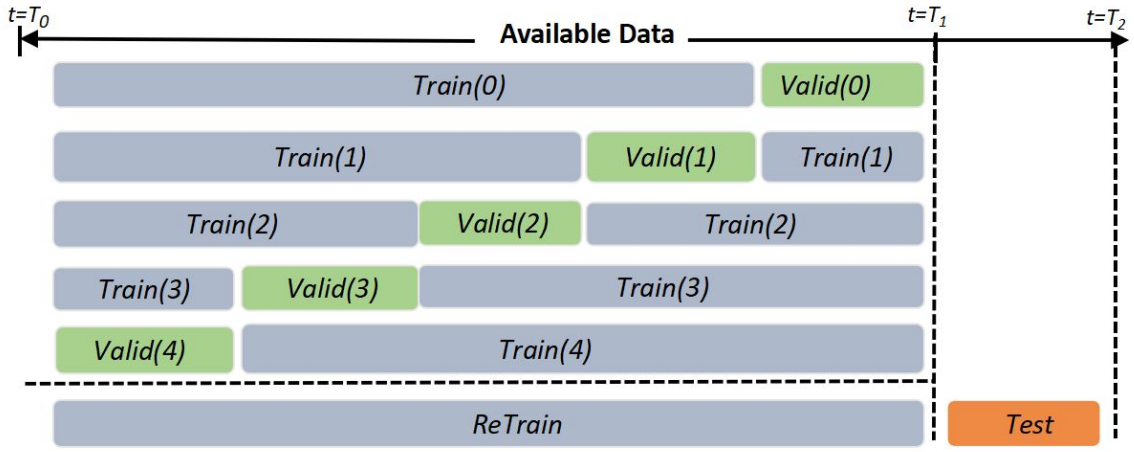


Figure 7.4 – Cross Validation Split.

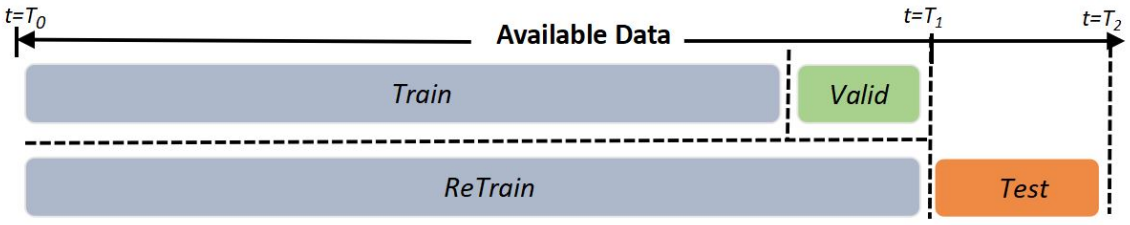


Figure 7.5 – Train-Validation Split.

7.7 Results and Analysis

7.7.1 Whether stocks are self predictable?

Can we use stock historical prices to predict its future? To answer this question, we use random forest as the classification algorithm (comparison with other models will be performed in Section 7.7.3) and then compare its performance on various feature sets generated solely

based each stock's own past data. The *lag* and *window* feature sets can be extracted from each stock's past on different time windows, as described in Section 7.5. We chose two typical window sizes: 5 and 22 which represent respectively one week and one month of trading days. We compared the prediction performance using different feature sets on different time windows and their results is shown in Table 7.4. It can be noticed that even with more than 200 technical indicators generated from the past, stocks future is still hardly predictable (score slightly better than 0.5). Increasing the window size from 5 to 22 does not bring significant uplift. Figure 7.6 presents the histogram of AUC scores obtained on those 463 stocks using different feature sets. From the left figure, we can see that the use of window features, i.e. 220 technical indicators generated from the past, does not provide an improvement in average AUC. And the right figure shows that increasing window size from 5 to 22 does not bring much advantage neither.

Feature Set	window size	feature dim	Avg AUC	Std AUC
Lag + window	5	220	0.5051	0.0153
Lag + window	22	220	0.5093	0.0159
Lag	5	5	0.5039	0.0156
Lag	22	22	0.5028	0.0155

Table 7.4 – Prediction evaluation of 483 stocks using random forest with sequential validation scheme.

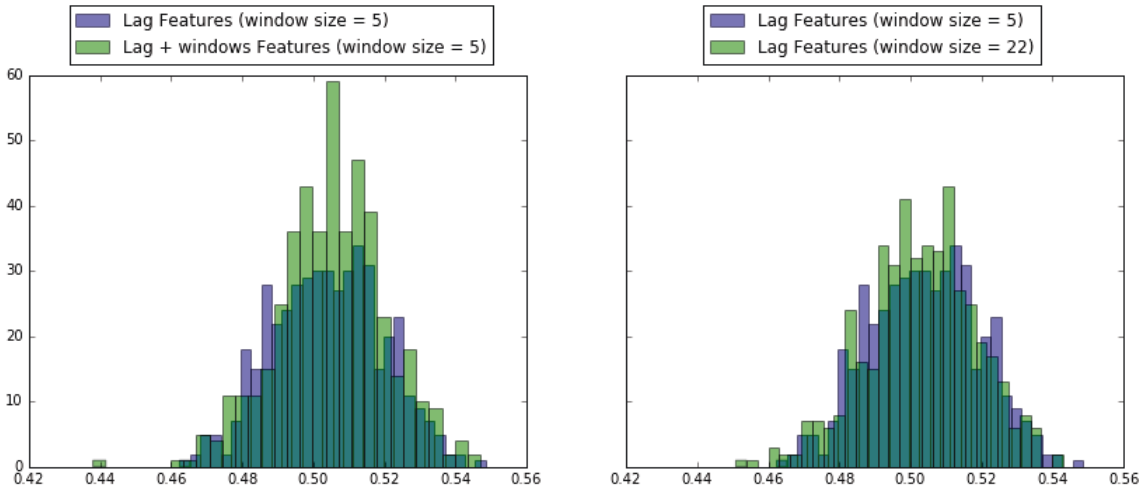


Figure 7.6 – Histogram of AUC using Random Forest

We further repeated our experiments using other classification algorithms and observed the same pattern. Therefore, we conclude that **Stock movement direction is hardly predictable from its own past data**. This conclusion somehow confirms the EMH at the stock level.

7.7.2 What features can we use to predict stock movement direction?

If a stock's own past data does not contains enough information to predict its future, can we use other data as input features to increase the prediction performance?

Each market index is an aggregated indicator presenting a weighted average value on a given market. It might be the case that foreign market indexes could be used to predict – say – US stocks. We collected data of 8 market indexes in total, as shown in Table 7.2. Among those 8, 3 from US, 2 from Europe and 3 from Asia. We built lag and window features on past data of those indexes and used them as input features to predict stocks of S&P 500, which belongs to US market. Since both Asian and European markets close earlier than US markets, we can use their today's return data as input features for American stocks. However we can only use yesterday's return data of US market indexes to predict today's stocks is US market. The comparison results using feature sets generated from different indexes is shown in Table 7.5. Compared to previous experiments using features generated from a stock's own past, index features can indeed dramatically increase the prediction performance. Especially, for the case at hand, European indexes seem to have the most predictive power. The histograms of their prediction performances on 463 stocks are compared in Figure 7.7.

It is worth noticing that European markets close 4.5 hours ahead of US markets, whereas Asian markets close 12 to 15 hours ahead of US markets and US indexes from previous day in fact represent data with 24 hours time lag to our prediction. It seems more recent information is, better predictive power it provides.

Feature Set	window size	Avg AUC	Std AUC
Lag + US Lag	5	0.4983	0.0148
Lag + Asia Lag	5	0.5687	0.0257
Lag + Europe Lag	5	0.6669	0.0389
Lag + Global Lag	5	**0.6702**	0.0400
Lag + Window	5	0.6641	0.0394

Table 7.5 – Prediction evaluation of 483 stocks using random forest with sequential validation scheme.

And again, we repeated our experiments using other classification algorithms and observed the same pattern. Therefore, we conclude that **stocks from US markets can be better predicted with European and Asian indexes.** Hence proving that the belief that stock prices cannot be predicted using historical prices is not true at all scales: very recent data can make a strong difference.

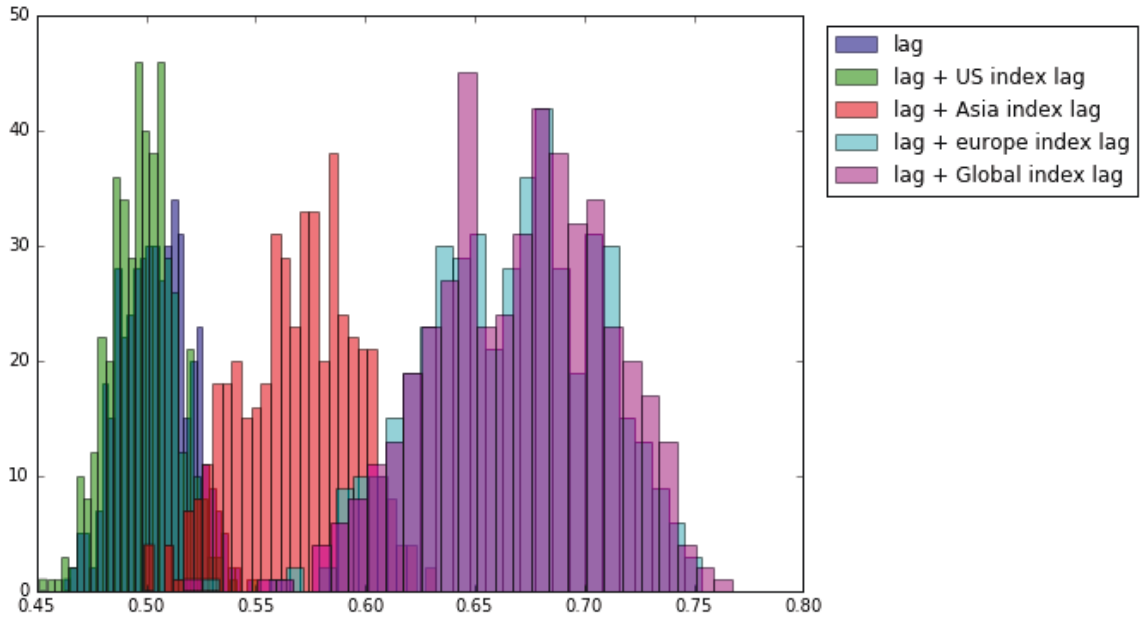


Figure 7.7 – Histogram of AUC using Random Forest using different index features

7.7.3 What is the best model for stock movement direction prediction?

In this section, we study the impact of the model on the prediction performance. We compare lasso penalized logistic regression, artificial neural network, random forest and gradient boosted trees.

Details about the parameters we grid searched are presented in Table 7.6. The performances of each of the optimized models are presented in Table 7.7. Notice that both validation and test set performances are measured, in order to prevent overfitting in this parameter tuning stage.

In this study, logistic regression with lasso constraint outperforms other models both on validation data and on test data. But we have to notice that the difference among fined tuned models is not significant, especially compared to the uplift brought by using different index as seen previously.

Logistic Regression (Lasso)	$C \in \{0.01, 0.05, 0.1, 0.5, 1, 5, 10, 100\}$
Random Forest	`max_features` $\in \{0.6, 0.8, 1.0\}$
	`max_depth` $\in \{2, 3, 4, 5, 6, 8, 10, 15, 20\}$
Neural Network	hidden nodes $\in \{16, 32, 64, 128\}$
Gradient Boosted Trees	`colsample_bytree` $\in \{0.6, 0.8, 1.0\}$
	`subsample` $\in \{0.6, 0.8, 1.0\}$
	`learning_rate` $\in \{0.01, 0.02, 0.05, 0.1, 0.2\}$

Table 7.6 – Grid Searched Model Parameters

Therefore, we conclude that, on this dataset, **logistic regression with lasso penalization**

Model Name	Avg Validation AUC	Avg Test AUC
Logistic Regression (Lasso)	**0.6942**	**0.6172**
Random Forest	0.6853	0.6103
Neural Network	0.6829	0.6111
Gradient Boosted Trees	0.6835	0.6127
Blended Model	**0.6953**	**0.6176**

Table 7.7 – Prediction performance on different classification models.

achieves slightly better performances than random forests, boosted trees and neural nets

7.7.4 What is the best validation scheme?

Cross validation is a very popular technique in machine learning tasks. However, we argue that, in a time series context, it has to be naturally adapted to take time into account. More specifically, what should be avoided is to take into account the future to make predictions in the past. Yet, this is the case if standard cross validation is applied as shown in Figure 7.4. Using a single split, as shown in Figure 7.5, fixes the problem of using the future just like the split we propose. Hence, we compared the sequential split used throughout this study with the two others mentioned validation schemes by measuring their prediction performance correlation with the test data. The results in Table 7.8 show that the sequential validation split correlates the most among the other two.

Model Name	Validation Scheme	Validation-Test Correlation
Logistic Regression (Lasso)	Sequential Validation	**0.83**
	Cross Validation	0.81
	Single Validation	0.77

Table 7.8 – Validation Schemes Comparison

Hence, we conclude that, at least on this dataset but we believe more generally too, **sequential split is a better choice than general cross validation and single split**.

7.7.5 Are there stocks more easily predictable than others?

Prediction performance differs significantly across stocks. It is therefore interesting to see if there are groups of stocks that are more amenable to predictions than others. It could also provide some investment suggestions and potential trading strategies. Table 7.9 shows that top

10 stocks have 10 points better than average performance. It is also worth noticing that the test performance uplift is also consistent with uplift on validation, which confirms again the use of our validation scheme.

Top 10 stocks Avg Validation AUC	Top 10 stocks Avg Test AUC
0.77 (+10.7%)	0.69 (+11.4%)

Table 7.9 – Prediction performance of top 10 stocks

The top 10 most predictable stocks among 463 S&P 500 components are listed in Table 7.10. Notice that 6 of 10 are in financial sector.

Ticker Symbol	Security	GICS Sector
AMP	Ameriprise Financial	Financials
MMM	3M Company	Industrials
IVZ	Invesco Ltd.	Financials
TROW	T. Rowe Price Group	Financials
AMG	Affiliated Managers Group Inc	Financials
UTX	United Technologies	Industrials
BEN	Franklin Resources	Financials
APD	Air Products & Chemicals Inc	Materials
BLK	BlackRock	Financials
PCAR	PACCAR Inc.	Industrials

Table 7.10 – Evaluations on selected top 10 stocks using logistic regression

The average prediction performance per sector is also presented in Table 7.11. Not surprisingly, the most predictable sector is the financial sector, closely followed by industrials and materials. The least predictable sectors are utilities, consumer staples, telecommunication services.

GICS Sector	Nb of companies	Avg Valid AUC	Avg Test AUC
financials	67	0.730	0.669
industrials	65	0.722	0.647
materials	25	0.709	0.637
information technology	69	0.705	0.646
energy	34	0.689	0.624
health care	61	0.685	0.602
consumer discretionary	85	0.685	0.618
real estate	31	0.676	0.535
telecommunication services	4	0.673	0.594
consumer staples	36	0.668	0.580
utilities	28	0.633	0.517

Table 7.11 – Evaluations on selected top 10 stocks using logistic regression

To summarize, **the financial sector is more easily predictable than other sectors of S&P 500.**

7.7.6 Is it possible to predict the S&P 500 index movement direction?

In the previous sections, we tried to predict the movement direction of each individual stock of S&P 500. In this section we try to predict the S&P 500 index itself using indexes of other markets. Similar experiments have been released recently using the Tensorflow framework [5] by C. Elston. In the mentioned experiments, the authors adopted the single train-test split and used a feed forward neural net with two hidden layers as classification algorithm. We implemented their algorithm and compared their results with our fine-tuned models using the presented sequential validation scheme. Table 7.12 sums up the comparison. Logistic regression with lasso constraint still outperforms other models.

Model Name	Validation AUC on sequential split
Elston's algorithm	0.7623
Logistic Regression (Lasso)	**0.7861**
Random Forest	0.7799
Neural Network	0.7775
Gradient Boosted Trees	0.7798

Table 7.12 – Prediction performance on different classification models.

Compared to the average validation AUC on 463 stocks, we obtained a better performance predicting S&P 500 index. Hence, we conclude that **S&P 500 index is easier to predict than its components and our proposed models outperform the one proposed by Elston**.

7.8 Conlcusion and future directions

In this paper, we tried to predict the movement direction of 463 stocks of S&P 500 using standard machine learning algorithms and stocks themselves as features. We find out that, as it is well known in the financial domain, stocks are hardly predictable using their own past. However we were surprised to discover that recent data consisting of near closed indexes have considerable predictive power on stocks. Better algorithms do improve the prediction accuracy but the uplift still remains insignificant compared to taking into account these recently closed indexes. We also discovered that stocks of financial sector are significantly more easily predictable than other stocks. We further compared our models with Elston's algorithm and achieved better performance in predicting S&P 500 index movement direction.

5. https://cloud.google.com/solutions/machine-learning-with-financial-time-series-data

Many promising future directions are to be investigated. The use of macroeconomic data could provide another source of information. Interest rates (TS), consumer price index (CPI), industrial production (IP), government consumption (GC), private consumption (PC), gross national product (GNP) and gross domestic product (GDP) etc. are also publicly available to improve this study. Besides, trading volume data could be another source of information to further increase prediction accuracy. Moreover, going from predictions to trading strategies is a natural path to follow.

CHAPTER 8

CONCLUSION AND FUTURE WORKS

> Life is like riding a bicycle. To keep your balance, you must keep moving.
>
> *Albert Einstein*

As described in Chapter 2, the omnipresence of data has changed the rules of the games across various sectors especially of e-commerce and finance. As the president of Alibaba, the Chinese Internet giant, once said, "Nine years ago, when Alibaba shifted its position from an e-commerce company to a data company, we had a huge fight internally and finally decided that we were shifting. So we haven't called ourselves an e-commerce company internally for nine years".

Throughout this thesis, we have shown how AI can be leveraged to solve real-world problems though four concrete applications: semantic search, search result ranking, product categorization and stock prediction.

In this chapter, we first summarize our work in Section 8.1, then we illustrate some perspectives for future works in Section 8.2.

8.1 Summary

In Chapter 4, we introduced the notion of "term entropy" and proposed a novel term weighting scheme, which often serves as text similarity measurement and thus is the foundation of some higher level tools, such as collaborative filtering, text matching etc. Tf-idf, another popular term weighting scheme carefully reviewed in this chapter, is based on the idea that the importance of a term cannot be decided on its number of occurrences in the database alone. Rather, term importance, as we defined it, is based on how concentrated were the purchases it led to. This notion was implemented through the computation of term entropy that we defined in this chapter. Numerical experiments, performed on real-world purchase data, showed encouraging results for the entropy-based term weighting over tf-idf in improving semantic search performance under the context of e-commerce.

Later, in Chapter 5, we have continued our research on product search but this time, instead of focusing on the semantic aspect of search queries, we have pursued their behavior aspect and proposed a novel reranking strategy aiming at maximize the profitability of the search result ranking. Several reranking strategies were benchmarked along on a real-world data set of user events. In addition, we used an evaluation metric adapted to e-commerce data, which measures the percent revenue generated by the top k items of the search results. Such metric is considered to be closer to the one used by e-commerce marketers in real world.

A text-based reranking according to the BM25 between the products' description and the query's keywords allows the top four products to capture on average about 25% of the query's revenue. This is much less than reranking products according to the clicks they gathered following the query over the last 30 days, which increases this percentage to about 48%. A linear

autoregressive method forecasting the number of purchases from past time-series of daily clicks, add-to-basket and purchases further reaches about 55%. The strength of the latter approach lies in its implicit exploiting of correlation of all major user events with purchases in a time series nature.

Chapter 6 summarized an AI competition that Cdiscount held on a public platform, challenging the data science community to predict the correct class of a product based on its description and image. This competition gave us a unique opportunity to compare some of the state-of-the-art classification algorithms on real world dataset and many meaningful insights were discovered during in-depth analysis of those winning solutions.

The five winning contributions of the challenge were able to predict the correct category of 66–68% of the products in the testing set. Most of the algorithms were based on simple linear classifiers; in particular, the logistic regression appeared in three contributions. When dealing with noisy, imperfect data, the preliminary processing steps thus appeared to be more crucial than the choice of a complex, non-linear classifier. A distinguishing feature of the two most accurate algorithms was their training of ensemble of thousands of models on random subsets of the data, whose predictions were then averaged to get the final predicted category: we thus assume this to be a key ingredient to their success.

We also released the whole dataset to the public for the purpose of reproducible science, which could also provide a common playground for researchers of related fields to improve over existing text and image based classification algorithms in a context of very large number of classes.

Finally, in Chapter 7, inspired by our previous work in Chapter 5 where a time series model was built to predict daily sales, we took the challenge to predict one of the most difficult time series data but also the one with the most potential value: stock and the results were quite promising.

We attempted to predict the movement direction of 463 stocks of S&P 500 using various machine learning algorithms and stocks themselves as features. We found out that, as it is well known in the financial domain, stocks were hardly predictable using their own past. However we were surprised, in a good way, to discover that recent data consisting of near closed indexes have considerable predictive power on stocks. Better algorithms did improve the prediction accuracy but the uplift still remained insignificant compared to taking into account these recently closed indexes. We also discovered that stocks of financial sector were significantly more easily predictable than other stocks. With respect to predicting the S&P 500 index movement direction itself, a comparison of our models with Elston's algorithm was conducted and a better perfor-

mance was recorded using our models. We also provided a publicly available Python notebook [1] reproducing some of the key results of our research, just as did Elston [2].

8.2 Future works

With the work realized by this thesis, we managed to tackle some of the most challenging problems faced by AI practitioners. Meanwhile, as a natural consequence, interesting aspects to continue working on appeared. In this section, we will describe some promising perspectives for future works.

In Chapter 4 and 5, we have targeted on product search and its related result ranking problem. The term weighting scheme proposed in Chapter 4 has made significant improvement on search accuracy but it is still indifferent to the containing query, such that the same term has the same importance in different queries. Effort in removing such synonymic effect from query analysis has been made by many researchers of this field and should constitute a promising direction to follow. As for the reranking strategy proposed in Chapter 5, its performance is heavily relied to the prediction accuracy of daily sales. Using more sophisticated and complex non-linear models, rather than the auto-regression model used in this study should prove of valuable.

Furthermore, categorization is one of the most fundamental tasks in machine learning and has been studied actively for decades. Automatic product categorization having a significant potential financial benefit for the company, any improvement on its accuracy would surely be highly appreciated. We've noticed that the winning solutions of this categorization challenge, presented in Chapter 6 are mainly based on text description and neglected the importance of images. It's our firm belief that combining the power of text and images would yield a higher categorization accuracy.

Finally, in Chapter 7, we revealed the importance of data in stock prediction tasks. Using more adequate data as features would produce much significant uplift than building complex models. Therefore, a promising direction to further boost the stock prediction accuracy is to fully deploy market data, rather than using the price data alone in the current study. Trading volumes, macro-economic indicators, commodity prices etc. are all valuable source of information. Another interesting direction to follow is trading strategy building based on AI based prediction results. How to optimize the entry and exit point to minimize the trading risk while maximize the potential benefit would certainly worth devoting efforts on.

The thesis only covers a small tip of the iceberg of what AI can do to improve our daily lives

1. https://github.com/skyjiao/stock prediction sp500
2. https://cloud.google.com/solutions/machine-learning-with-financialtime-series-data

and there will always be the next land to conquer. I'd like to kindly end this thesis by a quote from Eliezer Yudkowsky :

"Anything that could give rise to smarter-than-human intelligence - in the form of Artificial Intelligence, brain-computer interfaces, or neuroscience-based human intelligence enhancement - wins hands down beyond contest as doing the most to change the world. Nothing else is even in the same league."

BIBLIOGRAPHY

Agichtein, E., Brill, E., and Dumais, S. (2006). Improving web search ranking by incorporating user behavior information. In *Proceedings of ACM Conference on Research and Development on Information Retrieval (SIGIR)*.

Agrawal, R., Halverson, A., Kenthapadi, K., Mishra, N., and Tsaparas, P. (2009). Generating labels from clicks. In *Proceedings of ACM Conference on Web Search and Data Mining (WSDM)*.

Ahmad, F. and Kondrak, G. (2005). Learning a spelling error model from search query logs. In *Proceedings of the conference on Human Language Technology and Empirical Methods in Natural Language Processing*, pages 955–962. Association for Computational Linguistics.

Alexander, S. S. (1961). Price movements in speculative markets: Trends or random walks. *Industrial Management Review (pre-1986)*, 2(2):7.

Azar, P. D. and Lo, A. W. (2016). The wisdom of twitter crowds: Predicting stock market reactions to fomc meetings via twitter feeds. *The Journal of Portfolio Management*, 42(5):123–134.

Baeza-Yates, R. and Maarek, Y. (2012). Usage data in web search: benefits and limitations. In *Scientific and Statistical Database Management*, pages 495–506.

Bahrammirzaee, A. (2010). A comparative survey of artificial intelligence applications in finance: artificial neural networks, expert system and hybrid intelligent systems. *Neural Computing and Applications*, 19(8):1165–1195.

Balakrishnan, V. and Zhang, X. (2014). Implicit user behaviours to improve post-retrieval document relevancy. *Computers in Human Behavior*, 33:104–112.

Ballings, M., Van den Poel, D., Hespeels, N., and Gryp, R. (2015). Evaluating multiple classifiers for stock price direction prediction. *Expert Systems with Applications*, 42(20):7046–7056.

Bird, S. (2006). Nltk: the natural language toolkit. In *Proceedings of the COLING/ACL on Interactive presentation sessions*, pages 69–72. Association for Computational Linguistics.

Blanzieri, E. and Bryl, A. (2008). A survey of learning-based techniques of email spam filtering. *Artificial Intelligence Review*, 29(1):63–92.

Buscher, G., Dengel, A., Biedert, R., and Elst, L. V. (2012). Attentive documents: Eye tracking as implicit feedback for information retrieval and beyond. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 1(2):9.

Buscher, G., Dumais, S. T., and Cutrell, E. (2010). The good, the bad, and the random: an eye-tracking study of ad quality in web search. In *Proceedings of the 33rd international ACM SIGIR conference on Research and development in information retrieval*, pages 42–49. ACM.

Chan, T.-H., Jia, K., Gao, S., Lu, J., Zeng, Z., and Ma, Y. (2015). Pcanet: A simple deep learning baseline for image classification? *IEEE Transactions on Image Processing*, 24(12):5017–5032.

Chen, A.-S., Leung, M. T., and Daouk, H. (2003). Application of neural networks to an emerging financial market: forecasting and trading the taiwan stock index. *Computers & Operations Research*, 30(6):901–923.

Chen, H. and Karger, D. R. (2006). Less is more: probabilistic models for retrieving fewer relevant documents. In *Proceedings of the 29th annual international ACM SIGIR conference on Research and development in information retrieval*, pages 429–436. ACM.

Chen, M., Hao, Y., Hwang, K., Wang, L., and Wang, L. (2017). Disease prediction by machine learning over big data from healthcare communities. *IEEE Access*.

Chen, M. C., Anderson, J. R., and Sohn, M. H. (2001). What can a mouse cursor tell us more?: correlation of eye/mouse movements on web browsing. In *CHI'01 extended abstracts on Human factors in computing systems*, pages 281–282. ACM.

Ciregan, D., Meier, U., and Schmidhuber, J. (2012). Multi-column deep neural networks for image classification. In *Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on*, pages 3642–3649. IEEE.

Clarke, C. L., Craswell, N., and Soboroff, I. (2009). Overview of the trec 2009 web track. Technical report, WATERLOO UNIV (ONTARIO).

Cochran, W. (1953). *Sampling techniques*. John Wiley, Oxford.

Committee, N. P. (2013). Understanding asset prices. Nobel Prize in Economics documents 2013-1, Nobel Prize Committee.

Cortes, C. and Vapnik, V. (1995). Support-vector networks. *Machine learning*, 20(3):273–297.

Cover, T. M. and Thomas, J. A. (1991). Entropy, relative entropy and mutual information. *Elements of Information Theory*, pages 12–49.

Crammer, K., Dekel, O., Keshet, J., Shalev-Shwartz, S., and Singer, Y. (2006). Online passive-aggressive algorithms. *Journal of Machine Learning Research*, 7:551–585.

Craswell, N. and Szummer, M. (2007). Random walks on the click graph. In *Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval*, pages 239–246. ACM.

Craswell, N., Zoeter, O., Taylor, M., and Ramsey, B. (2008). An experimental comparison of click position-bias models. In *Proceedings of the 2008 International Conference on Web Search and Data Mining*, pages 87–94. ACM.

Croft, W. B., Metzler, D., and Strohman, T. (2010). *Search engines: Information retrieval in practice*. Addison-Wesley Reading.

Cruz, J. A. and Wishart, D. S. (2006). Applications of machine learning in cancer prediction and prognosis. *Cancer informatics*, 2:59.

Cutrell, E. and Guan, Z. (2007). Eye tracking in msn search: Investigating snippet length, target position and task types. *City*, pages 1–13.

Dechow, P. M., Hutton, A. P., Meulbroek, L., and Sloan, R. G. (2001). Short-sellers, fundamental analysis, and stock returns. *Journal of Financial Economics*, 61(1):77–106.

Dupret, G. E. and Piwowarski, B. (2008). A user browsing model to predict search engine click data from past observations. In *Proceedings of the 31st annual international ACM SIGIR conference on Research and development in information retrieval*, pages 331–338. ACM.

Fama, E. F. (1965). The behavior of stock-market prices. *The journal of Business*, 38(1):34–105.

Fama, E. F. (1991). Efficient capital markets: Ii. *The journal of finance*, 46(5):1575–1617.

Friedman, J., Hastie, T., and Tibshirani, R. (2001). *The elements of statistical learning*, volume 1. Springer series in statistics New York.

Gallagher, L. A. and Taylor, M. P. (2002). Permanent and temporary components of stock prices: Evidence from assessing macroeconomic shocks. *Southern Economic Journal*, pages 345–362.

Gidofalvi, G. and Elkan, C. (2001). Using news articles to predict stock price movements. *Department of Computer Science and Engineering, University of California, San Diego*.

Goel, S., Broder, A., Gabrilovich, E., and Pang, B. (2010). Anatomy of the long tail: ordinary people with extraordinary tastes. In *Proceedings of the third ACM international conference on Web search and data mining*, pages 201–210. ACM.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, pages 424–438.

Guo, F., Liu, C., Kannan, A., Minka, T., Taylor, M., Wang, Y.-M., and Faloutsos, C. (2009). Click chain model in web search. In *Proceedings of the 18th international conference on World wide web*, pages 11–20. ACM.

Guresen, E., Kayakutlu, G., and Daim, T. U. (2011). Using artificial neural network models in stock market index prediction. *Expert Systems with Applications*, 38(8):10389–10397.

Hamilton, J. D. (1994). *Time series analysis*, volume 2. Princeton university press.

Han, E.-H. S., Karypis, G., and Kumar, V. (2001). Text categorization using weight adjusted k-nearest neighbor classification. In *Pacific-asia conference on knowledge discovery and data mining*, pages 53–65. Springer.

Hasan, M. A., Parikh, N., Singh, G., and Sundaresan, N. (2011). Query suggestion for e-commerce sites. In *Proceedings of the fourth ACM international conference on Web Search and Data Mining*, pages 765–774.

Herlocker, J. L., Konstan, J. A., Borchers, A., and Riedl, J. (1999). An algorithmic framework for performing collaborative filtering. In *Proceedings of the 22nd annual international ACM SIGIR conference on Research and Development in Information Retrieval*, pages 230–237.

Hornik, K., Stinchcombe, M., and White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural networks*, 2(5):359–366.

Hotho, A., Nürnberger, A., and Paaß, G. (2005). A brief survey of text mining. In *Ldv Forum*, volume 20, pages 19–62.

Huang, C.-J., Yang, D.-X., and Chuang, Y.-T. (2008). Application of wrapper approach and composite classifier to the stock trend prediction. *Expert Systems with Applications*, 34(4):2870–2878.

Jain, V. and Varma, M. (2011). Learning to re-rank: query-dependent image re-ranking using click data. In *Proceedings of the 20th international conference on World Wide Web (WWW)*. ACM.

Jensen, M. C. (1978). Some anomalous evidence regarding market efficiency. *Journal of financial economics*, 6(2-3):95–101.

Jiao, Y., Cornec, M., and Jakubowicz, J. (2015). An entropy-based term weighting scheme and its application in e-commerce search engines. In *International Symposium on Web Algorithms (iSWAG)*.

Joachims, T. (1996). A probabilistic analysis of the rocchio algorithm with tfidf for text categorization. Technical report, Carnegie-mellon univ pittsburgh pa dept of computer science.

Joachims, T. (1998). Text categorization with support vector machines: Learning with many relevant features. *Machine learning: ECML-98*, pages 137–142.

Joachims, T. (2002). Optimizing search engines using clickthrough data. In *Proceedings of the eighth ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 133–142. ACM.

Joachims, T., Granka, L., Pan, B., Hembrooke, H., and Gay, G. (2005). Accurately interpreting clickthrough data as implicit feedback. In *Proceedings of ACM Conference on Research and Development on Information Retrieval (SIGIR)*.

Johnson, D. E., Oles, F. J., Zhang, T., and Goetz, T. (2002). A decision-tree-based symbolic rule induction system for text categorization. *IBM Systems Journal*, 41(3):428–437.

Johnson, R. and Zhang, T. (2015a). Effective use of word order for text categorization with convolutional neural networks. In *Proceedings of the North American Chapter of the Association for Computational Linguistics (NAACL'15)*, number 2011, pages 103–112.

Johnson, R. and Zhang, T. (2015b). Semi-supervised convolutional neural networks for text categorization via region embedding. In *Advances in Neural Information Processing Systems*, pages 919–927.

Kara, Y., Boyacioglu, M. A., and Baykan, Ö. K. (2011). Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the istanbul stock exchange. *Expert systems with Applications*, 38(5):5311–5319.

Kaundal, R., Kapoor, A. S., and Raghava, G. P. (2006). Machine learning techniques in disease forecasting: a case study on rice blast prediction. *BMC bioinformatics*, 7(1):485.

Kazem, A., Sharifi, E., Hussain, F. K., Saberi, M., and Hussain, O. K. (2013). Support vector regression with chaos-based firefly algorithm for stock market price forecasting. *Applied soft computing*, 13(2):947–958.

Kearney, C. and Liu, S. (2014). Textual sentiment in finance: A survey of methods and models. *International Review of Financial Analysis*, 33:171–185.

Kelly, D. and Belkin, N. J. (2004). Display time as implicit feedback: understanding task effects. In *Proceedings of the 27th annual international ACM SIGIR conference on Research and development in information retrieval*, pages 377–384. ACM.

Khaidem, L., Saha, S., and Dey, S. R. (2016). Predicting the direction of stock market prices using random forest. *arXiv preprint arXiv:1605.00003*.

Kim, J., Oard, D. W., and Romanik, K. (2000). Using implicit feedback for user modeling in internet and intranet searching.

Koller, D. and Sahami, M. (1997). Hierarchically classifying documents using very few words. Technical report, Stanford InfoLab.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105.

Larkey, L. S. and Croft, W. B. (1996). Combining classifiers in text categorization. In *Proceedings of the 19th annual international ACM SIGIR conference on Research and development in information retrieval*, pages 289–297. ACM.

Lee, M.-C. (2009). Using support vector machine with a hybrid feature selection method to the stock trend prediction. *Expert Systems with Applications*, 36(8):10896–10904.

Li, H., Xu, J., et al. (2014). Semantic matching in search. *Foundations and Trends® in Information Retrieval*, 7(5):343–469.

Li, Q., Tian, M., Liu, J., and Sun, J. (2015). An implicit relevance feedback method for cbir with real-time eye tracking. *Multimedia Tools and Applications*, pages 1–17.

Lin, Y., Guo, H., and Hu, J. (2013). An svm-based approach for stock market trend prediction. In *Neural Networks (IJCNN), The 2013 International Joint Conference on*, pages 1–7. IEEE.

Liu, T.-Y., Xu, J., Qin, T., Xiong, W., and Li, H. (2007). Letor: Benchmark dataset for research on learning to rank for information retrieval. In *Proceedings of SIGIR workshop on learning to rank for information retrieval*.

Malkiel, B. G. and Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, 25(2):383–417.

McCallum, A., Nigam, K., et al. (1998). A comparison of event models for naive bayes text classification. In *AAAI-98 workshop on learning for text categorization*, volume 752, pages 41–48. Madison, WI.

McCallum, A. K. (1996). Bow: A toolkit for statistical language modeling, text retrieval, classification and clustering.

McCallum, A. K. (2002). Mallet: A machine learning for language toolkit.

McDonnell, P. (2014). Time based ranking. US Patent 8,909,655.

Medhat, W., Hassan, A., and Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, 5(4):1093–1113.

Metzler, D., Dumais, S., and Meek, C. (2007). Similarity measures for short segments of text. In *Advances in Information Retrieval: 29th European Conference on IR Research, ECIR 2007, Rome, Italy, April 2-5, 2007, Proceedings*, volume 4425.

Naeini, M. P., Taremian, H., and Hashemi, H. B. (2010). Stock market value prediction using neural networks. In *Computer Information Systems and Industrial Management Applications (CISIM), 2010 International Conference on*, pages 132–136. IEEE.

Nguyen, T. H., Shirai, K., and Velcin, J. (2015). Sentiment analysis on social media for stock movement prediction. *Expert Systems with Applications*, 42(24):9603–9611.

Nurmi, P., Lagerspetz, E., Buntine, W., Floréen, P., and Kukkonen, J. (2008). Product retrieval for grocery stores. In *Proceedings of the 31st annual international ACM SIGIR conference on Research and development in information retrieval*, pages 781–782. ACM.

Pagolu, V. S., Challa, K. N. R., Panda, G., and Majhi, B. (2016). Sentiment analysis of twitter data for predicting stock market movements. *arXiv preprint arXiv:1610.09225*.

Paik, J. H. (2013). A novel tf-idf weighting scheme for effective ranking. In *Proceedings of the 36th international ACM SIGIR conference on Research and Development in Information Retrieval*, pages 343–352.

Palan, S. (2004). The efficient market hypothesis and its validity in today's markets.

Pantel, P., Lin, D., et al. (1998). Spamcop: A spam classification & organization program. In *Proceedings of AAAI-98 Workshop on Learning for Text Categorization*, pages 95–98.

Parikh, N., Sriram, P., and Al Hasan, M. (2013). On segmentation of ecommerce queries. In *Proceedings of the 22nd ACM international conference on Information & Knowledge Management*, pages 1137–1146.

Parikh, N. and Sundaresan, N. (2008). Inferring semantic query relations from collective user behavior. In *Proceedings of the 17th ACM conference on Information and Knowledge Management*, pages 349–358.

Patel, J., Shah, S., Thakkar, P., and Kotecha, K. (2015). Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. *Expert Systems with Applications*, 42(1):259–268.

Peters, E. E. (1996). *Chaos and order in the capital markets: a new view of cycles, prices, and market volatility*, volume 1. John Wiley & Sons.

Porter, M. (2001). Snowball: A language for stemming algorithms.

Qian, B. and Rasheed, K. (2007). Stock market prediction with multiple classifiers. *Applied Intelligence*, 26(1):25–33.

Rajaraman, A. and Ullman, J. D. (2011). *Mining of massive datasets*. Cambridge University Press.

Ramachandran, P. (2005). Discovering user preferences by using time entries in click-through data to improve search engine results. In *Discovery Science*, pages 383–385. Springer.

Rezaeiye, P. P., Fazli, M. S., et al. (2014). Use hmm and knn for classifying corneal data. *arXiv preprint arXiv:1401.7486*.

Robertson, S. E., Walker, S., Jones, S., Hancock-Beaulieu, M. M., Gatford, M., et al. (1995). Okapi at trec-3. *Proceedings of the third Text REtrieval Conference (TREC-3)*.

Rodden, K., Fu, X., Aula, A., and Spiro, I. (2008). Eye-mouse coordination patterns on web search results pages. In *CHI'08 extended abstracts on Human factors in computing systems*, pages 2997–3002. ACM.

Roul, R. K., Devanand, O. R., and Sahay, S. (2014). Web document clustering and ranking using tf-idf based apriori approach. *IJCA Proceedings on ICACEA*.

Ruthven, I. (2008). Interactive information retrieval. *Annual review of information science and technology*, 42(1):43–91.

Sahami, M., Dumais, S., Heckerman, D., and Horvitz, E. (1998). A bayesian approach to filtering junk e-mail. In *Learning for Text Categorization: Papers from the 1998 workshop*, volume 62, pages 98–105.

Salton, G. and McGill, M. J. (1986). Introduction to modern information retrieval.

Sands, T. M., Tayal, D., Morris, M. E., and Monteiro, S. T. (2015). Robust stock value prediction using support vector machines with particle swarm optimization. In *Evolutionary Computation (CEC), 2015 IEEE Congress on*, pages 3327–3331. IEEE.

Schapire, R. E. and Singer, Y. (2000). Boostexter: A boosting-based system for text categorization. *Machine learning*, 39(2-3):135–168.

Sebastiani, F. (2002). Machine learning in automated text categorization. *ACM computing surveys (CSUR)*, 34(1):1–47.

Singh, G., Parikh, N., and Sundaresan, N. (2012). Rewriting null e-commerce queries to recommend products. In *Proceedings of the 21st international conference on World Wide Web (WWW)*. ACM.

Skuza, M. and Romanowski, A. (2015). Sentiment analysis of twitter data within big data distributed environment for stock prediction. In *Computer Science and Information Systems (FedCSIS), 2015 Federated Conference on*, pages 1349–1354. IEEE.

Spärck Jones, K. (1972). A statistical interpretation of term specifity and its application in retrieval. *Journal of Documentation*, 28(1):11–21.

Spärck Jones, K. (2004). Idf term weighting and ir research lessons. *Journal of documentation*, 60(5):521–523.

Spärck-Jones, K., Robertson, S. E., and Sanderson, M. (2007). Ambiguous requests: implications for retrieval tests, systems and theories. In *ACM SIGIR Forum*, volume 41, pages 8–17. ACM.

Spink, A., Jansen, B., Wolfram, D., and Saracevic, T. (2002a). From e-sex to e-commerce: Web search changes. *IEEE Computer*, 35(3):107–109.

Spink, A., Jansen, B. J., Wolfram, D., and Saracevic, T. (2002b). From e-sex to e-commerce: Web search changes. *IEEE Computer*, pages 35(3), 107–109.

Taylor, S. J. (2008). *Modelling financial time series*. world scientific.

Ticknor, J. L. (2013). A bayesian regularized artificial neural network for stock market forecasting. *Expert Systems with Applications*, 40(14):5501–5506.

Turban, E., King, D., Lee, J., Liang, T., and Turban, D. (2015). *Electronic commerce: A managerial and social networks perspective*. Springer.

Vapnik, V. N. and Kotz, S. (1982). *Estimation of dependences based on empirical data*, volume 40. Springer-Verlag New York.

Veilumuthu, A. and Ramachandran, P. (2007). Discovering implicit feedbacks from search engine log files. In *Discovery Science*, pages 231–242. Springer.

Voorhees, E. M. (2003). Overview of trec 2003. In *Proceedings of the Text REtrieval Conference*.

Walker, S. and Duncan, D. (1967). Estimation of the probability of an event as a function of several independent variables. *Biometrika*, 54(1867):167–179.

Wang, K., Gloy, N., and Li, X. (2010). Inferring search behaviors using partially observable markov (pom) model. In *Proceedings of the third ACM international conference on Web search and data mining*, pages 211–220. ACM.

Wang, Y. (2014). Stock price direction prediction by directly using prices data: an empirical study on the kospi and hsi. *International Journal of Business Intelligence and Data Mining*, 9(2):145–160.

White, R. W. and Buscher, G. (2012). Text selections as implicit relevance feedback. In *Proceedings of the 35th international ACM SIGIR conference on Research and development in information retrieval*, pages 1151–1152. ACM.

Wiener, N. (1956). The theory of prediction. *Modern Mathematics for Engineers*.

Xu, B., Guo, X., Ye, Y., and Cheng, J. (2012). An improved random forest classifier for text categorization. *JCP*, 7(12):2913–2920.

Xue, G.-R., Zeng, H.-J., Chen, Z., Yu, Y., Ma, W.-Y., Xi, W., and Fan, W. (2004). Optimizing web search using web click-through data. In *Proceedings of the thirteenth ACM international conference on Information and knowledge management*, pages 118–126. ACM.

Yang, B., Parikh, N., Singh, G., and Sundaresan, N. (2014). A study of query term deletion using large-scale e-commerce search logs. In *Advances in Information Retrieval*, pages 235–246.

Yang, Y. and Liu, X. (1999). A re-examination of text categorization methods. In *Proceedings of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval*, pages 42–49. ACM.

Yu, B. and Xu, Z.-b. (2008). A comparative study for content-based dynamic spam classification using four machine learning algorithms. *Knowledge-Based Systems*, 21(4):355–362.

Yuan, Y. (2013). Forecasting the movement direction of exchange rate with polynomial smooth support vector machine. *Mathematical and Computer Modelling*, 57(3):932–944.

Yue, Y., Patel, R., and Roehrig, H. (2010). Beyond position bias: Examining result attractiveness as a source of presentation bias in clickthrough data. In *Proceedings of the 19th international conference on World wide web*, pages 1011–1018. ACM.

Żbikowski, K. (2015). Using volume weighted support vector machines with walk forward testing and feature selection for the purpose of creating stock trading strategy. *Expert Systems with Applications*, 42(4):1797–1805.

Zhang, C., Liu, C., Zhang, X., and Almpanidis, G. (2017). An up-to-date comparison of state-of-the-art classification algorithms. *Expert Systems with Applications*, 82:128–150.

Zhang, H. (2004). The optimality of naive Bayes. In *Proceedings of the Seventeenth International Florida Artificial Intelligence Research Society Conference*, Miami Beach. FL: AAAI Press.