SENTIMENT ANALYSIS

Mining Opinions, Sentiments, and Emotions

BING LIU

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Sentiment analysis is the computational study of people's opinions, sentiments, emotions, and attitudes. This fascinating problem is increasingly important in business and society. It offers numerous research challenges but promises insight useful to anyone interested in opinion analysis and social media analysis.

This book gives a comprehensive introduction to the topic from a primarily natural language processing point of view to help readers understand the underlying structure of the problem and the language constructs that are commonly used to express opinions and sentiments. It covers all core areas of sentiment analysis; includes many emerging themes, such as debate analysis, intention mining, and fake-opinion detection; and presents computational methods to analyze and summarize opinions. It will be a valuable resource for researchers and practitioners in natural language processing, computer science, management sciences, and the social sciences.

Bing Liu is a professor of computer science at the University of Illinois at Chicago. His current research interests include sentiment analysis and opinion mining, data mining, machine learning, and natural language processing. He has published extensively in top conferences and journals, and his research has been cited on the front page of the *New York Times*. He is also the author of two books: *Sentiment Analysis and Opinion Mining* (2012) and *Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data* (first edition, 2007; second edition, 2011). He currently serves as the Chair of ACM SIGKDD and is an IEEE Fellow.

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Contents

Preface

Opinion and sentiment and their related concepts, such as evaluation, appraisal, attitude, affect, emotion, and mood, are about our subjective feelings and beliefs. They are central to human psychology and are key influencers of our behaviors. Our beliefs and perceptions of reality, as well as the choices we make, are to a considerable degree conditioned on how others see and perceive the world. For this reason, our views of the world are very much influenced by others' views, and whenever we need to make a decision, we often seek out others' opinions. This is true not only for individuals but also for organizations. From an application point of view, we naturally want to mine people's opinions and feelings toward any subject matter of interest, which is the task of *sentiment analysis*. More precisely, sentiment analysis, which is also called *opinion mining*, is a field of study that aims to extract opinions and sentiments from natural language text using computational methods.

The inception and rapid growth of sentiment analysis coincide with those of social media on the web, such as reviews, forum discussions, blogs, and microblogs, because for the first time in human history, we now have a huge volume of opinion data recorded in digital forms. These data, also called *user-generated content*, prompted researchers to mine them to discover useful knowledge. This naturally led to the problem of sentiment analysis or opinion mining because these data are full of opinions. That these data are full of opinions is not surprising, because the primary reason why people post messages on social media platforms is to express their views and opinions, and therefore sentiment analysis is at the very core of social media analysis. Since early 2000, sentiment analysis has grown to be one of the most active research areas in natural language processing. It is also widely studied in data mining, web mining, and information retrieval. In fact, the research has spread from computer science to management science and social science because of its importance to business and society as a whole. In recent years, industrial activities surrounding sentiment analysis have also thrived. Numerous start-ups have emerged. Many large corporations, for example, Microsoft, Google, Hewlett-Packard, and Adobe, have also built their own in-house systems. Sentiment analysis systems have found applications in almost every business, health, government, and social domain.

Although no silver bullet algorithm can solve the sentiment analysis problem, many deployed systems are able to provide useful information to support real-life applications. I believe it is now a good time to document the knowledge that we have gained in research, and, to some extent, in practice, in a book. Obviously, I don't claim that I know everything that is happening in the industry, as businesses do not publish or disclose their algorithms. However, I have built a sentiment analysis system myself in a start-up company and served clients on projects involving social media data sets in a large variety of domains. Over the years, many developers of sentiment analysis systems in the industry have also told me roughly what algorithms they were using. Thus, I can claim that I have a reasonable knowledge of practical systems and their capabilities and firsthand experience in solving real-life problems. I try to pass along those nonconfidential pieces of information and knowledge in this book.

In writing this book, I aimed to take a balanced approach, analyzing the sentiment analysis problem from a linguistic angle to help readers understand the underlying structure of the problem and the language constructs commonly used to express opinions and sentiments and presenting computational methods to analyze and summarize opinions. Like many natural language processing tasks, most published computational techniques use machine learning or data mining algorithms with the help of text-specific clues or features. However, if we only focus on such computational algorithms, we will miss the deep insights of the problem, which in turn will hinder our progress on the computational front. Most existing machine learning algorithms are black boxes. They do not produce human-interpretable models. When something goes wrong, it is hard to know the cause and how to fix it.

In presenting linguistic constructs and perspectives, I do not follow the linguistic tradition in writing because the knowledge and the way that the knowledge is presented in the traditional linguistics literature are mainly for people to understand rather than for computers to operationalize to solve real-life problems. Although the knowledge of human beings and instructions for computers can largely intersect, they also have major differences. As a case in point, when I was working on the problem of mining opinions from conditional sentences, I read several linguistics books about conditionals. However, to my surprise, I found almost no linguistic knowledge that can be operationalized computationally to help solve the problem. I believe this is partially because the current computation technologies are not mature enough to have the same understanding capability as people and partially because much of the linguistic knowledge is not meant for computers to use. Another feature of this book is that it is not just about studying the language for human understanding per se, as much of the traditional linguistic literature does; it is also about practical applications of mining sentiment and opinion expressed in natural language, for which we not only want to recognize sentiment or opinion expressions and their polarities (or orientations) but also to extract several other pieces of important information associated with sentiment or opinion. For example, we want to identify the real-world entities or topics that a sentiment or opinion is about. These entities or topics are called *opinion* (or *sentiment*) *targets*. Extracting opinion targets is extremely important in practice. For example, in the sentence "*I am disgusted by tax increase for the poor*," if we only find that the sentence expresses a negative sentiment and/or an emotion of *disgust* from the sentence author, it is not that useful in practice. But if we also find that the negative sentiment is toward '*tax increase for the poor*,' which is the target of the negative sentiment or emotion, the information becomes much more valuable. I hope this book can serve to encourage linguists to develop a comprehensive theory about sentiment and opinion and their associated concepts.

I write this book as an introductory text to the field of sentiment analysis and as a research survey. In many places, it is one or the other, and in some other places, it is a mixture of both. The reason for this mixed or somewhat unusual presentational style is that there are few mature techniques or algorithms for sentiment analysis, although numerous researchers have attempted to solve each subproblem. In many cases, we can see from the accuracy of the results of the published papers that they are not yet ready for prime time. Another reason for the mixed presentational style of this book is that most existing research methods are direct applications of machine learning and data mining algorithms employing text features. Because many books on machine learning and data mining cover these algorithms extensively, these algorithms are thus not detailed in this book. This book also does not detail the basics of linguistics or natural language processing, such as part-of-speech tagging, syntactic parsing, shallow parsing, and grammar. Although these topics are very important to sentiment analysis too, again, they have been covered in numerous books on natural language processing. This book thus assumes that readers know the basics of machine leaning and natural language processing.

I tried to cover all major developments of the field in this book. It is thus quite comprehensive. Evidence of this is that the book cites more than six hundred publications from all major conferences and journals. I organize the book as follows. Chapter 1 introduces the book and gives the motivations for the study of sentiment analysis. We see that sentiment analysis is a fascinating and yet challenging problem with almost unlimited practical applications. Chapter 2 defines the sentiment analysis problem and discusses many of its related issues. Here we see that although sentiment analysis is a natural language processing problem, it can be defined structurally. Through the definition, we can transform unstructured text to structured data. This facilitates subsequent qualitative and quantitative analyses, which are critical for real-life applications. We also see that sentiment analysis is a multifaceted problem with many challenging and interrelated subproblems.

Chapter 3 studies the topic of document-level sentiment classification, which classifies an opinion document (e.g., a product review) as expressing a positive or negative sentiment. Chapter 4 studies the same classification problem but focuses on each individual sentence. Related problems of sentiment rating prediction, transfer learning, and multilingual sentiment classification are also discussed in these two chapters.

Chapters 5 and 6 go to the fine-grained level to study the most important topic of aspect-based sentiment analysis, which not only classifies sentiment but also identifies the target of sentiment or opinion. Most practical sentiment analysis or opinion mining systems in industry are based on this fine-grained level of analysis. Chapter 5 focuses on aspect sentiment classification, and Chapter 6 focuses on aspect or target extraction.

Chapter 7 describes research that compiles sentiment lexicons. A sentiment lexicon is a list of words and phrases (e.g., *good*, *amazing*, *bad*, *horrible*) that people often use to express positive or negative opinions. Chapter 8 studies opinions expressed in comparative sentences. Chapter 9 focuses on opinion summarization and opinion search. Chapter 10 looks into a different type of sentiment (agreement and disagreement) expressed in online debates and discussions, which involve extensive interactive exchanges among participants. Chapter 11 investigates intention mining, which aims to discover intentions expressed in language.

Chapter 12 switches to a very different topic: detecting fake or deceptive online opinions. Chapter 13 studies the problem of ranking online reviews based on their usefulness so that users can view the most useful reviews first. Chapter 14 concludes the book and discusses some future research.

The book is suitable for students, researchers, and practitioners who are interested in social media analysis and natural language processing in general and sentiment analysis or opinion mining in particular. It is written not only for the computer science audience but also for researchers and practitioners in management sciences and social sciences. Consumer sentiments and public opinions are central to many management and social science areas such as marketing, economics, communication, and political science. Lecturers can readily use the book in class for courses on natural language processing, social media analysis, social computing, and text and data mining. Lecture slides are available online.

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ways. My wife has taken care of almost everything at home and put up with me and the long hours that I have spent on this book. I dedicate this book to them.

Bing Liu

Chicago, USA

July 10, 2014

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Introduction

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Sentiment analysis, also called *opinion mining*, is the field of study that analyzes people's opinions, sentiments, appraisals, attitudes, and emotions toward entities and their attributes expressed in written text. The entities can be products, services, organizations, individuals, events, issues, or topics. The field represents a large problem space. Many related names and slightly different tasks, for example, *sentiment analysis*, *opinion mining*, *opinion analysis*, *opinion extraction*, *sentiment mining*, *subjectivity analysis*, *affect analysis*, *emotion analysis*, and *review mining*, are now all under the umbrella of *sentiment analysis*. The term *sentiment analysis* perhaps first appeared in Nasukawa and Yi (2003), and the term *opinion mining* first appeared in Dave et al. (2003). However, research on *sentiment* and *opinion* began earlier (Wiebe, 2000; Das and Chen, 2001; Tong, 2001; Morinaga et al., 2002; Pang et al., 2002; Turney, 2002). Even earlier related work includes interpretation of metaphors; extraction of sentiment adjectives; affective computing; and analysis of subjectivity, viewpoints, and affects (Wiebe, 1990, 1994; Hearst, 1992; Hatzivassiloglou and McKeown, 1997; Picard, 1997; Wiebe et al., 1999). An early patent on text classification included sentiment, appropriateness, humor, and many other concepts as possible class labels (Elkan, 2001). Since existing research and applications of sentiment analysis have focused primarily on written text, it has been an active research field of natural language processing (NLP). However, the topic has also been widely studied in data mining, web mining, and information retrieval because many researchers in these fields deal with text data. My own first paper (Hu and Liu, 2004) on the topic was published in the proceedings of the data mining conference KDD (SIGKDD International Conference on Knowledge Discovery and Data Mining) in 2004. This paper defined the aspect-based sentiment analysis and summarization framework and some basic ideas and algorithms for solving the problem that are commonly used in research and industrial systems today.

Not surprisingly, there has been some confusion among practitioners and even researchers about the difference between *sentiment* and *opinion* and whether the field should be called *sentiment analysis* or *opinion mining*. Because the field originated from computer science rather than linguistics, little discussion has concerned the difference between the two words. In Merriam-Webster's dictionary, *sentiment* is defined as an attitude, thought, or judgment prompted by feeling, whereas *opinion* is defined as a view, judgment, or appraisal formed in the mind about a particular matter. The difference is quite subtle, and each contains some elements of the other. The definitions indicate that an opinion is more of a person's concrete view about something, whereas a sentiment is more of a feeling. For example, the sentence "*I am concerned about the current state of the economy*" expresses a sentiment, whereas the sentence "*I think the economy is not doing well*" expresses an opinion. In a conversation, if someone says the first sentence, we can respond by saying, "*I share your sentiment*," but for the second sentence, we would normally say, "*I agree/disagree with you*." However, the underlying meanings of the two sentences are related because the sentiment depicted in the first sentence is likely to be a feeling caused by the opinion in the second sentence. Conversely, we can also say that the first sentiment sentence implies a negative opinion about the economy, which is what the second sentence is saying. Although in most cases opinions imply positive or negative sentiments, some opinions do not, for example, "*I think he will go to Canada next year*."

Regarding the name of the field, *sentiment analysis* is used almost exclusively in industry, whereas both *opinion mining* and *sentiment analysis* are commonly employed in academia. In this book, I use the terms *sentiment analysis* and *opinion mining* interchangeably. Furthermore, I use the term *opinion* to mean the whole concept of sentiment, evaluation, appraisal, or attitude and associated information, such as the opinion target and the person who holds the opinion (see the formal definition in Section 2.1), and I use the term *sentiment* to mean the underlying positive or negative feeling implied by opinion. Sentiment analysis mainly focuses on opinions that express or imply positive or negative sentiments, also called *positive or negative opinions* in everyday language. This type of opinion is similar to the concept of *attitude* in social psychology. For example, Eagly and Chaiken (1998, p. 1) defined an attitude as "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor." In discussing positive and negative sentiments, we must also consider expressions without any implied sentiment, which we call *neutral* expressions. Apart from sentiment and opinion, there are also the concepts of *affect*, *emotion*, and *mood*, which are psychological states of mind. We study natural language expressions of such states in detail in Section 2.3.

Sentences expressing opinions or sentiments are usually *subjective* sentences as opposed to *objective* sentences, which state facts, because opinions and sentiments are inherently subjective. However, objective sentences can imply positive or negative sentiments of their authors too, because they may describe desirable or undesirable facts. For example, based on our commonsense knowledge, we know that "*I bought the car yesterday and it broke today*" and "*after sleeping on the mattress for a month, a valley has formed in the middle*" describe two undesirable facts, and we can safely infer that the sentence authors feel negatively about the car and the mattress. Sentiment analysis also studies such objective sentences. In a nutshell, sentiment analysis or opinion mining aims to identify positive and negative opinions or sentiments expressed or implied in text and also the targets of these opinions or sentiments (e.g., *the car* and *the mattress* in the preceding sentences). A more formal definition is given in Section 2.1.

Although sentiment analysis studies opinion text, there was almost no research on it from either the linguistics community or the NLP community before the year 2000. This is partly because almost no opinionated text was recorded in digital forms before then, although throughout history, spoken or written communication never had a shortage of opinion. With the explosive growth of the web and social media in the past fifteen years, we now have a constant flow of opinion data recorded in digital forms. Without these data, much of the existing research would not have been possible. It is thus no surprise that the inception and rapid growth of sentiment analysis coincide with the growth of social media on the web.

Over the years, social media systems on the web have provided excellent platforms to facilitate and enable audience participation, engagement, and community, which has resulted in our new participatory culture. From reviews and blogs to YouTube, Facebook, and Twitter, people have embraced these platforms enthusiastically because they enable their users to freely and conveniently voice their opinions and communicate their views on any subject across geographic and spatial boundaries. They also allow people to easily connect with others and to share their information. This participatory web and communications revolution has transformed our everyday lives and society as a whole. It has also popularized two major research areas, namely, *social network analysis* and *sentiment analysis*. Although social network analysis is not a new research area, as it started in the 1940s and 1950s when management science researchers began to study social actors (people in organizations) and their interactions and relationships, social media has certainly fueled its explosive growth in the past fifteen years. Sentiment analysis, conversely, is a new research area that essentially grew out of social media on the web.

Since the year 2002, research in sentiment analysis has been very active. Apart from the availability of a large volume of opinion data in social media, opinions and sentiments also have a very wide range of applications simply because opinions are central to almost all human activities. Whenever we need to make a decision, we often seek out others' opinions. This is true not only for individuals but also for organizations. It is thus no surprise that the industry and applications surrounding sentiment analysis have flourished since around 2006. On one hand, this application need provided a strong motivation for research. On the other, sentiment analysis also offers numerous challenging and fascinating research problems whose solutions have never before been attempted. In this book, I systematically define and discuss these problems and present the current state-of-the-art techniques for studying them.

Because a key function of social media is for people to express their views and opinions, sentiment analysis is right at the center of research and application of social media itself. It is now well recognized that, to extract and exploit information in social media, sentiment analysis is a necessary technology. One can even take a sentiment-centric view of social media content analysis because the most important information that one wants to extract from the social media content is what people talk about and what their opinions are. These are exactly the core tasks of sentiment analysis. Furthermore, we can claim that topics, events, and individuals discussed in social media are unlikely to be important if few people have expressed opinions about them. Human nature being what it is, everything that we consider important arouses our inner feelings or emotions, which are expressed with opinions and sentiments.

Apart from topics and opinions about topics, social media also allows us to study the participants themselves. We can produce a sentiment profile of each social media participant based on his or her topical interests and opinions about these interests expressed in the users' posts, because a person's topical interests and opinions reflect the nature and preferences of the person. Such information can be used in many applications, for example, recommending products and services and determining which political candidates to vote for. Additionally, social media participants can not only post messages but also interact with one another through discussions and debates, which involve sentiments such as *agreement* and *disagreement* (or *contention*). Discovery of such information is also of great importance. For example, contentious social and political issues and views of opposing positions can be exploited to frame political issues and to predict election results.

Owing to the importance of opinions in social media, imposters often game the system by posting fake or deceptive opinions to promote some target products, services, and ideological agendas. Detecting such fake or deceptive opinions is an important challenge, which again offers fertile ground for novel research and applications.

Although sentiment analysis originated from computer science, in recent years, it has spread to management sciences and social sciences because of its importance to business and society as a whole. Thus sentiment analysis research not only advances the field of NLP but also advances research in management science, political science, and economics, as these fields are all concerned with consumer and public opinions. It is thus not hard to imagine that sentiment analysis using social media can profoundly change the direction of research and practice in these fields. This book serves as an up-to-date and introductory text as well as a comprehensive survey of this important and fascinating subject.

1.1 Sentiment Analysis Applications

Opinions are very important to businesses and organizations because they always want to find consumer or public opinions about their products and services. Local and federal governments also want to know public opinions about their existing or proposed policies. Such opinions will enable relevant government decision makers to respond quickly to the fast-changing social, economic, and political climates. In international politics, every government wants to monitor the social media of other countries to find out what is happening in these countries and what people's views and sentiments are about current local and international issues and events. Such information is very useful to diplomacy, international relations, and economic decision making. Besides businesses, organizations, and government agencies, individual consumers also want to know the opinions of others about products, services, and political candidates before purchasing the products, using the services, and making election decisions.

In the past, when an individual needed opinions, he or she asked friends and family. When an organization or a business needed public or consumer opinions, it conducted surveys, opinion polls, and focus groups. When governments wanted to know what was happening in other countries, they monitored the traditional news media, for example, newspapers, radio, and TV, in these countries, and even sent spies to these countries to collect such information. Acquiring and analyzing public and consumer opinions have long been a huge business for marketing, public relations, and political campaign firms.

Nowadays, individuals, organizations, and government agencies are increasingly using the content in social media for decision making. If an individual wants to buy a consumer product, he or she is no longer limited to asking his or her friends and family for opinions because there are many user reviews and discussions in public forums on the web about the product. For an organization, it may no longer be necessary to conduct surveys, opinion polls, or focus groups to gather public or consumer opinions about the organization's products and services because an abundance of such information is publicly available. Governments can also easily obtain public opinions about their policies and measure the pulses of other nations simply by monitoring their social media.

In recent years, we have witnessed how opinionated posts on social media sites have helped reshape business and sway public sentiment, profoundly impacting our social and political lives. For instance, such posts have mobilized the masses for political change, such as during the Arab Spring in 2011. However, finding and monitoring opinion sites on the web and distilling the information contained in them remains a formidable task because of the diversity of sites. Each site typically contains a huge volume of opinion text that is not always easily deciphered from long blogs and forum posts. The average human reader will have difficulty identifying relevant sites and extracting and summarizing the opinions in them. Automated sentiment analysis systems are thus needed.

Opinionated documents not only exist on the web (often called external data); many organizations have internal data, for example, customer feedback collected from e-mails and call centers and results from surveys conducted by the organizations. It is critical to analyze both kinds of data to tease out the key product and service issues and to summarize customer opinions.

In recent years, sentiment analysis applications have spread to almost every possible domain, from consumer products, health care, tourism, hospitality, and financial services to social events and political elections. There are now hundreds of companies in this space, start-up companies and established large corporations, that have built or are in the process of building their own in-house capabilities, such as Google, Microsoft, Hewlett-Packard, Amazon, eBay, SAS, Oracle, Adobe, Bloomberg, and SAP. I myself have implemented a sentiment analysis system, called Opinion Parser, and worked on projects for clients in more than forty domains: automobile, mobile phone, earphone, printer, fridge, washing machine, stove, Blu-ray, laptop, home theater, television, e-book, GPS, LCD monitor, dieting, hair care product, coffee maker, mattress, paint, cruise, restaurant, hotel, cosmetics, fashion, drug, soft drink, beer and wine, movie, video editing software, financial software, search engine, health insurance, banking, investment, green technology, box-office revenue prediction for new movies, summer Olympic bidding, governor election, presidential election, and public mood during the 2008–9 financial crisis.

In addition to business interests, applications are also widespread in government agencies. Internally, agencies monitor social media to discover public sentiments and citizen concerns. Such monitoring is especially big in China, where social media has become the most popular channel for the general public to voice their opinions about government policies and to expose corruptions, sex scandals, and other wrongdoings of government officials. It is also the quickest and most popular way to report negative events in everyday lives. Weibo, which literally means “microblog” in Chinese and is similar to Twitter, is the most popular platform for such revelations. Several commercial social media monitoring tools are already available. The core technology in these tools is sentiment analysis. Externally, intelligence services discover issues and events being discussed in the social media of other countries and public sentiment about the issues and events by monitoring the main social media sites of these countries.

Besides real-life applications, many application-oriented research papers have also been published. For example, several researchers have used sentiment information to predict movie success and box-office revenue. Mishne and Glance (2006) showed that positive sentiment is a better predictor of movie success than simple buzz (keyword) count. Sadikov et al. (2009) made the same prediction using sentiment and other features. Liu et al. (2007) reported a sentiment model for predicting box-office revenue. The method consists of two steps. The first step builds a topic model based on probabilistic latent semantic analysis (PLSA) (Hofmann, 1999) using only sentiment words in a set of movie reviews. Sentiment words, also called opinion words, are words in a language that indicate desirable or undesirable states. For example, *good*, *great*, and *beautiful* are positive sentiment words, and *bad*, *awful*, and *dreadful* are negative sentiment words. The second step builds an autoregressive model employing both the revenues and sentiment topics in the past few days to predict future revenues. This same revenue prediction problem was also attempted in Asur and Huberman (2010) using both the tweet volume and the tweet sentiment. A linear regression–based approach using movie review text and movie meta-data was reported in Joshi et al. (2010). My own group also used tweet sentiment to predict movie revenues several years ago and found that they could be predicted fairly easily and accurately. We simply applied our Opinion Parser system to identify and combine positive and negative opinions about each movie and user intentions to watch it. No additional model or algorithm was used.

Several researchers have also analyzed sentiments of public opinions in the context of electoral politics. For example, in O'Connor et al. (2010), a sentiment score was computed based simply on counting positive and negative sentiment words, which was shown to correlate well with presidential approval, political election polls, and consumer confidence surveys. In Bermingham and Smeaton (2011), tweet volume and positive and negative tweets were utilized as the independent variables and polling results as values for the dependent variable to train a linear regression model to predict election results. In Chung and Mustafaraj (2011) and Gayo-Avello et al. (2011), several limitations of current works on using Twitter data to predict political elections were discussed, one of them being poor sentiment analysis accuracy. The works in Diakopoulos and Shamma (2010) and Sang and Bos (2012) used manually annotated sentiments of tweets for election prediction. Tumasjan et al. (2010) even showed that simple party mentions on Twitter can be a good predictor of election results. In other related works, Yano and Smith (2010) reported a method for predicting comment volumes of political blogs, Chen et al. (2010) studied political standpoints, and Khoo et al. (2012) analyzed sentiment in political news articles about economic policies and political figures.

Another popular application area is stock market prediction. Das and Chen (2007) identified opinions from message board posts by classifying each post into one of three sentiment classes: bullish (optimistic), bearish (pessimistic), or neutral (neither bullish nor bearish). The resulting sentiments across all stocks were then aggregated and used to predict the Morgan Stanley High-Tech Index. Instead of using bullish and bearish sentiments, Zhang et al. (2010) identified positive and negative public moods on Twitter and used them to predict the movement of stock market indices such as the Dow Jones, S&P 500, and NASDAQ. They showed that when emotions on Twitter fly high, that is, when people express a lot of hope, fear, or worry, the Dow goes down the next day. When people have less hope, fear, or worry, the Dow goes up. Along a similar line, Bollen et al. (2011) used Twitter moods to predict the movement of the Dow Jones Industrial Average (DJIA). In particular, the authors analyzed the text content of tweets to generate a six-dimensional daily time series of public mood: calm, alert, sure, vital, kind, and happy. The resulting mood time series were correlated with the DJIA to assess their ability to predict changes in the DJIA over time. Their results indicate that the accuracy of standard stock market prediction models can be significantly improved when certain mood dimensions are included, that is, calm and happiness, but not others. Instead of treating sentiments from all relevant Twitter authors equally, Bar-Haim et al. (2011) identified expert investors based on their past predictions of bullish and bearish stocks. Such expert investors are then used as one of the features in training stock price movement predictors. Feldman et al. (2011) reported a focused investigation of sentiment analysis of stock-related articles. Zhang and Skiena (2010) used blog and news sentiment to design trading strategies. Si et al. (2013) combined a topic-based sentiment time series and the index time series to predict the S&P 100 index's daily movements using vector autoregression. The topic-based sentiment analysis system first uses a nonparametric topic model to identify daily topics related to stocks and then computes people's sentiments about these topics.

In addition to research in the preceding three popular application areas, numerous papers have also been published on using sentiment analysis to help other types of applications. For example, in McGlohon et al. (2010), product reviews were used to rank products and merchants. In Hong and Skiena (2010), the relationships between the National Football League betting line and public opinions in blogs and on Twitter were studied. In Miller et al. (2011), sentiment flow in social networks was investigated. In Mohammad and Yang (2011), sentiments in males were used to find how genders differed on emotional axes. In Mohammad (2011), emotions in novels and fairy tales were tracked. In Sakunkoo and Sakunkoo (2009), social influences in online book reviews were studied, and in Groh and Hauffa (2011), sentiment analysis was used to characterize social relations. A deployed general-purpose sentiment analysis system and some case studies were reported in Castellanos et al. (2011).

1.2 Sentiment Analysis Research

Pervasive real-life applications provided strong motivations for research, but applications alone are not enough to generate strong research interests in academia. Researchers also need challenging technical problems. Sentiment analysis has provided plenty of such problems, most of which had not been attempted before, either in the NLP or linguistics communities. The novelty factor coupled with widespread applications and the availability of social media data attracted numerous researchers to the field. Since the year 2000, the field has grown rapidly to become one of the most active research areas in NLP, data mining, and web mining and is also widely studied in management sciences (Hu et al., 2006; Archak et al., 2007; Das and Chen, 2007; Dellarocas et al., 2007; Ghose et al., 2007; Park et al., 2007; Chen and Xie, 2008). Although sentiment analysis has been studied in different disciplines, their focuses are not the same. For example, in management science, the main focus is on the impact of consumer opinions on businesses and how to exploit such opinions to enhance business practices. However, for NLP and data mining, the objective is to design effective algorithms and models to extract opinions from natural language text and to summarize them suitably.

In terms of natural language understanding, sentiment analysis can be regarded as an important subarea of semantic analysis because its goal is to recognize topics that people talk about and their sentiments toward the topics. In the next few subsections, I briefly describe the key research topics covered in this book and also connect sentiment analysis with some general NLP tasks.

1.2.1 Different Levels of Analysis

Sentiment analysis research has been mainly carried out at three levels of granularity: document level, sentence level, and aspect level. We briefly introduce them here.

> **Document level.** The task at the document level is to classify whether a whole opinion document expresses a positive or negative sentiment (Pang et al., 2002; Turney, 2002). It is thus known as *document-level sentiment classification*. For example, given a product review, the system determines whether the review expresses an overall positive or negative opinion about the product. This level of analysis implicitly assumes that each document expresses opinions on a single entity (e.g., a single product or service). Thus it is not applicable to documents that evaluate or compare multiple entities, for which more fine-grained analysis is needed. We study document-level sentiment analysis in Chapter 3.

> **Sentence level.** The next level is to determine whether each sentence expresses a positive, negative, or neutral opinion. Note that "neutral opinion" usually means "no opinion." This level of analysis is closely related to *subjectivity classification* (Wiebe et al., 1999), which distinguishes sentences that express factual information (called *objective sentences*) from sentences that express subjective views and opinions (called *subjective sentences*). However, subjectivity is not equivalent to sentiment or opinion because, as we discussed earlier, many objective sentences can imply sentiments or opinions, for example, "*We bought the car last month and the windshield wiper has fallen off*." Conversely, many subjective sentences may not express any opinion or sentiment, for example, "*I think he went home after lunch*." We study sentence-level sentiment analysis in Chapter 4.

> **Aspect level.** Neither document-level nor sentence-level analyses discover what people like and dislike exactly. In other words, they do not tell what each opinion is about, that is, the target of opinion. For example, if we only know that the sentence "*I like the iPhone 5*" is positive, it is of limited use unless we know that the positive opinion is about the *iPhone 5*. One may say that if we can classify a sentence to be positive, everything in the sentence can take the positive opinion. However, that will not work either, because a sentence can have multiple opinions, for example, "*Apple is doing very well in this poor economy*." It does not make much sense to classify this sentence as positive or negative because it is positive about *Apple* but negative about *economy*. To obtain this level of fine-grained results, we need to go to the aspect level. This level of analysis was earlier called *feature level*, as in *feature-based opinion mining and summarization* (Hu and Liu, 2004; Liu, 2010), which is now called *aspect-based sentiment*

> *analysis*. Instead of looking at language units (documents, paragraphs, sentences, clauses, or phrases), aspect-level analysis directly looks at opinion and its target (called *opinion target*). Realizing the importance of opinion targets allows us to have a much better understanding of the sentiment analysis problem. Let us see another example sentence: "*Although the service is not great, I still love this restaurant*." This sentence clearly has a positive tone, but we cannot say that this sentence is entirely positive. We can only say that the sentence is positive about the *restaurant* (emphasized), but it is still negative about its *service* (not emphasized). If someone reading the opinion cares a lot about the service, he probably will not go to eat at the restaurant. In applications, opinion targets (e.g., *restaurant* and *service* in the preceding sentence) are often described by entities (e.g., *restaurant*) and/or their different aspects (e.g., *service* of the restaurant). Thus, the goal of this level of analysis is to discover sentiments on entities and/or their aspects. On the basis of this level of analysis, a summary of opinions about entities and their aspects can be produced. We study aspect-level sentiment analysis in Chapters 5 and 6. Note that in some applications, the user may only be interested in opinions about entities. In that case, the system can just ignore its aspects. Aspect-level analysis is what is needed in applications, and almost all real-life sentiment analysis systems in industry are based on this level of analysis.

Besides different levels of analysis, there are two different types of opinions, that is, *regular opinions* and *comparative opinions* (Jindal and Liu, 2006b):

- A regular opinion expresses a sentiment about a particular entity or an aspect of the entity, for example, "*Coke tastes very good*" expresses a positive sentiment or opinion on the aspect *taste* of *Coke*. This is the most common type of opinion.
- A comparative opinion compares multiple entities based on some of their shared aspects, for example, "*Coke tastes better than Pepsi*" compares *Coke* and *Pepsi* based on their tastes (an aspect) and expresses a preference for *Coke* (see Chapter 8).

Along with these basic tasks, researchers have also studied opinion summarization and opinion search, which we study in Chapter 9.

1.2.2 Sentiment Lexicon and Its Issues

Not surprisingly, the most important indicators of sentiments are *sentiment words*, also called *opinion words*. For example, *good*, *wonderful*, and *amazing* are positive sentiment words, and *bad*, *poor*, and *terrible* are negative sentiment words. Apart from individual words, there are also phrases and idioms, for example, *cost an arm and a leg*. Sentiment words and phrases are instrumental to sentiment analysis. A list of such words and phrases is called a *sentiment lexicon* (or *opinion lexicon*). Over the years, researchers have designed numerous algorithms to compile such lexicons. We discuss these algorithms in Chapter 7.

Although sentiment words and phrases are important, they are far from sufficient for accurate sentiment analysis. The problem is much more complex. We highlight several issues in the following:

1. A positive or negative sentiment word may have opposite *orientations* or *polarities* in different application domains or sentence contexts. By orientation or polarity, we mean whether a sentiment or opinion is positive, negative, or neutral. For example, *suck* usually indicates negative sentiment, for example, "*This camera sucks*," but it can also imply positive sentiment, for example, "*This vacuum cleaner really sucks*." Thus, we say that the orientations of sentiment words can be domain dependent or even sentence context dependent.

2. A sentence containing sentiment words may not express any sentiment. This phenomenon happens in several types of sentences. Question (interrogative) sentences and conditional sentences are two main types, for example, "*Can you tell me which Sony camera is good*?" and "*If I can find a good camera in the shop, I will buy it*." Both these sentences contain the sentiment word *good*, but neither expresses a positive or negative opinion about any specific camera. However, that is not to say that all conditional sentences and interrogative sentences express no opinion or sentiment, for example, "*Does anyone know how to repair this terrible printer*?" and "*If you are looking for a good car, get a Ford Focus*." We discuss such sentences further in Chapter 4.

3. Sarcastic sentences with or without sentiment words are hard to deal with, for example, "*What a great car! It stopped working in two days*." Sarcasm is not so common in consumer reviews about products and services but is common in political discussions, which make political opinions hard to deal with. We discuss such sentences also in Chapter 4.

4. Many sentences without sentiment words can imply positive or negative sentiments or opinions of their authors. For example, "*This washer uses a lot of water*" implies a negative opinion about the washer because it uses a lot of resources (water). Many such sentences are actually objective sentences that express some factual information. For example, “*After sleeping on the mattress for two days, a valley has formed in the middle*” expresses a negative opinion about the quality of the mattress. This sentence can be regarded as objective because it states a fact, although *valley* is used as a metaphor here. As we can see, these two sentences contain no sentiment words, but they both express something undesirable, which indicate negative opinions.

All these issues present major challenges. In fact, these are just some of the difficult problems. More are discussed in Chapter 7.

1.2.3 Analyzing Debates and Comments

There are generally two types of text content in social media: standalone posts, such as reviews and blogs, and online dialogues, such as debates and discussions. Online dialogues are conversational and typically involve interactive exchanges of two or more participants, which are in contrast to standalone posts, which are mostly independent of one another. Online dialogues are usually full of opinions. In addition to positive and negative sentiments, they also contain *agreements* and *disagreements* (or *contentions*), which are regarded as an interactive form of sentiment or opinion. Furthermore, owing to user interactions, additional analyses can be performed. For instance, we can discover the stance of each person in a debate, group people into different ideological camps, mine agreement and disagreement expressions, discover contentious issues, and pairwise user arguing nature (Mukherjee and Liu, 2012). Because debates or discussions are supposed to be exchanges of arguments and reasoning among participants who are engaged in deliberations to achieve some common goals, we can study whether each participant indeed behaves accordingly, that is, giving reasoned arguments with justifiable claims or just exhibiting dogmatism and egotistic clashes of ideologies. Such analyses are very useful to social scientists, for example, in the fields of political science and communications (Mukherjee et al., 2013).

Comments are posts that comment about a published article (e.g., a news article, a blog post, or a review), a video, a picture, or a piece of music. They often consist of a mixture of standalone posts and dialogues. From comments about an online article, we can observe several types of comment posts, for example, reviews of the article, questions to the author of the article or to other readers, answers to questions, and discussions among readers and between readers and the article author. We study the analysis of debates and comments in Chapter 10.

1.2.4 Mining Intentions

Intention is defined as a course of action that a person or a group of persons intends to follow. Mining intentions expressed in social media have many applications, for example, making product recommendations and discovering likely voters for a political candidate. Although intention and sentiment are two different concepts, they are related in several ways. First, one may attach some sentiment or emotion to the involved entity in an intention sentence, for example, "*I am dying to see* Life of Pi." Here the intention of the person has reached the emotional level. Second, when one expresses a desire to get a particular item, one often has a positive opinion about the item. For example, from "*I want to buy an iPhone 5*," it is probably safe to infer that the person has a good impression about the iPhone 5. These two cases represent a new kind of sentiment, *aspiration*. The two example sentences both expressed positive aspirations. Third, some opinions are expressed as intentions, for example, "*I want to throw this camera out of the window*" and "*I am going to return this camera to the shop*." So far, mining of intentions has not received much research attention, but I believe it has a great potential for applications. Chapter 11 discusses the problem and presents an intention mining algorithm based on the idea of transfer learning (Chen et al., 2013).

1.2.5 Opinion Spam Detection and Quality of Reviews

A key feature of social media is that it enables anyone from anywhere in the world to freely express his views and opinions without disclosing his true identity and without the fear of undesirable consequences. These opinions are thus highly valuable. However, this anonymity comes with a price. It makes it easy for people with hidden agendas or malicious intentions to game the system by posting fake opinions to promote or to discredit some target products, services, organizations, or individuals without disclosing their true intentions, or the person or organization for whom they are secretly working. Such individuals are called *opinion spammers*, and their activity is called *opinion spamming* (Jindal and Liu, 2007, 2008).

Opinion spamming has become a major issue in social media. In addition to individuals who give fake opinions in reviews and forum discussions, there are also commercial companies that are in the business of writing fake reviews and bogus blogs for their clients. Several high-profile cases of fake reviews have been reported in the news (Streitfeld, August 25, 2012; Harmon, February 14, 2004; Streitfeld, January 26, 2012; Kost, September 15, 2012). It is important to detect such spamming activities to ensure that the opinions on the web are trusted sources of valuable information. Unlike extraction of positive and negative opinions, opinion spam detection is not just a NLP problem but also a data mining problem as it involves analyzing the posting behaviors of reviewers. Besides academic research, some review hosting companies filter fake reviews on their sites, for example, Yelp.com and Dianping.com. Chapter 12 studies the problem and the current state-of-the-art detection algorithms.

A related research problem is to assess the quality or utility of each online review. The objective here is to identify those reviews that are of high quality and rank them at the top so that the user can read them first to get the maximum information. This topic and its associated algorithms are discussed in Chapter 13.

To end this section, I would like to mention that there are several other books on sentiment analysis or opinion mining: a multiauthor volume edited by Shanahan et al. (2006), an older survey book by Pang and Lee (2008), a newer survey book by Liu (2012), and a monograph by Cambria and Hussain (2012). All four books have excellent contents and have helped me in writing this book. However, since the first two books were published, there have been significant advances in the field. Researchers now have a much better understanding of the whole spectrum of the problem, its structure and core issues. Numerous new models and methods have also been proposed. The research in the area has not only deepened but also broadened significantly. Earlier research in the field focused mainly on document- and sentence-level sentiment and subjectivity classification, which is insufficient for real-life applications. Practical applications almost always demand aspect-level analysis. Although the third book, which is also authored by me, is relatively new, it is a research survey. The last book focuses on using commonsense knowledge in opinion mining. This new book is much more comprehensive. First, it includes details of many important algorithms. Following these algorithms, interested readers can implement a practical sentiment analysis system without much difficulty. Second, it goes beyond much of the current analysis of standalone (or independent) posts to cover analysis and mining of interactive social media forms (e.g., debates and comments) and intentions. These inclusions significantly broaden the research area and make it more comprehensive.

1.3 Sentiment Analysis as Mini NLP

Sentiment analysis is commonly seen as a subarea of NLP. Since its inception, sentiment analysis has expanded the NLP research significantly because it has introduced many challenging research problems that had not been studied before. However, research in the past fifteen years seems to indicate that rather than being a subproblem of NLP, sentiment analysis is actually more like a mini version of the full NLP or a special case of the full NLP. That is, every subproblem of NLP is also a subproblem of sentiment analysis, and vice versa. The reason for this is that sentiment analysis touches every core area of NLP, such as lexical semantics, coreference resolution, word sense disambiguation, discourse analysis, information extraction, and semantic analysis. We discuss some of these general NLP problems in various chapters in the context of sentiment analysis as part of the approaches proposed by researchers to solve the sentiment analysis problem. In this sense, sentiment analysis offers an excellent platform for all NLP researchers to make tangible and focused progress on all fronts of NLP, with the potential of making a huge research and practical impact. Clearly solving a simpler version of NLP is much more manageable. It is also much easier to achieve major progresses and breakthroughs. A NLP researcher of any area can start to solve a corresponding problem in sentiment analysis without changing his or her research topic or area. The only thing that he or she needs to change is the corpus, which should be an opinion corpus.

In general, sentiment analysis is a semantic analysis problem, but it is highly focused and confined because a sentiment analysis system does not need to fully “understand” each sentence or document; it only needs to comprehend some aspects of it, for example, positive and negative opinions and their targets. Owing to some special characteristics of sentiment analysis, it allows much deeper language analyses to be performed to gain better insights into NLP than in the general setting because the complexity of the general setting of NLP is simply overwhelming. Although general natural language understanding is still far from us, with the concerted effort of researchers from different NLP areas, we may be able to solve the sentiment analysis problem, which, in turn, can give us critical insight into how to deal with general NLP.

Through this book, I would like to encourage researchers from other areas of NLP to continue working on their favorite NLP problems but using opinion corpora, which will directly or indirectly help solve the sentiment analysis problem.

1.4 My Approach to Writing This Book

In this book, we explore this fascinating topic. Although the book deals with the natural language text, which is called *unstructured data*, I try to take a structured approach to writing this book. The next chapter formally defines the sentiment analysis problem, which allows us to see a structure for it. From the definition, we will be able to state the key tasks of sentiment analysis. In the subsequent chapters, I describe existing techniques for performing the tasks. The book not only discusses key research concepts but also looks at the technology from an application point of view to help practitioners in the field. This practical guidance is based on my research, consulting, and start-up experiences. When I talk about industrial systems, I will not reveal the names of companies or their systems for confidentiality reasons.

Although I try to cover all major ideas and techniques in this book, it has become an impossible task. In the past decade, a huge number of research papers (probably more than two thousand) have been published on the topic. Although most papers appeared at NLP conferences and in NLP journals, many papers have also been published in data mining, web mining, machine learning, information retrieval, e-commerce, management science, and many other fields. It is thus almost impossible to write a book that covers the ideas in every published paper. I am sorry if your good ideas or techniques are overlooked.

Finally, background knowledge in the following areas will be helpful in reading this book: NLP (Manning and Schutze, 1999; Indurkhya and Damerau, 2010), machine learning (Mitchell, 1997; Bishop, 2006), data mining (Tan et al., 2005; Liu, 2006, 2011; Han et al., 2011), and information retrieval (Manning et al., 2008). As mentioned earlier, a large number of research papers solve the sentiment analysis problem by applying machine learning and data mining algorithms with NLP syntactic and semantic features.

2

The Problem of Sentiment Analysis

◈

In this chapter, we define an abstraction of the sentiment analysis problem. This abstraction gives us a statement of the problem and enables us to see a rich set of interrelated subproblems. It is often said that if we cannot structure a problem, we probably do not understand the problem. The objective of the definitions is thus to abstract a structure from the complex and intimidating unstructured natural language text. The structure serves as a common framework to unify various existing research directions and enable researchers to design more robust and accurate solution techniques by exploiting the interrelationships of the subproblems. From a practical application point of view, the definitions let practitioners see what subproblems need to be solved in building a sentiment analysis system, how the subproblems are related, and what output should be produced.

Unlike factual information, sentiment and opinion have an important characteristic, namely, they are subjective. The subjectivity comes from many sources. First of all, different people may have different experiences and thus different opinions. For example, one person bought a camera of a particular brand and had a very good experience with it. She naturally has a positive opinion or sentiment about the camera. However, another person who also bought a camera of the same brand had some issues with it because he might just be unlucky and got a defective unit. He thus has a negative opinion. Second, different people may see the same thing in different ways because everything has two sides. For example, when the price of a stock is falling, one person may feel very sad because he bought the stock when the price was high, but another person may be very happy because it is an opportunity to short sell the stock to make good profits. Furthermore, different people may have different interests and/or different ideologies. Owing to such different subjective experiences, views, interests, and ideologies, it is important to examine a collection of opinions from many people rather than only one opinion from a single person, because such an opinion represents only the subjective view of that single person, which is usually not sufficient for action. With a large number of opinions, some form of summary becomes necessary (Hu and Liu, 2004). Thus, the problem definition should also state what kind of summary may be desired. Along with the problem definitions, the chapter also discusses the important concepts of affect, emotion, and mood.

Throughout this chapter and the whole book, I mainly use product reviews and sentences from such reviews as examples to introduce the key concepts, but the ideas and the resulting definitions are general and applicable to all forms of formal and informal opinion text such as news articles, tweets (Twitter posts), forum discussions, blogs, and Facebook posts. They are also applicable to all domains, including social and political domains. Because product reviews are highly focused and opinion rich, they allow us to see different issues more clearly than other forms of opinion text. Conceptually, there is no fundamental difference between product reviews and other forms of opinion text, except some superficial differences and the degree of difficulty in dealing with them. For example, tweets are short (at most 140 characters) and informal, and often include Internet slang and emoticons. Owing to the length limit, the authors are usually straight to the point. Thus, it is often easier to achieve a higher sentiment analysis accuracy for tweets. Reviews are also easier because they are highly focused with little irrelevant information. Forum discussions are perhaps the hardest to deal with because the users there can discuss anything and often are involved in interactive exchanges with one another. Different application domains also have different degrees of difficulty. Opinions about products and services are usually the easiest to deal with. Opinions about social and political issues are much harder because of complex topic and sentiment expressions, sarcasms, and ironies. These often need analysis at the pragmatics level, which can be difficult without sufficient background knowledge of the local social and political contexts. These explain why many commercial systems are able to perform sentiment analysis of opinions about products and services reasonably well but fare poorly on opinionated social and political texts.

2.1 Definition of Opinion

As discussed in Chapter 1, sentiment analysis mainly studies opinions that express or imply positive or negative sentiment. We define the problem in this context. We use the term *opinion* as a broad concept that covers sentiment, evaluation, appraisal, or attitude and associated information such as opinion target and the person who holds the opinion, and we use the term *sentiment* to mean only the underlying positive or negative feeling implied by opinion. Owing to the need to analyze a large volume of opinions, in defining opinion, we consider two levels of abstraction: *a single opinion* and *a set of opinions*. In this section, we focus on defining a single opinion and describing the tasks involved in extracting an opinion. Section 2.2 focuses on a set of opinions, where we define *opinion summary*.

2.1.1 Opinion Definition

We use the following review (Review A) about a camera to introduce the problem (an ID number is associated with each sentence for easy reference):

Review A: Posted by John Smith Date: September 10, 2011

(1) *I bought a Canon G12 camera six months ago*. (2) *I simply love it*. (3) *The picture quality is amazing*. (4) *The battery life is also long*. (5) *However, my wife thinks it is too heavy for her*.

From this review, we notice the following:

> **Opinion, sentiment, and target.** Review A has several opinions with positive or negative sentiments about the Canon G12 camera. Sentence 2 expresses a positive sentiment about the Canon camera as a whole. Sentence 3 expresses a positive sentiment about its picture equality. Sentence 4 expresses a positive sentiment about its battery life. Sentence 5 expresses a negative sentiment about the camera's weight.
>
> These opinions enable us to make a crucial observation about sentiment analysis. That is, an opinion has two key components: a *target g* and a *sentiment s* on the target, (g, s), where g can be any entity or aspect of the entity on which an opinion has been expressed, and s is a positive, negative, or neutral sentiment or a numeric sentiment rating. *Positive*, *negative*, and *neutral* are called *sentiment* or *opinion orientations*. For example, the target of the sentiment in sentence 2 is the *Canon G12 camera*, the target of the sentiment in sentence 3 is the *picture quality of Canon G12*, and the target of sentence 5 is the *weight of Canon G12* (*weight* is indicated by *heavy*). Target is also called *topic* by some researchers.

> **Opinion holder.** Review A contains opinions from two persons, who are called *opinion sources* or *opinion holders* (Kim and Hovy, 2004; Wiebe et al., 2005). The holder of the opinions in sentences 2, 3, and 4 is the author of the review ("John Smith"), but for sentence 5, it is the author's wife.

> **Time of opinion.** The date of the review was September 10, 2011. This date is useful because one often wants to know the opinion trend, or how opinions change over time.

With this example, we can define opinion as a quadruple.

> **Definition 2.1 (Opinion):** An *opinion* is a quadruple,
>
> (g, s, h, t),

> where *g* is the *sentiment target*, *s* is the *sentiment* of the opinion about the target *g*, *h* is the *opinion holder* (the person or organization who holds the opinion), and *t* is the *time* when the opinion is expressed.

The four components here are essential. It is generally problematic if any of them is missing. For example, the time component is often very important in practice because an opinion two years ago is not the same as an opinion today. Not having an opinion holder is also problematic. For example, an opinion from a very important person (VIP) (e.g., the U.S. president) is probably more important than an opinion from the average Joe on the street. An opinion from an organization is typically more important than an opinion from a private individual. For instance, the opinion implied by "*Standard & Poor's downgraded the credit rating of Greece*" is very important for the international financial market and even the international politics.

One thing that we want to stress about the definition is that *opinion has target*. Recognizing this point is important for two reasons: first, in a sentence with multiple targets (which are usually expressed as nouns or noun phrases), we need to identify the specific target for each positive or negative sentiment. For example, "*Apple is doing very well in this poor economy*" has a positive sentiment and a negative sentiment. The target for the positive sentiment is *Apple*, and the target for the negative sentiment is *economy*. Second, words or phrases, such as *good*, *amazing*, *bad*, and *poor*, that express sentiments (called *sentiment* or *opinion terms* or expressions) and sentiment targets often have some specific syntactic relations (Hu and Liu, 2004; Zhuang et al., 2006; Qiu et al., 2011) that allow us to design algorithms to extract both sentiment expressions and sentiment targets, which are two core tasks of sentiment analysis (see Section 2.1.6).

The opinion defined here is just one type of opinion, called *regular opinion* (e.g., "*Coke tastes great*"). Another type is *comparative opinion* (e.g., "*Coke tastes better than Pepsi*"), which needs a different definition (Liu, 2006, 2011; Jindal and Liu, 2006b). Section 2.4 further discusses different types of opinions. Chapter 8 defines and analyzes comparative opinions in detail. For the rest of this section, we focus on only regular opinions, which, for simplicity, we just call opinions.

2.1.2 Sentiment Target

> **Definition 2.2 (Sentiment target):** The *sentiment target*, also known as the *opinion target*, of an opinion is the entity or a part or attribute of the entity that the sentiment has been expressed upon.

For example, in sentence 3 of Review A, the target is the *picture quality of Canon G12*, although the sentence mentioned only the *picture quality*. The target is not just the *picture quality*, because without knowing that the picture quality belongs to the Canon G12 camera, the opinion in the sentence is of little use.

An entity can be decomposed and represented hierarchically (Liu, 2006, 2011).

> **Definition 2.3 (Entity):** An *entity* e is a product, service, topic, person, organization, issue, or event. It is described with a pair, e: (T, W), where T is a hierarchy of *parts*, *subparts*, and so on, and W is a set of *attributes* of e. Each part or subpart also has its own set of attributes.

For example, a particular camera model is an entity, e.g., Canon G12. It has a set of attributes (e.g., *picture quality*, *size*, and *weight*), and a set of parts (e.g., *lens*, *viewfinder*, and *battery*). *Battery* also has its own set of attributes (e.g., *battery life* and *battery weight*). A topic can be an entity too, for example, *tax increase*, with its subtopics or parts *tax increase for the poor*, *tax increase for the middle class*, and *tax increase for the rich*.

This definition describes an entity hierarchy based on the *part-of* relation. The root node is the name of the entity, like Canon G12 in Review A. All the other nodes are parts and subparts. An opinion can be expressed on any node and any attribute of the node. For instance, in Review A, sentence 2 expresses a positive sentiment or opinion about the entity Canon G12 as a whole, and sentence 3 expresses a positive sentiment or opinion about the picture quality attribute of the camera. Clearly we can also express opinions about any part or component of the camera.

In the research literature, entities are also called *objects*, and attributes are also called *features* (as in product features) (Hu and Liu, 2004; Liu, 2010). We choose not to use the terms *object* and *feature* in this book because “object” can be confused with the term *object* used in grammar, and “feature” can be confused with *feature* used in machine learning to mean a data attribute. In recent years, the term *aspect* has become popular and covers both *part* and *attribute* (see Section 2.1.4).

Entities may be called other names in specific application domains. For example, in politics, entities are usually *political candidates*, *issues*, and *events*. There is no term that is perfect for all application domains. The term *entity* is chosen because most current applications of sentiment analysis study opinions about various forms of named entities, for example, products, services, brands, organizations, events, and people.

2.1.3 Sentiment of Opinion

> **Definition 2.4** (**Sentiment**): *Sentiment* is the underlying feeling, attitude, evaluation, or emotion associated with an opinion. It is represented as a triple,
>
> $$(y, o, i),$$
>
> where *y* is the *type* of the sentiment, *o* is the *orientation* of the sentiment, and *i* is the *intensity* of the sentiment.

Sentiment type. Sentiment can be classified into several types. There are linguistic-based, psychology-based, and consumer research–based classifications. Here I choose to use a consumer research–based classification because I feel it is simple and easy to use in practice. Consumer research classifies sentiment broadly into two categories: *rational sentiment* and *emotional sentiment* (Chaudhuri, 2006).

> **Definition 2.5 (Rational sentiment)**: *Rational sentiments* are from rational reasoning, tangible beliefs, and utilitarian attitudes. They express no emotions.

We also call opinions expressing rational sentiment the *rational opinions*. The opinions in the following sentences imply rational sentiment: "*The voice of this phone is clear*" and "*This car is worth the price.*"

> **Definition 2.6 (Emotional sentiment)**: *Emotional sentiments* are from nontangible and emotional responses to entities that go deep into people's psychological states of mind.

We also call opinions expressing emotional sentiment *emotional opinions*. The opinions in the following sentences imply emotional sentiment: "*I love the iPhone*," "*I am so angry with their service people*," "*This is the best car ever*," and "*After our team won, I cried*."

Emotional sentiment is stronger than rational sentiment and is usually more important in practice. For example, in marketing, to guarantee the success of a new product in the market, positive sentiment from a large population of consumers has to reach the emotional level. Rational positive sentiment may not be sufficient.

Each of these broad categories can be further divided into smaller categories. We will discuss some possible subdivisions of rational sentiment in Section 2.4.2 and different emotions in Section 2.3. In applications, the user is also free to design her own categories.

Sentiment orientation. It can be *positive*, *negative*, or *neutral*. Neutral usually means the absence of sentiment or no sentiment. Sentiment orientation is also called *polarity*, *semantic orientation*, or *valence* in the research literature.

Sentiment intensity. Sentiment of each type can still have different levels of strength or intensity. People often use two ways to express intensity of their feelings in text. The first is to choose sentiment expressions (words or phrases) with suitable strengths. For example, *good* is weaker than *excellent*, and *dislike* is weaker than *detest*. Recall *sentiment words* are words in a language that are often used to express positive or negative sentiments. For example, *good*, *wonderful*, and *amazing* are positive sentiment words, and *bad*, *poor*, and *terrible* are negative sentiment words. The second is to use *intensifiers* and *diminishers*, which are terms that change the degree of the expressed sentiment. An intensifier increases the intensity of a positive or negative expression, whereas a diminisher decreases the intensity of that expression. Common English intensifiers include *very*, *so*, *extremely*, *dreadfully*, *really*, *awfully*, *terribly*, and so on, and common English diminishers include *slightly*, *pretty*, *a little bit*, *a bit*, *somewhat*, *barely*, and so on.

Sentiment rating. In practical applications, we often use some discrete ratings to express sentiment intensity. Five levels (e.g., 1–5 stars) are commonly employed, which can be interpreted as follows based on the two types of sentiment in Definitions 2.5 and 2.6:

· *emotional positive* (+2 or 5 stars)

· *rational positive* (+1 or 4 stars)

· *neutral* (0 or 3 stars)

· *rational negative* (−1 or 2 stars)

· *emotional negative* (−2 or 1 star)

Clearly it is possible to have more rating levels based on different intensities in each type of sentiment. However, they become difficult to differentiate based on the natural language text alone because of its highly subjective nature and the fact that people's spoken or written expressions may not fully match with their psychological states of mind. For example, the sentence "*This is an excellent phone*" expresses a stronger rational evaluation of the phone than the sentence "*This is a good phone*," while "*I love this phone*" expresses an emotional evaluation about the phone. However, whether "*This is an excellent phone*" and "*I love this phone*" represent completely different psychological states of mind of the authors is hard to say. In practice, the five levels are sufficient for most applications. If these five levels are not enough in some applications, I suggest dividing *emotional positive* (and, respectively, *emotional negative*) into two levels. Such applications are likely to involve sentiment about social or political events or issues, for which people can be highly emotional.

2.1.4 Opinion Definition Simplified

Opinion as defined in Definition 2.1, although concise, may not be easy to use in practice, especially in the domain of online reviews of products, services, and brands. Let us first look at the sentiment (or opinion) target. The central concept here is *entity*, which is represented as a hierarchy with an arbitrary number of levels. This can be too complex for practical applications because NLP is a very difficult task. Recognizing parts and attributes of an entity at different levels of detail is extremely hard. Most applications also do not need such a complex analysis. Thus, we simplify the hierarchy to two levels and use the term *aspect* to denote both *part* and *attribute*. In the simplified tree, the root node is still the entity itself, and the second level (also the leaf level) nodes are different aspects of the entity.

The definition of sentiment in Definition 2.4 can be simplified too. In many applications, positive (denoted by +1), negative (denoted by −1), and neutral (denoted by 0) orientations alone are already enough. In almost all applications, five levels of ratings are sufficient, for example, 1–5 stars. In both cases, sentiment can be represented with a single value. The other two components in the triple can be folded into this value.

This simplified framework is what is typically used in practical sentiment analysis systems. We now redefine the concept of opinion (Hu and Liu, 2004; Liu, 2010).

> **Definition 2.7 (Opinion)**: An *opinion* is a quintuple,
>
> $$(e, a, s, h, t),$$
>
> where e is the target entity, a is the target aspect of entity e on which the opinion has been given, s is the sentiment of the opinion on aspect a of entity e, h is the opinion holder, and t is the opinion posting time; s can be *positive*, *negative*, or *neutral*, or a *rating* (e.g., 1–5 stars). When an opinion is only on the entity as a whole, the special aspect GENERAL is used to denote it. Here e and a together represent the opinion target.

Sentiment analysis (or opinion mining) based on this definition is often called *aspect-based sentiment analysis*, or *feature-based sentiment analysis* as it was called earlier in Hu and Liu (2004) and Liu (2010).

We should note that owing to the simplification, the quintuple representation of opinion may result in information loss. For example, *ink* is a part of *printer*. A printer review might say "*The ink of this printer is expensive*." This sentence does not say that the printer is expensive (*expensive* here indicates the aspect *price*). If one does not care about any attribute of the ink, this sentence just gives a negative opinion about the ink (which is an aspect of the printer entity). This results in information loss. However, if one also wants to study opinions about different aspects of the ink, then the ink needs to be treated as a separate entity. The quintuple representation still applies, but an extra mechanism will be required to record the part-of relationship between ink and printer. Of course, conceptually, we can also extend the flat quintuple relation to a *nested relation* to make it more expressive. However, as we explained earlier, too complex a definition can make the problem extremely difficult to solve in practice. Despite this limitation, Definition 2.7 does cover the essential information of an opinion sufficiently for most applications.

In some applications, it may not be easy to distinguish entity and aspect, or there may be no need to distinguish them. Such cases often occur when people discuss political or social issues, for example, "*I hate property tax increases*." We may deal with them in two ways. First, because we can regard *property tax increase* as a general issue and it thus does not belong to any specific entity, we can treat it as an entity with the aspect GENERAL. Second, we can regard *property tax* as an entity and *property tax increases* as one of its aspects to form a hierarchical relationship. Whether to treat an issue or topic as an aspect or an entity can also depend on the specific context. For example, in commenting about a local government, one says, "*I hate the proposed property tax increase*." Because it is the local government that imposes and levies property taxes, the specific local government may be regarded as an entity and *the proposed property tax increase* as one of its aspects.

Not all applications need all five components of an opinion. In some applications, the user may not need the aspect information. For example, in brand management, the user typically is interested only in opinions about product brands (entities). This is sometimes called *entity-based sentiment analysis*. In some other applications, the user may not need to know the opinion holder or the time of opinion. Then these components can be ignored.

Definition 2.7 provides a framework to transform unstructured text to structured data. The quintuple is basically a database schema, based on which the extracted opinions can be put into a database table. Then a rich set of qualitative, quantitative, and trend analyses of opinions can be performed using a whole suite of database management systems and online analytical processing (OLAP) tools.

2.1.5 Reason and Qualifier for Opinion

We can in fact perform an even finer-grained analysis of opinions. Let us use the sentence "*This car is too small for a tall person*" to explain. It expresses a negative sentiment about the *size* aspect of the car. However, only reporting the negative sentiment for size does not tell the whole story because it can mean *too small* or *too big*. In the sentence, we call "*too small*" the *reason* for the negative sentiment about size. Furthermore, the sentence does not say that the car is too small for everyone but only *for a tall person*. We call *for a tall person* the *qualifier* of the opinion. We now define these concepts.

> **Definition 2.8 (Reason for opinion)**: A reason for an opinion is the cause or explanation of the opinion.

In practical applications, discovering the reasons for each positive or negative opinion can be very important because it may be these reasons that enable one to perform actions to remedy the situation. For example, the sentence "*I do not like the picture quality of this camera*" is not as useful as "*I do not like the picture quality of this camera because the pictures are quite dark*." The first sentence does not give the reason for the negative sentiment about the picture quality, and it is thus difficult to know what to do to improve the picture quality. The second sentence is more informative because it gives the reason or cause for the negative sentiment. The camera manufacturer can make use of this piece of information to improve the picture quality of the camera. In most industrial applications, such reasons are called *problems* or *issues*. Knowing the issues allows businesses to find ways to address them. In this regard, Twitter may not be the best source of opinions for businesses because of the length limit of each tweet, which makes it hard for people to express the detailed reasons for their opinions.

> **Definition 2.9 (Qualifier of opinion)**: A qualifier of an opinion limits or modifies the meaning of the opinion.

Knowing the qualifier is also important in practice because it tells what the opinion is good for. For example, "*This car is too small for a tall person*" does not say that the car is too small for everyone but just for tall people. For a person who is not tall, this opinion does not apply.

However, as we have seen, not every opinion comes with an explicit reason and/or an explicit qualifier. "*The picture quality of this camera is not great*" does not have a reason or a qualifier. "*The picture quality of this camera is not good for night shots*" has a qualifier *for night shots*, but does not give a specific reason for the negative sentiment. "*The picture quality of this camera is not good for* *night shots as the pictures are quite dark*" has a reason for the negative sentiment (*the pictures are quite dark*) and also a qualifier (*for night shots*). Sometimes the qualifier and the reason may not be in the same sentence and/or may be quite implicit, for example, "*The picture quality of this camera is not great*. *Pictures of night shots are very dark*" and "*I am six feet five inches tall*. *This car is too small for me*." Such reasons and qualifiers are very hard to identify and to extract. An expression can also serve multiple purposes. For example, *too small* in the preceding sentence indicates the *size* aspect of the car, a *negative sentiment* about the size, and also the *reason* for the negative sentiment or opinion.

2.1.6 Objective and Tasks of Sentiment Analysis

With the definitions in Sections 2.1.1–2.1.5, we can now present the core objective and the key tasks of (aspect-based) sentiment analysis.

Objective of sentiment analysis. Given an opinion document *d*, discover all opinion quintuples (*e*, *a*, *s*, *h*, *t*) in *d*. For more advanced analysis, discover the reason and qualifier for the sentiment in each opinion quintuple.

> **Key tasks of sentiment analysis.** The key tasks of sentiment analysis can be derived from the five components of the quintuple (Definition 2.7). The first component is the entity, and the first task is to extract entities. The task is similar to named entity recognition (NER) in information extraction (Mooney and Bunescu, 2005; Sarawagi, 2008; Hobbs and Riloff, 2010). However, as defined in Definition 2.3, an entity can also be an event, issue, or topic, which is usually not a named entity. For example, in "*I hate tax increase*," the entity is *tax increase*, which is an issue or topic. In such cases, entity extraction is basically the same as aspect extraction, and the difference between entity and aspect becomes blurry. In some applications, there may not be a need to distinguish them.
>
> After extraction, we need to categorize the extracted entities, as people often write the same entity in different ways. For example, Motorola may be written as Mot, Moto, and Motorola. We need to recognize that they all refer to the same entity. We detail these in Section 6.7.

> **Definition 2.10 (Entity category and entity expression):** An *entity category* represents a unique entity, whereas an *entity expression* or *mention* is an actual word or phrase that indicates an entity category in the text.

Each entity or entity category should have a unique name in a particular application. The process of grouping or clustering entity expressions into entity categories is called *entity resolution* or *grouping*.

For aspects of entities, the problem is basically the same as for entities. For example, *picture*, *image*, and *photo* refer to the same aspect for cameras. We thus need to extract aspect expressions and resolve them.

> **Definition 2.11 (Aspect category and aspect expression):** An *aspect category* of an entity represents a unique aspect of the entity, whereas an *aspect expression* or *mention* is an actual word or phrase that indicates an aspect category in the text.

Each aspect or aspect category should also have a unique name in a particular application. The process of grouping aspect expressions into aspect categories (aspects) is called *aspect resolution* or *grouping*.

Aspect expressions are usually nouns and noun phrases but can also be verbs, verb phrases, adjectives, adverbs, and other constructions. They can also be explicit or implicit (Hu and Liu, 2004).

> **Definition 2.12 (Explicit aspect expression):** Aspect expressions that appear in an opinion text as nouns or noun phrases are called *explicit aspect expressions*.

For example, *picture quality* in "*The picture quality of this camera is great*" is an explicit aspect expression.

> **Definition 2.13 (Implicit aspect expression):** Aspect expressions that are not nouns or noun phrases but indicate some aspects are called *implicit aspect expressions*.

For example, *expensive* is an implicit aspect expression in "*This camera is expensive*." It implies the aspect *price*. Many implicit aspect expressions are adjectives and adverbs used to describe or qualify some specific aspects, for example, *expensive* (price), and *reliably* (reliability). They can also be verbs and verb phrases, for example, "*I can install the software easily*" and "*This machine can play DVDs, which is its best feature*." *Install* indicates the aspect of *installation*, and *can play DVDs* indicates the function aspect of *playing DVDs*. Implicit aspect expressions are not just adjectives, adverbs, verbs, and verb phrases; they can be arbitrarily complex. For example, in "*This camera will not easily fit in my pocket*," *fit in my pocket* indicates the aspect *size* (and/or *shape*). In the sentence "*This restaurant closes too early*," *closes too early* indicates the aspect of *closing time* of the restaurant. In both cases, some commonsense knowledge may be needed to recognize them.

Aspect extraction is a very challenging problem, especially when it involves verbs and verb phrases. In some cases, it is even very hard for human beings to recognize and annotate. For example, in a vacuum cleaner review, one wrote, "*The vacuum cleaner does not get the crumbs out of thick carpets*," which seems to describe only one very *specific* aspect, *get the crumbs out of thick carpets*. However, in practice, it may be more useful to decompose it into two different aspects indicated by (1) *get the crumbs*, and (2) *thick carpets*. Aspect 1 represents *the suction power* of the vacuum cleaner about *crumbs*, and aspect 2 represents *suction* power related to *thick carpets*. Both aspects are important and useful because the user may be interested in knowing whether the vacuum can suck crumbs and whether it works well with thick carpets.

The third component in the opinion definition is the sentiment. For this, we need to perform sentiment classification or regression to determine the sentiment orientation or score on the involved aspect and/or entity. The fourth and fifth components are opinion holder and opinion posting time, respectively. They also have expressions and categories as entities and aspects. I will not repeat their definitions. Note that opinion holder (Bethard et al., 2004; Kim and Hovy, 2004; Choi et al., 2005) is also called *opinion source* (Wiebe et al., 2005). For product reviews and blogs, opinion holders are usually the authors of the posts and are easy to extract. Opinion holders are more difficult to extract from news articles, which often explicitly state the person or organization that holds an opinion.

On the basis of the preceding discussion, we can now define a model of entity and a model of opinion document (Liu, 2006, 2011) and summarize the main sentiment analysis tasks.

Model of entity. An entity e is represented by itself as a whole and a finite set of its aspects $A = \{a_1, a_2, \ldots, a_n\}$; e can be expressed in text with any one of a finite set of its entity expressions $\{ee_1, ee_2, \ldots, ee_s\}$. Each aspect $a \in A$ of entity e can be expressed with any one of a finite set of its aspect expressions $\{ae_1, ae_2, \ldots, ae_m\}$.

Model of opinion document. An opinion document d contains opinions about a finite set of entities $\{e_1, e_2, \ldots, e_r\}$ and a subset of aspects of each entity. The opinions are from a finite set of opinion holders $\{h_1, h_2, \ldots, h_p\}$ and are given at a particular time point t.

Given a set of opinion documents D, sentiment analysis performs the following eight main tasks:

Task 1 (entity extraction and resolution). Extract all entity expressions in D, and group synonymous entity expressions into entity clusters (or categories). Each entity expression cluster refers to a unique entity e.

Task 2 (aspect extraction and resolution). Extract all aspect expressions of the entities, and group these aspect expressions into clusters. Each aspect expression cluster represents a unique aspect a.

Task 3 (opinion holder extraction and resolution). Extract the holder expression of each opinion from the text or structured data and group them. The task is analogous to tasks 1 and 2.

Task 4 (time extraction and standardization). Extract the posting time of each opinion and standardize different time formats.

Task 5 (aspect sentiment classification or regression). Determine whether an opinion about an aspect a (or entity e) is positive, negative, or neutral (classification), or assign a numeric sentiment rating score to the aspect (or entity) (regression).

Task 6 (opinion quintuple generation). Produce all opinion quintuples (e, a, s, h, t) expressed in D based on the results from tasks 1–5. This task is seemingly very simple but it is in fact quite difficult in many cases, as Review B (following) shows.

For more advanced analysis, we can also perform the following two additional tasks, which are analogous to task 2:

Task 7 (opinion reason extraction and resolution). Extract reason expressions for each opinion, and group all reason expressions into clusters. Each cluster represents a unique reason for the opinion.

Task 8 (opinion qualifier extraction and resolution). Extract qualifier expressions for each opinion, and group all qualifier expressions into clusters. Each cluster represents a unique qualifier for the opinion.

Although reasons for and qualifiers of opinions are useful, their extraction and grouping are very challenging. Little research has been done about them so far.

We use an example review to illustrate the tasks (a sentence ID is again associated with each sentence) and the analysis results.

Review B: Posted by bigJohn Date: September 15, 2011

(1) I bought a Samsung camera and my friend brought a Canon camera yesterday. (2) In the past week, we both used the cameras a lot. (3) The photos from my Samy are not clear for night shots, and the battery life is short too. (4) My friend was very happy with his camera and loves its picture quality. (5) I want a camera that can take good photos. (6) I am going to return it tomorrow.

Task 1 should extract the entity expressions *Samsung*, *Samy*, and *Canon* and group *Samsung* and *Samy* together because they represent the same entity. Task 2 should extract aspect expressions *picture*, *photo*, and *battery life* and group *picture* and *photo* together as they are synonyms for cameras. Task 3 should find that the holder of the opinions in sentence 3 is bigJohn (the blog author) and that the holder of the opinions in sentence 4 is bigJohn's friend. Task 4 should find that the time when the blog was posted is September 15, 2011. Task 5 should find that sentence 3 gives a negative opinion on the *picture quality* of the Samsung camera and a negative opinion also to its *battery life*. Sentence 4 gives a positive opinion to the *Canon camera* as a whole and also to its *picture quality*. Sentence 5 seemingly expresses a positive opinion, but it does not. To generate opinion quintuples for sentence

4, we need to know what *his camera* and *its* refer to. Task 6 should finally generate the following opinion quintuples:

1. (Samsung, picture_quality, negative, bigJohn, Sept-15-2011)

2. (Samsung, battery_life, negative, bigJohn, Sept-15-2011)

3. (Canon, GENERAL, positive, bigJohn's_friend, Sept-15-2011)

4. (Canon, picture_quality, positive, bigJohn's_friend, Sept-15-2011)

With more advanced mining and analysis, we also find the reasons and qualifiers of opinions. *None* means unspecified.

1. (Samsung, picture_quality, negative, bigJohn, Sept-15-2011)
Reason for opinion: picture not clear
Qualifier of opinion: night shots

2. (Samsung, battery_life, negative, bigJohn, Sept-15-2011)
Reason for opinion: short battery life
Qualifier of opinion: none

3. (Canon, GENERAL, positive, bigJohn's_friend, Sept-15-2011)
Reason for opinion: none
Qualifier of opinion: none

4. (Canon, picture_quality, positive, bigJohn's_friend, Sept-15-2011)
Reason for opinion: none
Qualifier of opinion: none

2.2 Definition of Opinion Summary

Unlike facts, opinions are subjective (although they may not be all expressed in subjective sentences). An opinion from a single opinion holder is usually not sufficient for action. In almost all applications, the user needs to analyze opinions from a large number of opinion holders. This tells us that a summary of opinions is necessary. The question is what an opinion summary should be. On the surface, an opinion summary is just like a multi-document summary because we need to summarize multiple opinion documents, for example, reviews. It is, however, very different from a traditional multidocument summary. Although there are informal descriptions about what a traditional multidocument summary should be, it is never formally defined. A traditional multidocument summary is often just "defined" operationally based on each specific algorithm that produces the summary. Thus different algorithms produce different kinds of summaries. The resulting summaries are also hard to evaluate. An opinion summary in its core form, conversely, can be defined precisely based on the quintuple definition of opinion and easily evaluated. That is, all opinion summarization algorithms should aim to produce the same summary. Although they may still produce different final summaries, that is due to their different accuracies. This core form of opinion summary is called the *aspect-based opinion summary* (or *feature-based opinion summary*) (Hu and Liu, 2004; Liu et al., 2005).

> **Definition 2.14 (Aspect-based opinion summary)**: The *aspect-based opinion summary* about an entity *e* is of the following form:
>
> **GENERAL:**
> number of opinion holders who are positive about entity *e*
> number of opinion holders who are negative about entity *e*
>
> ---
>
> **Aspect 1:**
> number of opinion holders who are positive about aspect 1 of entity *e*
> number of opinion holders who are negative about aspect 1 of entity *e*
> …
>
> ---
>
> **Aspect *n*:**
> number of opinion holders who are positive about aspect *n* of entity *e*
> number of opinion holders who are negative about aspect *n* of entity *e*

where GENERAL represents the entity *e* itself and *n* is the total number of aspects of *e*.

The key features of this opinion summary definition are that it is based on positive and negative opinions about each entity and its aspects and that it is quantitative. The quantitative perspective is reflected by the numbers of positive or negative opinions. In an application, the number counts can also be replaced by percentages. The quantitative perspective is especially important in practice. For example, 20% of the people being positive about a product is very different from 80% of the people being positive about the product.

To illustrate this form of summary, we summarize a set of reviews of a digital camera, called *digital camera 1*, in Figure 2.1. This is called a *structured summary*, in contrast to a traditional text summary of a short document generated from one or multiple long documents. In the figure, 105 reviews expressed positive opinions about the camera itself, denoted by GENERAL, and 12 expressed negative opinions. *Picture quality* and *battery life* are two camera aspects. Seventy-five reviews expressed positive opinions about the picture quality, and forty-two expressed negative opinions. We also added <Individual review sentences>, which can be a link pointing to the sentences and/or the whole reviews that contain the opinions (Hu and Liu, 2004; Liu et al., 2005). With this summary, one can easily see how existing customers feel about the camera. If one is interested in a particular aspect and additional details, one can drill down by following the <Individual review sentences> link to see the actual opinion sentences or reviews.

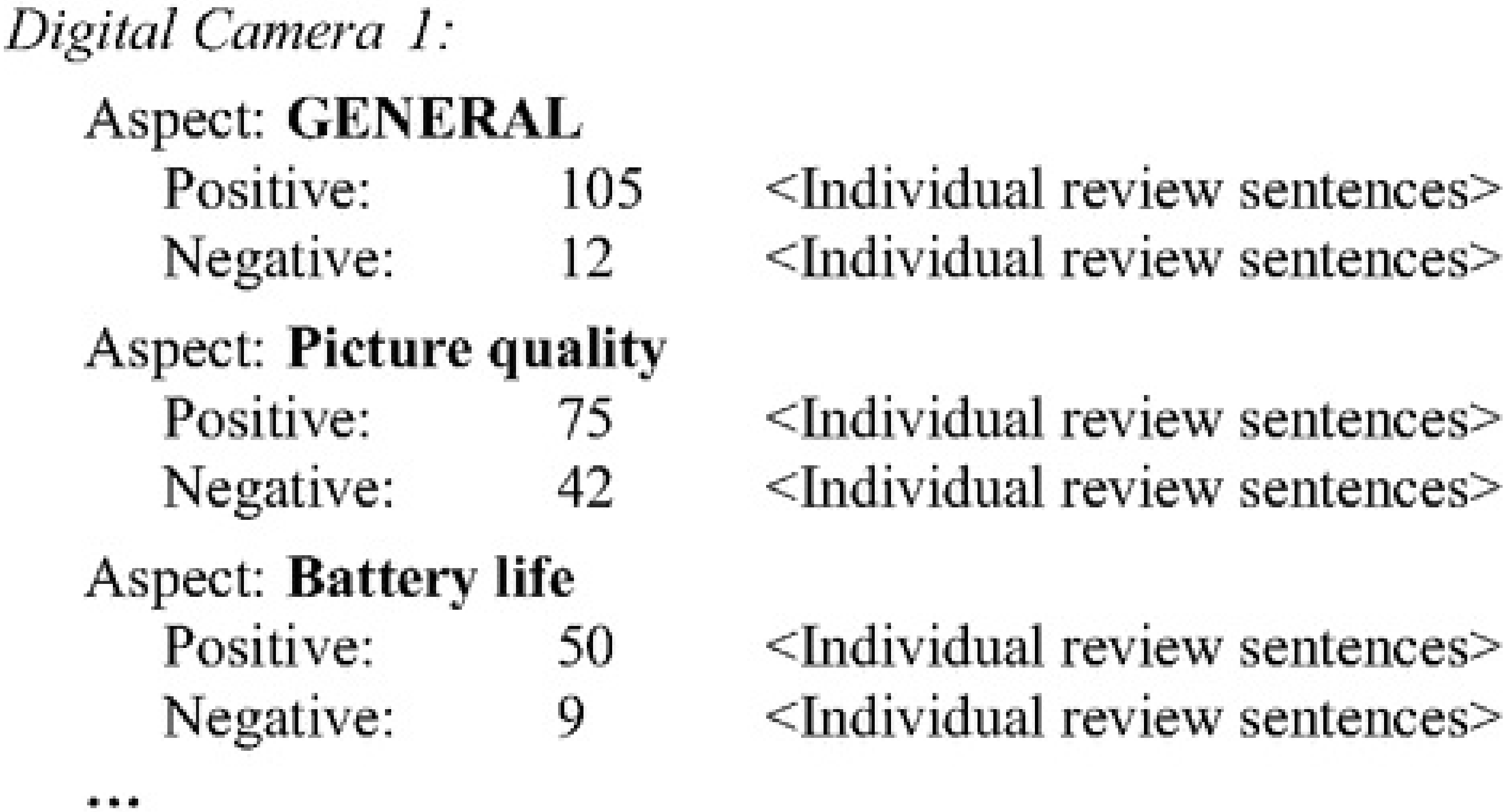

Figure 2.1. An aspect-based opinion summary.

In a more advanced analysis, we can also summarize opinion reasons and qualifiers in a similar way. On the basis of my experience, qualifiers for opinion statements are rare, but reasons for opinions are quite common. To perform the task, we need another level of summary. For example, in Figure 2.1, we may want to summarize the reasons for the poor picture quality based on the sentences in <Individual review sentences>. We may find that thirty-five people say the pictures are not bright enough and seven people say that the pictures are blurry. This kind of summary is useful in practice because both businesses and individual consumers want to know the main issues of a product. However, this level of detail is more difficult to extract because a reason is usually a phrase, a clause, or even a sentence.

Based on the idea of an aspect-based summary, researchers have proposed many opinion summarization algorithms and also extended this form of summary to some other, more specialized forms. We study them in Chapter 9.

2.3 Affect, Emotion, and Mood

We now discuss emotional sentiment, which is about *affect*, *emotion*, and *mood*. These concepts have been studied extensively in several fields, for example, psychology, philosophy, and sociology. However, investigations in these fields are seldom concerned with language expressions used to express such feelings. Their main concerns are people's psychological states of mind; theorizing what affect, emotion, and mood are; what constitute basic emotions; what physiological reactions happen (e.g., heart rate changes, blood pressure, sweating); what facial expressions, gestures, and postures are; and measuring and investigating the impact of such mental states. These mental states have also been exploited extensively in application areas such as marketing, economics, and education.

However, even with such extensive research, understanding these concepts is still slippery and confusing because different theorists often have somewhat different definitions for them and even do not completely agree with each other about what emotion, mood, and affect are. For example, on emotion, different theorists have proposed that there are from two to twenty basic human emotions, and some do not believe there is such a thing called basic emotions at all (Ortony and Turner, 1990). In most cases, emotion and affect are regarded as synonymous, and indeed, all three terms are sometimes used interchangeably. Affect is also used as an encompassing term covering all topics related to emotion, feeling, and mood. To make matters worse, in applications, researchers and practitioners use these concepts loosely in whatever way they feel like to without following any established definitions. Thus one is often left puzzled by just what an author means when the word *emotion*, *mood*, or *affect* is used. In most cases, the definition of each term also uses one or more of the other terms, resulting in circular definitions, which causes further confusion. The good news for NLP researchers and practitioners is that in practical applications of sentiment analysis, we needn't be too concerned with such an unsettled state of affairs because, in practice, we can pick up and use whatever emotion or mood states suitable for the applications at hand.

This section first tries to create a reasonable understanding of these concepts and their relationships for our NLP tasks in general and sentiment analysis in particular. It then puts these three concepts in the context of sentiment analysis and discusses how they can be handled in sentiment analysis.

2.3.1 Affect, Emotion, and Mood in Psychology

We start the discussion with the dictionary definitions of *affect*, *emotion*, and *mood*.[1] The concept of *feeling* is also included, as all three concepts are about human feelings. From the definitions, we can see how difficult it is to explain or articulate these concepts:

- *Affect*. Feeling or emotion, especially as manifested by facial expression or body language.
- *Emotion*. A mental state that arises spontaneously rather than through conscious effort and is often accompanied by physiological changes.
- *Mood*. A state of mind or emotion.
- *Feeling*. An affective state of consciousness, such as that resulting from emotions, sentiments, or desires.

These definitions are confusing from a scientific point of view because we do not see a clear demarcation for each concept. We turn to the field of psychology to look for a better definition for each of them. The convergence of views and ideas among theorists in the past twenty years gives us a workable classification scheme.

An *affect* is commonly defined as a neurophysiological state consciously accessible as the simplest raw (nonreflective) feeling evident in moods and emotions (Russell, 2003). The key point here is that such a feeling is primitive and not directed at an object. For example, you are watching a scary movie. If you are affected, it moves you and you experience a feeling of being scared. Your mind further processes this feeling and expresses it to yourself and the world around you. The feeling is then displayed as an *emotion*, such as crying, shock, and screaming.

Emotion is thus the indicator of affect. Owing to cognitive processing, emotion is a compound (rather than primitive) feeling concerned with a specific object, such as a person, an event, a thing, or a topic. It tends to be intense and focused and lasts a short period of time. *Mood*, like emotion, is a feeling or affective state, but it typically lasts longer than emotion and tends to be more unfocused and diffused. Mood is also less intense than emotion. For example, you may wake up feeling happy and stay that way for most of the day.

In short, emotions are quick and tense, whereas moods are more diffused and prolonged feelings. For example, we can get very angry very quickly, but it is difficult to stay very angry for a long time. The anger emotion may subside into an irritable mood that can last quite a long time. An emotion is usually very specific, triggered by noticeable events, which means that an emotion has a specific target. In this sense, emotion is like a rational sentiment or opinion. Conversely, a mood can be caused by multiple events, and sometimes it may not have any specific targets or causes. Mood typically also has a dimension of future expectation. It can involve a structured set of beliefs about general expectations of a future experience of pleasure or pain, or of positive or negative affect in the future (Batson et al., 1992).

Because sentiment analysis is not so much concerned with affect as defined above, in the following we focus only on *emotion* and *mood* in the psychological context. Let us start with emotion. Emotion has been frequently mentioned in sentiment analysis. Because it has a target or an involved entity (or object), it fits the sentiment analysis context naturally. Almost all real-life applications are interested in opinions and emotions about some target entities or objects.

Theorists in psychology have grouped emotions into categories. However, as we mentioned earlier, there is still not a set of agreed basic (or primary) emotions among theorists. In Ortony and Turner (1990), the basic emotions proposed by several theorists were compiled to show there is a great deal of disagreement. We reproduce them in Table 2.1.

Table 2.1. Basic emotions from different theorists

Source	**Basic emotions**
Arnold (1960)	Anger, aversion, courage, dejection, desire, despair, fear, hate, hope, love, sadness,
Ekman et al. (1982)	Anger, disgust, fear, joy, sadness, surprise
Gray (1982)	Anxiety, joy, rage, terror,
Izard (1971)	Anger, contempt, disgust, distress, fear, guilt, interest, joy, shame, surprise
James (1884)	Fear, grief, love, rage
McDougall (1926)	Anger, disgust, elation, fear, subjection, tender emotion, wonder
Mowrer (1960)	Pain, pleasure
Oatley and Jobnson-Laird (1987)	Anger, disgust, anxiety, happiness, sadness
Panksepp (1982)	Expectancy, fear, rage, panic
Plutchik (1980)	Acceptance, anger, anticipation, disgust, joy, fear, sadness, surprise

Tomkins (1984)	Anger, interest, contempt, disgust, distress, fear, joy, shame, surprise
Watson (1930)	Fear, love, rage
Weiner and Graham (1984)	Happiness, sadness
Parrott (2001)	Anger, fear, joy, love, sadness, surprise

In Parrott (2001), apart from the basic emotions, secondary and tertiary emotions were also proposed (see Table 2.2). These secondary and tertiary emotions are useful in some sentiment analysis applications because the set of basic emotions may not be fine-grained enough. For example, in one of the applications that I worked on, the client was interested in detecting *optimism* in the financial market. Optimism is not a basic emotion in the list of any theorist, but it is a secondary emotion for *joy* in Table 2.2. Note that although the words in Table 2.2 describe different emotions or states of mind, they can also be used as part of an emotion lexicon in sentiment analysis to spot different kinds of emotions. Of course, they need to be significantly expanded to include those synonymous words and phrases to form a reasonably complete emotion lexicon. In fact, there are some emotion lexicons that have been compiled by researchers, which we discuss in Section 4.8. Note again that for sentiment analysis, we do not need to be concerned with the disagreement of theorists. For a particular application, we can choose the types of emotions that are useful to the application. We also do not need to worry about whether they are primary, second, or tertiary.

Table 2.2. Primary, secondary, and tertiary emotions from Parrott (2001)

Primary emotion	Secondary emotion	Tertiary emotion
Anger	Disgust	Contempt, loathing, revulsion
	Envy	Jealousy
	Exasperation	Frustration
	Irritability	Aggravation, agitation, annoyance, crosspatch, grouchy, grumpy
	Rage	Anger, bitter, dislike, ferocity, fury, hatred, hostility, outrage, resentment, scorn, spite, vengefulness, wrath

	Torment	Torment
Fear	Horror	Alarm, fear, fright, horror, hysteria, mortification, panic, shock, terror
	Nervousness	Anxiety, apprehension (fear), distress, dread, suspense, uneasiness, worry
Joy	Cheerfulness	Amusement, bliss, gaiety, glee, jolliness, joviality, joy, delight, enjoyment, gladness, happiness, jubilation, elation, satisfaction, ecstasy, euphoria
	Contentment	Pleasure
	Enthrallment	Enthrallment, rapture
	Optimism	Eagerness, hope
	Pride	Triumph
	Relief	Relief
	Zest	Enthusiasm, excitement, exhilaration, thrill, zeal
Love	Affection	Adoration, attractiveness, caring, compassion, fondness, liking, sentimentality, tenderness
	Longing	Longing
	Lust/Sexual desire	Desire, infatuation, passion
Sadness	Disappointment	Dismay, displeasure
	Neglect	Alienation, defeatism, dejection, embarrassment, homesickness, humiliation, insecurity, insult, isolation, loneliness, rejection
	Sadness	Depression, despair, gloom, glumness, grief, melancholy, misery, sorrow, unhappy, woe
	Shame	Guilt, regret, remorse
	Suffering	Agony, anguish, hurt
	Sympathy	Pity, sympathy

Surprise	Surprise	Amazement, astonishment

The *emotion annotation and representation language* (EARL) proposed by the Human-Machine Interaction Network on Emotion (HUMAINE) (HUMAINE, 2006) has classified forty-eight emotions into different kinds of positive and negative orientations or valences (Table 2.3). This is useful to us because sentiment analysis is mainly interested in expressions with positive or negative orientations or polarities (also called *valences*). However, we should take note that some emotions do not have positive or negative orientations, for example, *surprise* and *interest*. Some psychologists felt that these should not be regarded as emotions (Ortony and Turner, 1990) simply because they do not have positive or negative orientations or valences. For the same reason, they are not commonly used in sentiment analysis.

Table 2.3. HUMAINE polarity annotations of emotions

Negative and forceful	Negative and passive	Quiet positive
Anger	Boredom	Calm
Annoyance	Despair	Content
Contempt	Disappointment	Relaxed
Disgust	Hurt	Relieved
Irritation	Sadness	Serene
Negative and not in control	Positive and lively	Caring
Anxiety	Amusement	Affection
Embarrassment	Delight	Empathy
Fear	Elation	Friendliness
Helplessness	Excitement	Love
Powerlessness	Happiness	

Worry	Joy	
	Pleasure	
Negative thoughts	Positive thoughts	Reactive
Doubt	Courage	Interest
Envy	Hope	Politeness
Frustration	Pride	Surprised
Guilt	Satisfaction	
Shame	Trust	
Agitation		
Stress		
Shock		
Tension		

We now turn to mood. The types of mood are similar to the types of emotion, except that the types of emotions that last only momentarily will not usually be moods, for example, *surprise* and *shock*. Thus, the words or phrases used to express moods are similar to those for emotions. However, because mood is a feeling that lasts a relatively long time, is diffused, and may not have a clear cause or target object, it is hard to recognize unless a person explicitly says it, for example, "*I feel sad today*." We can also monitor one's writings over a period of time to assess his prevailing mood in the period, which can help discover people with prolonged mental or other medical conditions (e.g., chronic depression) and even the tendency to commit suicides or crimes.

It is also interesting to discover the mood of the general population, for example, public mood, and the general atmosphere between organizations or countries, for example, the mood of U.S. and Russian relations, by monitoring the traditional news media and/or social media over a period of time.

2.3.2 Affect, Emotion, and Mood in Sentiment Analysis

The preceding discussions are only about people's states of mind, which are the subjects of study of psychologists. However, for sentiment analysis, we need to know how such feelings are expressed in natural language and how they can be recognized. This leads us to the linguistics of affect, emotion, and mood. Affect as defined by psychologists as a primitive response or feeling with no target is not much of interest to us as almost everything written in text or displayed in the form of facial expressions and other visible signs have already gone through some cognitive processing to become emotion or mood. However, we note that the term *affect* is still commonly used in linguistics and many other fields to mean emotion and mood.

Wikipedia has a good page describing the linguistic aspect of emotion and mood. There are two main ways that human beings express themselves: speech and writing. In addition to choices of grammatical and lexical expressions, which are common to both speech and writing (see later), speaker emotion can also be conveyed through paralinguistic mechanisms such as intonations, facial expressions, body movements, biophysical signals, or changes, gestures, and posture. In writing, special punctuation (e.g., repeated exclamation marks, !!!!), capitalization of all letters of a word, emoticons, lengthening of words (e.g., *slooooow*), and so on, are frequently used, especially in social media.

Regarding choices of grammatical and lexical expressions, there are several common ways that people express emotions or moods:

1. use emotion or mood words or phrases such as *love*, *disgust*, *angry*, and *upset*

2. describe emotion-related behaviors, for example, "*He cried after he saw his mother*" and "*After he received the news, he jumped up and down for a few minutes like a small boy.*"

3. use intensifiers – as we discussed in Section 2.1.3, common English intensifiers include *very, so, extremely, dreadfully, really, awfully* (e.g., *awfully bad*), *terribly* (e.g., *terribly good*), *never* (e.g., "*I will never buy any product from them again*"), *the sheer number of, on earth* (e.g., "*What on earth do you think you are doing*?"), *the hell* (e.g., "*What the hell are you doing*?"), *a hell of a*, and so on; to emphasize further, intensifiers may be repeated, for example, "*This car is very very good*"

4. use superlatives – arguably, many superlative expressions also express emotions, for example, "*This car is simply the best*"

5. use pejorative (e.g., "*He is a fascist.*"), laudatory (e.g., "*He is a saint.*"), and sarcastic expressions (e.g., "*What a great car, it broke the second day*")

6. use swearing, cursing, insulting, blaming, accusing, and threatening expressions

My experience is that using these clues is sufficient for recognizing emotion and mood in text, although in linguistics, adversative forms, honorific and deferential language, interrogatives, tag questions, and the like may also be employed to express emotional feelings, but their uses are rare and are also hard to recognize computationally.

In Sections 3.6 and 4.8, we study existing methods for recognizing or classifying emotions in text. To design new emotion detection algorithms, in addition to considering the preceding clues, we should be aware that there is a cognitive gap between people's true psychological states of mind and the language that they use to express such states. There are many reasons (e.g., being polite and do not want people to know one's true feelings) that they may not fully match. Thus, language does not always represent psychological reality. For example, when one says "*I am happy with this car*," one may not have any emotional reaction toward the car, although the emotion word *happy* is used. Furthermore, emotion and mood are difficult to distinguish in written text (Alm, 2008). We normally do not distinguish them. When we say emotion, we mean emotion or mood.

Because emotions have targets, and most of them also imply positive or negative sentiment, they can be represented and handled in very much the same way as rational opinions. Although a rational opinion emphasizes a person's evaluation about an entity and an emotion emphasizes a person's feeling caused by an entity, emotion can essentially be regarded as sentiment with a stronger intensity (see Section 2.1.3). It is often the case that when the sentiment of a person becomes strong, she becomes emotional. For example, "*The hotel manager is not professional*" expresses a rational opinion, whereas "*I almost cried when the hotel manager talked to me in a hostile manner*" indicates that the author's sentiment reached the emotional level of *sadness* and/or *anger*. The sentiment orientation of an emotion naturally inherits the polarity of the emotion, for example, *sad*, *anger*, *disgust*, and *fear* are negative, and *love* and *joy* are positive. Clearly, at the emotional level, sentiment becomes more fine-grained. Additional mechanisms are needed to recognize different types of emotions in writing, as we discussed earlier.

Owing to the similarity of emotion and rational opinion in essence, we can still use the quadruple or quintuple representation of opinion (Definitions 2.1 and 2.7) to represent emotion. However, if we want to be more precise, we can give it a separate definition based on the quadruple (Definition 2.1) or quintuple (Definition 2.7) definitions, as the meanings of some components in the tuple are not exactly the same as they were in the opinion definition, because emotions focus on personal feelings, whereas rational opinions focus on evaluations of external entities.

> **Definition 2.15 (Emotion)**: An *emotion* is a quintuple,

(e, a, m, f, t),

> where *e* is the target entity, *a* is the target aspect of *e* that is responsible for the emotion, *m* is the emotion type or a pair representing an emotion type and an intensity level, *f* is the feeler of the emotion, and *t* is the time when the emotion is expressed.

For example, for the emotion expressed in the sentence "*I am so upset with the manager of the hotel*," the entity is *the hotel*, the aspect is *the manager* of the hotel, the emotion type is *anger*, and the emotion feeler is *I* (the sentence author). If we know the time when the emotion was expressed, we can add it to the quintuple representation. As another example, in "*After hearing of his brother's death, he burst into tears*," the target entity is *his brother's death*, which is an event, and there is no aspect. The emotion type is *sadness* and the emotion feeler is *he*.

In practical applications, we should integrate the analysis of rational opinions and emotions and also include the sentiment orientation or polarity of each emotion, that is, whether it is positive (desirable) or negative (undesirable) for the feeler. If that is required, a sentiment component can be included in Definition 2.14 to make it a sextuple.

Cause of emotion. In Section 2.1.5, we discussed the reasons for opinions. In a similar way, emotions have causes as emotions are usually caused by some internal or external events. Here we use the word *cause* instead of *reason* because an emotion is an effect produced by a cause (usually an event) rather than a justification or explanation in support of an opinion. In the preceding sentence, *his brother's death* is the cause for his sadness emotion. Actually, *his brother's death* is both the target entity and the cause. In many cases, the target and the cause of an emotion are different. For example, in "*I am so mad with the hotel manager because he refused to refund my booking fee*," the target entity is *the hotel*, the target aspect is *the manager* of the hotel, and the cause of the *anger* emotion is *he refused to refund my booking fee*. There is a subtle difference between *his brother's death* and *he refused to refund my booking fee*. The latter states an action performed by *he* (the *hotel manager*) that causes the *sadness* emotion. He is the agent of the undesirable action. The sentiment on the hotel manager is negative. The sentence also explicitly stated the anger is toward the hotel manager, In the case of *his brother's death*, *his brother* or *death* alone is not the target of the emotion. It is the whole event that is the target and the cause of the sadness emotion.

Unlike rational opinions, in many emotion and mood sentences, the authors may not explicitly state the entities (e.g., named entities, topics, issues, actions and events) that are responsible for the emotions or moods, for example, "*I felt a bit sad this morning*" and "*There is sadness in her eyes*." The reason is that since a rational opinion sentence focuses on both the opinion target and the sentiment on the target, the opinion holder is often omitted (e.g., "*The pictures from this camera are* *great*”) whereas an emotion sentence focuses on the feeling of the feeler (e.g., “*There is sadness in her eyes*”). This means that a rational opinion sentence contains both sentiments and their targets explicitly, but may or may not give the opinion holder. An emotion sentence always has feelers and emotion expressions, but may or may not state the emotion target or the cause (e.g., “*I love this car*” and “*I felt sad this morning*”). This does not mean that some emotions do not have targets and/or causes. They do, but the targets and/or causes may be expressed in previous sentences or implied by the context, which makes extracting targets and/or causes difficult. In the case of mood, the causes may be implicit or even unknown and are thus not stated in the text.

2.4 Different Types of Opinions

Opinions can actually be classified along many dimensions. We discuss some main classifications in this section.

2.4.1 Regular and Comparative Opinions

The type of opinion that we have defined is called the *regular opinion* (Liu, 2006, 2011). Another type is *comparative opinion* (Jindal and Liu, 2006b).

Regular opinion. A *regular opinion* is often referred to simply as an *opinion* in the literature. It has two main subtypes (Liu, 2006, 2011), as follows:

Direct opinion. A *direct opinion* is an opinion that is expressed directly on an entity or an entity aspect, for example, "*The picture quality is great*."

Indirect opinion. An *indirect opinion* is an opinion that is expressed indirectly on an entity or aspect of an entity based on some positive or negative effects on some other entities. This subtype often occurs in the medical domain. For example, the sentence "*After injection of the drug, my joints felt worse*" describes an undesirable effect of the drug on *my joints*, which indirectly gives a negative opinion or sentiment to the drug. In this case, the entity is *the drug* and the aspect is *effect on joints*. Indirect opinions also occur in other domains, although less frequently. In these cases, they are typically expressed as *benefits* (positive) or *issues* (negative) of entities, for example, "*With this machine, I can finish my work in one hour, which used to take me five hours*" and "*After switching to this laptop, my eyes felt much better*." In marketing, benefits of a product or service are regarded as major selling points of the product or service. Thus, extracting such benefits is of practical interest.

Current research mainly focuses on direct opinions, which are easier to deal with. Indirect opinions are often harder to handle. For instance, in the drug domain, the system needs to know whether the desirable or undesirable state occurs before or after using a drug. The sentence "*Since my joints were painful, my doctor put me on this drug*" does not express any opinion about the drug because *painful joints* happened before using *this drug*.

Comparative opinion. A *comparative opinion* expresses a relation of similarities or differences between two or more entities and/or a preference of the opinion holder based on some shared aspects of the entities (Jindal and Liu, 2006a, 2006b). For example, the sentences "*Coke tastes better than Pepsi*" and "*Coke tastes the best*" express two comparative opinions. A comparative opinion is usually expressed using the *comparative* or *superlative* form of an adjective or adverb, although not always (e.g., *prefer*). The definitions in Sections 2.1 and 2.2 do not cover comparative opinion. Comparative opinions have many types. We define and discuss them in Chapter 8.

2.4.2 Subjective and Fact-Implied Opinions

Opinions and sentiments are by nature subjective because they are about people's subjective views, appraisals, evaluations, and feelings. But when they are expressed in actual text, they do not have to appear as subjective sentences. People can use objective or factual sentences to express their happiness and displeasure because facts can be desirable or undesirable. Conversely, not all subjective sentences express positive or negative sentiments, for example, "*I think he went home*," which is a belief and has no orientation. On the basis of subjectivity, we can classify opinions into two types, *subjective opinions* and *fact-implied opinions*. We define them as follows.

Subjective opinion. A *subjective opinion* is a regular or comparative opinion given in a subjective statement, for example,

"*Coke tastes great*."

"*I think Google's profit will go up next month*."

"*This camera is a masterpiece*."

"*We are seriously concerned about this new policy*."

"*Coke tastes better than Pepsi*."

We broadly classified subjective opinions into two categories: *rational opinions* and *emotional opinions* (Section 2.1.3). We have seen different emotions in Section 2.3. Rational opinions can also be categorized. Here we discuss one classification scheme based on the *appraisal system* of Martin and White (2005), who categorized opinions (which they called *attitudes*) into three types: *affect*, *judgment*, and *appreciation*. *Affect* concerns *emotions*, and *judgment* concerns opinions about intelligent entities, such as people in the *social* and *ethical* domain, and *appreciation* concerns opinions about nonintelligent entities in the *aesthetic* domain. Here we only discuss judgment and appreciation.

Judgment can be further divided into *normality*, *capacity*, *tenacity*, *veracity*, and *propriety*:

· *Normality* is about how *special* one is. It covers positive opinions related to concepts such as *lucky*, *fortunate*, *cool*, *predictable*, *fashionable*, and *celebrated* and negative opinions related to concepts such as *unlucky*, *odd*, *eccentric*, *unpredictable*, and *obscure*.

· *Capacity* is about how *capable* one is. It covers positive opinions related to concepts such as *powerful*, *vigorous*, *insightful*, *clever*, and *accomplished* and negative opinions related to concepts such as *weak*, *unsound*, *crippled*, *silly*, *foolish*, and *ignorant*.

- *Tenacity* is about how *dependable* one is. It covers positive opinions related to concepts such as *brave*, *cautious*, *dependable*, and *adaptable* and negative opinions related to concepts such as *cowardly*, *rash*, *impatient*, *undependable*, and *stubborn*.
- *Veracity* is about how *honest* one is. It covers positive opinions related to concepts such as *truthful*, *honest*, *credible*, *frank*, and *candid* and negative opinions related to concepts such as *dishonest*, *deceitful*, *lying*, *deceptive*, and *manipulative*.
- *Propriety* is about how *ethical* one is. It covers positive opinions related to concepts such as *moral*, *ethical*, *law abiding*, *fair*, *modest*, and *polite* and negative opinions related to concepts such as *immoral*, *evil*, *corrupt*, *unfair*, *arrogant*, and *rude*.

Appreciation can be divided into *reaction*, *composition*, and *valuation*. Reaction and composition also have two subtypes each.

- *Reaction* (*impact*) is about the question "*did it attract me*?" It covers positive opinions related to concepts such as *arresting*, *engaging*, *fascinating*, *exciting*, and *lively* and negative opinions related to concepts such as *dull*, *boring*, *tedious*, *uninviting*, and *unremarkable*.
- *Reaction* (*quality*) is about the question "*did I like it*?" It covers positive opinions related to concepts such as *fine*, *good*, *lovely*, *beautiful*, and *welcome* and negative opinions related to concepts such as *bad*, *yuk*, *plain*, *ugly*, and *repulsive*.
- *Composition* (*balance*) is about the question "*did it hang together*?" It covers positive opinions related to concepts such as *balanced*, *harmonious*, *consistent*, *logical*, and *curvaceous* and negative opinions related to concepts such as *unbalanced*, *discordant*, *uneven*, *contradictory*, and *distorted*.
- *Composition* (*complexity*) is about the question "*was it hard to follow*?" It covers positive opinions related to concepts such as *simple*, *pure*, *elegant*, *intricate*, *precise*, and *detailed* and negative opinions related to concepts such as *ornate*, *extravagant*, *byzantine*, *plain*, *monolithic*, and *simplistic*.
- *Valuation* is about the question "*was it worthwhile*?" It covers positive opinions related to concepts such as *deep*, *profound*, *innovative*, *valuable*, *priceless*, *worthwhile*, *timely*, and *helpful* and negative opinions related to concepts such as *shallow*, *fake*, *conventional*, *pricey*, *worthless*, *shoddy*, *dated*, and *useless*.

In applications, we can choose some of these categories based on our application needs. We are also free to design our own scheme as there is no universally accepted classification. There is another linguistic-based classification scheme in Asher et al. (2009). However, such generic classifications are too coarse for real-life applications. For example, based on the definition of valuation, the opinions expressed in the following four sentences all belong to the category of *valuation*:

"*This camera is pricey*."

"*The cost of this camera is very high*."

"*This camera is innovative*."

"*This camera is useless*."

However, they talk about different things with different sentiment targets. In normal applications, they should not be grouped together because they have very different target aspects. Only sentences 1 and 2 have the same target aspect of *price* (or *cost*). The target aspects of sentences 3 and 4 are quite different.

> **Fact-implied opinion.** A *fact-implied opinion* is a regular or comparative opinion implied in an objective or factual statement. Such an objective statement expresses a desirable or undesirable fact or action. This type of opinion can be further divided into two subtypes:

1. *Personal fact-implied opinion.* Such an opinion is implied by a factual statement about someone's personal experience, for example,

"I bought the mattress a week ago, and a valley has formed in the middle."

"I bought the toy yesterday and I have already thrown it into the trash can."

"My dad bought the car yesterday and it broke today."

"The battery life of this phone is longer than my previous Samsung phone."

Although factual, these sentences tell us whether the opinion holder is positive or negative about the product or his preference among different products. Thus, the opinions implied by these factual sentences are no different from subjective opinions.

2. *Nonpersonal fact-implied opinion.* This type is entirely different as it does not imply any personal opinion. It often comes from fact reporting, and the reported fact does not give any opinion from anyone, for example,

"Google's revenue went up by 30%."

"The unemployment rate came down last week."

"Google made more money than Yahoo! last month."

Unlike personal facts, these sentences do not express any experience or evaluation from any person. For instance, the first sentence does not have the same meaning as an opinion from a person who has used a Google product and expresses a desirable or undesirable fact about the Google product. Because these sentences do not give any personal opinion, they do not have opinion holders, although they do have sources of information. For example, the source of the information in the first sentence is likely to be Google itself, but it is a fact, not Google's subjective opinion.

We can still treat them as a type of opinion sentence for the following two reasons:

1. Each of the sentences does indicate a desirable and/or undesirable state for the involved entities or topics (i.e., *Google*, *Yahoo!*, and *unemployment rate*) based on commonsense knowledge.

2. The persons who post the sentences might be expressing positive or negative opinions implicitly about the involved entities. For example, the person who posted the first sentence on Twitter is likely to have a positive sentiment about Google; otherwise, the person would probably not post the fact. This kind of post occurs very frequently on Twitter, where Twitter users pick up some news headlines from the traditional media and post them on Twitter. Many people may also re-tweet them.

As we can see, it is important to distinguish personal facts and nonpersonal facts, as opinions induced from nonpersonal facts represent a very different type of opinion and need special treatment. How we deal with such facts depends on applications. My recommendation is to assign it the positive or negative orientation based on our commonsense knowledge of whether the sentence is about a desirable or undesirable fact to the involved entity, for example, Google. Users of the sentiment analysis system should be made aware of the convention so that they can make use of the opinion appropriately based on their applications.

Sometimes the author who posts such a fact may also give an explicit opinion, for example,

"*I am so upset that Google's share price went up today*."

The clause *Google's share price went up today* gives a nonpersonal fact-implied positive opinion about Google, but the author is negative about it. This is called a *meta-opinion*, an opinion about an opinion. We discuss how to deal with meta-opinions in Section 2.4.4.

If we turn the preceding facts into subjective sentences, the meanings become very different, for example, "*I think that Google's revenue will go up by at least 30% in the next quarter.*"

"*The unemployment rate will come down soon.*"

"*I think Google will make more money than Yahoo!*"

These sentences express only personal opinions.

Subjective opinions are usually easier to deal with because the number of words and phrases that can be used to explicitly express subjective feelings is limited, but this is not the case for fact-implied opinions. There seem to be an infinite number of desirable and undesirable facts, and every domain is different. However, there are still some patterns that can be exploited to infer opinions from facts. We discuss them in Chapter 5. Much of the existing research has focused only on subjective opinions, and only limited work has been done about fact-implied opinions (Zhang and Liu, 2011b).

2.4.3 First-Person and Non-First-Person Opinions

In some applications, it is important to distinguish statements expressing one's own opinions from statements expressing beliefs about someone else's opinions. For example, in a political election, one votes based on one's belief about each candidate's stances on issues rather than based on the true stances of the candidate, which may or may not be the same.

1. *First-person opinion.* Such an opinion states one's own attitude toward an entity. It can be from a person, a representative of a group, or an organization. Here are some example sentences expressing first-person opinions:

"Tax increase is bad for the economy."

"*I think Google's profit will go up next month*."

"*We are seriously concerned about this new policy*."

"*Coke tastes better than Pepsi*."

Notice that not every sentence needs to explicitly use the first-person pronoun *I* or *we* or to mention an organization name.

2. *Non-first-person opinion.* Such an opinion is expressed by a person stating someone else's opinion. That is, it is a belief of someone else's opinion about some entities or topics, for example,

"I think John likes Lenovo PCs."

"Jim loves his iPhone."

"President Obama supports tax increase."

"I believe Obama does not like wars."

2.4.4 Meta-Opinions

Meta-opinions are opinions about opinions. That is, a meta-opinion's target is also an opinion, which is usually contained in a subordinate clause. The opinion in the subordinate clause can express either a fact with an implied opinion or a subjective opinion. Let us see some examples:

"*I am so upset that Google's profit went up.*"

"*I am very happy that my daughter loves her new Ford car.*"

"*I am so sad that Germany lost the game.*"

These sentences look quite different from opinion sentences before. But they still follow the same opinion definition in Definition 2.7. It is just that the target of the meta-opinion in the main clause is now an opinion itself in the subordinate clause. For example, in the first sentence, the author is negative about *Google's profit went up*, which is the target of the meta-opinion in the main clause. So the meta-opinion is negative. However, its target is a regular fact-implied positive opinion about *Google's profit*. In practice, these two types of opinions should be treated differently. Because meta-opinions are rare, there is little research or practical work on them.

2.5 Author and Reader Standpoint

We can look at an opinion from two perspectives: that of the author (opinion holder) who posts the opinion and that of the reader who reads the opinion. Because opinions are subjective, naturally the author and the reader may not see the same thing in the same way. Let us use the following two example sentences to illustrate the point:

"*This car is too small for me*."

"*Google's profits went up by 30%*."

Because the author or the opinion holder of the first sentence felt the car was too small, a sentiment analysis system should output a negative opinion about the size of the car. However, this does not mean that the car is too small for everyone. A reader may actually like the small size and feel positive about it. This causes a problem because if the system outputs only a negative opinion about the size, the reader will not know whether it was too small or too large, and then she would not see this positive aspect for her. Fortunately, this problem can be dealt with by mining and summarizing opinion reasons (see Section 2.1.5). Here *too small* not only indicates a negative opinion about the size but also the reason for the negative opinion. With the reason, the reader can see a more complete picture of the opinion, which will help her to make a better decision. In a slightly related work, Greene and Resnik (2009) studied the influence of syntactic choices on perceptions of implicit sentiments. For example, for the same story, different headlines can imply different sentiments.

The second sentence represents a nonpersonal fact-implied opinion. As discussed in Section 2.4.2, the person who posts the fact is likely to be positive about Google. However, the readers may have different feelings. Those who have financial interests in Google should feel happy, but Google's competitors will not be thrilled. In Section 2.4.2, we choose to assign positive sentiment to the opinion because our commonsense knowledge says that the fact is desirable for Google. Users can decide how to use the opinion based on their application needs.

2.6 Summary

This chapter mainly defined the concepts of opinion and sentiment, the main tasks of sentiment analysis, and the framework of opinion summarization. The definitions abstracted a structure from the complex unstructured natural language text that forms the foundation of the field and serves as a common framework to unify various research directions. It also showed that sentiment analysis is a multifaceted problem with many interrelated subproblems rather than just a single problem. Researchers can exploit the relationships to design more robust and accurate solution techniques for sentiment analysis, and practitioners can see what is needed in building a sentiment analysis system. This chapter also classified and discussed various types of opinions, which may require different solution techniques to analyze them. Along with these definitions and discussions, the important concepts of affect, emotion, and mood were introduced and defined. They are closely related to, but are also different from, conventional rational opinions. Opinions emphasize evaluation or appraisal of some target objects, events, or topics (which are collectively called entities in this chapter), whereas emotions emphasize people's feelings caused by such entities. In almost all cases, emotions can be regarded as sentiments with strong intensities that have aroused people's inner or basic feelings. Emotions are also more fine-grained than positive or negative opinions, as there are many types of emotions. However, there are also emotions that do not have a positive or negative orientation or polarity, for example, *surprise*. Although one can be positively or negatively surprised, it is also possible that one is just surprised without a positive or negative polarity of feeling. As we mentioned in Section 2.3, there is still not a set of basic emotions on which all researchers agree, but this conceptual confusion among psychologists does not concern us too much as we can pick and choose emotion or mood types useful to our particular applications and deal with them just as we would with any other opinion.

After reading this chapter, I am sure that you would agree with me that on one hand, sentiment analysis is a highly challenging area of research involving many different tasks and perspectives, and on the other, it is also highly subjective in nature. Thus, I do not expect that you completely agree with me on everything in the chapter. I also do not claim that this chapter covered all the important aspects of sentiment and opinion. My goal is to present a reasonably precise definition of sentiment analysis (or opinion mining) and its related concepts, issues, and tasks. I hope I have succeeded to some extent.

1 http://www.thefreedictionary.com/subjective.

3

Document Sentiment Classification

◈

Starting from this chapter, we discuss the main research topics of sentiment analysis and their state-of-the-art algorithms. *Document sentiment classification* (or *document-level sentiment analysis*) is perhaps the most extensively studied topic in the field of sentiment analysis especially in its early days (see surveys by Pang and Lee, 2008; Liu, 2012). It aims to classify an opinion document (e.g., a product review) as expressing a positive or a negative opinion (or sentiment), which are called *sentiment orientations* or *polarities*. The task is referred to as document-level analysis because it considers each document as a whole and does not study entities or aspects inside the document or determine sentiments expressed about them. Arguably, this is the task that popularized sentiment analysis research. Its limitations also motivated the fine-grained task of aspect-based sentiment analysis (Hu and Liu, 2004) (Chapters 5 and 6) that is widely used in practice today.

Document sentiment classification is considered the simplest sentiment analysis task because it treats sentiment classification as a traditional text classification problem with sentiment orientations or polarities as the classes. Thus, any supervised learning algorithms can be applied directly to solve the problem. In most cases, the features used in classification are the same as those used in traditional text classification too. Owing to its simple problem definition and equivalence to text classification, it has served as the base task of several other research directions adapted from the general text classification, for example, cross-lingual and cross-domain sentiment classification.

To ensure that the task is meaningful in practice, existing literature on document sentiment classification makes the following implicit assumption (Liu, 2010).

> **Assumption 3.1:** Document sentiment classification assumes that the opinion document d (e.g., a product review) expresses opinions on a single entity e and contains opinions from a single opinion holder h.

Thus, strictly speaking, document sentiment classification can only be applied to a special type of opinion documents. We make this assumption explicit in the task definition.

> **Definition 3.1 (Document sentiment classification):** Given an opinion document d evaluating an entity, determine the overall sentiment s of the opinion holder about the entity. In other words,

> we determine sentiment *s* expressed on aspect GENERAL in the quintuple opinion definition of Section 2.1.4:
>
> $$(\_, GENERAL, s, \_, \_),$$
>
> where the entity, opinion holder, and time of opinion are assumed to be either known or irrelevant.

There are in fact two popular formulations of document-level sentiment analysis based on the type of values that *s* takes. If *s* takes categorical values, for example, positive and negative, it is a classification problem. If *s* takes numeric values or ordinal scores within a given range, for example, 1 to 5 stars, the problem becomes regression.

On the basis of the preceding discussions, we can see that this task is restrictive because, in general, an opinion document can evaluate more than one entity and the sentiment orientations on different entities can be different. The opinion holder may be positive about some entities and negative about others. In such a case, the task of document sentiment classification becomes less meaningful because it is not so useful to assign one sentiment to the entire document. Likewise, the task is also not so meaningful if multiple opinion holders express opinions in a single document because their opinions can be different too, for example, "*Jane has used this camera for a few months. She said that she loved it. However, my experience has not been great with the camera. The pictures are all quite dark.*"

Assumption 3.1 holds well for online reviews of products and services because each review usually focuses on evaluating a single product or service and is written by a single reviewer. However, the assumption may not hold for a forum discussion or blog post because in such a post, the author may express opinions on multiple entities and compare them. That is why most researchers used online reviews to perform the task of classification or regression.

In Sections 3.1 and 3.2, we discuss the classification problem of predicting categorical class labels. In Section 3.3, we discuss the regression problem of predicting sentiment rating scores. Most existing techniques for document-level classification use supervised learning, although there are also unsupervised methods. Sentiment regression has been done mainly using supervised learning. Several extensions to this research have also been attempted, most notably *cross-domain sentiment classification* (or *domain adaptation*) and *cross-language sentiment classification*, which we discuss in Sections 3.4 and 3.5, respectively.

Although this chapter describes several basic techniques in detail, it is mainly written in a survey style because there are a large number of published papers, and most existing techniques are direct applications of machine learning algorithms with feature engineering. No comprehensive and independent evaluation has been conducted to assess the effectiveness or accuracy of these large numbers of proposed techniques.

3.1 Supervised Sentiment Classification

Sentiment classification is usually formulated as a two-class classification problem: *positive* and *negative*. The training and testing data used are normally product reviews. Because every online review has a rating score assigned by its reviewer, for example, 1–5 stars, positive and negative classes can be determined easily using the ratings. A review with 4 or 5 stars is considered a *positive* review, and a review with 1 to 2 stars is considered a *negative* review. Most research papers do not use the neutral class (3-star ratings) to make the classification problem easier.

Sentiment classification is basically a text classification problem. However, traditional text classification mainly classifies documents of different topics, for example, politics, sciences, and sports. In such classifications, topic-related words are the key features. In sentiment classification, sentiment or opinion words that indicate positive or negative opinions are more important, for example, *great*, *excellent*, *amazing*, *horrible*, *bad*, *worst*, and so on. In this section, we present two approaches: (1) applying a standard supervised machine learning algorithm and (2) using a classification method designed specifically for sentiment classification.

3.1.1 Classification Using Machine Learning Algorithms

Because sentiment classification is a text classification problem, any existing supervised learning method can be directly applied, such as naïve Bayes classification or support vector machines (SVM) (Joachims, 1999; Shawe-Taylor and Cristianini, 2000). Pang et al. (2002) took this approach in classifying movie reviews into positive and negative classes, showing that using unigrams (a bag of words) as features in classification performed quite well with either naïve Bayes or SVM, although the authors also tried a number of other feature options.

In subsequent research, many more features and learning algorithms have been tried by a large number of researchers. Like most supervised learning applications, the key for sentiment classification is the engineering of effective features. Some of the example features are as follows:

Terms and their frequency. These features are individual words (unigram) and their n-grams with associated frequency counts. They are also the most common features used in traditional, topic-based text classification. In some cases, word positions may also be considered. The TFIDF weighting scheme from information retrieval may be applied too. As in traditional text classification, these features have been shown to be highly effective for sentiment classification.

Part of speech. The part of speech (POS) of each word is another class of features. It has been shown that adjectives are important indicators of opinion and sentiment. Thus, some researchers have treated adjectives as special features. However, one can also use all POS tags and their n-grams as features. In this book, we use the standard Penn Treebank POS tags, as shown in Table 3.1 (Santorini, 1990), to denote different parts of speech. The Penn Treebank site is http://www.cis.upenn.edu/~treebank/home.html.

Sentiment words and phrases. *Sentiment words* are natural features as they are words in a language for expressing positive or negative sentiments. For example, *good*, *wonderful*, and *amazing* are positive sentiment words, and *bad*, *poor*, and *terrible* are negative sentiment words. Most sentiment words are adjectives and adverbs, but nouns (e.g., *rubbish*, *junk*, and *crap*) and verbs (e.g., *hate* and *love*) can also be used to express sentiments. Besides individual words, there are also *sentiment phrases* and *idioms*, for example, *cost someone an arm and a leg*.

Rules of opinion. In addition to sentiment words and phrases, there are many other constructs or language compositions that can be used to express or imply sentiment or opinion. We list and discuss some of these expressions in Section 5.2.

Sentiment shifters. These are expressions that are used to change sentiment orientations, for example, from positive to negative or vice versa. Negation words are the most important class of sentiment shifters. For example, the sentence "*I don't like this camera*" is negative, although the word *like* is positive. There are also several other types of sentiment shifters. We discuss these in Sections 5.2, 5.3, and 5.4. Sentiment shifters also need to be handled with care because not all occurrences of such words mean sentiment changes. For example, *not* in "*not only…but also*" does not change sentiment orientation.

Syntactic dependency. Words' dependency-based features generated from parsing or dependency trees are also tried by researchers.

A large number of papers have been published on the topic in the literature. Here we can only briefly introduce some of them.

Table 3.1. Penn Treebank part-of-speech (POS) tags

Tag	Description	Tag	Description
CC	Coordinating conjunction	PRP$	Possessive pronoun
CD	Cardinal number	RB	Adverb
DT	Determiner	RBR	Adverb, comparative
EX	Existential *there*	RBS	Adverb, superlative
FW	Foreign word	RP	Particle
IN	Preposition or subordinating conjunction	SYM	Symbol
JJ	Adjective	TO	*to*
JJR	Adjective, comparative	UH	Interjection
JJS	Adjective, superlative	VB	Verb, base form
LS	List item marker	VBD	Verb, past tense
MD	Modal	VBG	Verb, gerund or present participle
NN	Noun, singular or mass	VBN	Verb, past participle
NNS	Noun, plural	VBP	Verb, non-3rd person singular

			present
NNP	Proper noun, singular	VBZ	Verb, 3rd person singular present
NNPS	Proper noun, plural	WDT	Wh-determiner
PDT	Predeterminer	WP	Wh-pronoun
POS	Possessive ending	WP$	Possessive wh-pronoun
PRP	Personal pronoun	WRB	Wh-adverb

In Gamon (2004), the authors performed classification of customer feedback data, which are usually short and noisy compared to reviews, and showed that deep linguistic features are beneficial to classification in addition to the surface features of word n-grams. Feature selection is also useful. The deep linguistic features were extracted from the phrase structure tree produced by NLPWin, a NLP system from Microsoft Research. The features included POS trigrams, constituent specific length measures (length of sentence, clause, adverbial/adjectival phrase, and noun phrase), constituent structure in the form of context-free phrase structure patterns for each constituent in the parse tree (e.g., DECL::NP VERB NP, a declarative sentence consisting of a noun phrase, a verbal head, and a second noun phrase), POS information coupled with semantic relations (e.g., "Verb–Subject–Noun" indicating a nominal subject to a verbal predicate), and logical form features provided by NLPWin, such as transitivity of a predicate and tense information.

Mullen and Collier (2004) introduced a set of sophisticated features to combine with n-grams. These new features are categorized into three main classes: (1) features related to sentiment values of words or phrases computed using pointwise mutual information (PMI) (Turney, 2002), (2) values of adjectives for the three factors introduced in Osgood et al. (1957), and (3) sentiment values of words or phrases in 1 and 2 that are near or in the sentence that mentions the entities being reviewed. The three Osgood factors are *potency* (strong or weak), *activity* (active or passive), and *evaluative* (good or bad), with values derived using WordNet relationships (Kamps et al., 2002). These additional features show some, but not a great deal of, improvements over lemmatized unigrams. We discuss PMI in Section 3.2.1.

In Joshi and Penstein-Rosé (2009), *dependency relations* and their generalizations were used as features in addition to word unigrams. The dependency parse for a given sentence is essentially a set of triples, each of which comprises a grammatical relation and a pair of words from the sentence between which the grammatical relation holds: $\{rel_i, w_j, w_k\}$, where rel_i is a dependency relation between words w_j and w_k. Word w_j is usually referred to as the *head word*, and w_k is usually referred to as the *modifier word*. A feature generated from such a dependency relation is of the form RELATION_HEAD_MODIFIER, which is then used as a standard bag-of-words-type of binary or frequency-based feature. For example, "*This is a great car*" has an adjectival modifier (amod) relation between *great* and *car*, which generates the feature amod_car_great. However, this feature is too specific and can only be used for *car*. We can back off or generalize the head word with its POS tag, amod_NN_great, which is a more general feature and can be applied to any noun. In Xia and Zong (2010), this was generalized further by using N to represent NN, NNS, NNP, NNPS, or PRP; J to represent JJ, JJS, or JJR; R to represent RB, RBS, or RBR; V to represent VB, VBZ, VBD, VBN, VBG, or VBP; and O to represent all other POS tags. The rel_i is also discarded so that, for example, amod_car_great is turned into two features, N_great and car_J. The same generalization strategy was also applied to traditional word bigrams. For classification, an ensemble model was proposed, which improved classification. An earlier work in Ng et al. (2006) also used dependency relations (adjective-noun, subject-verb, and verb-object), but no back-off generalization was applied. Their features include unigrams, bigrams, trigrams, sentiment words, and objective words. Feature selection based on weighted log-likelihood ratio was performed as well.

Mejova and Srinivasan (2011) compared various feature definitions and selection strategies. They first tested stemming, term frequency versus binary weighting, negation-enriched features, and n-grams or phrases, and then moved to feature selection using frequency-based vocabulary trimming, POS, and lexicon selection. Experiments based on three product and movie review data sets of various sizes showed that some techniques were more beneficial for larger data sets than for smaller ones. For large data sets, a classifier trained only on a small number of features that are ranked high by mutual information (MI) outperformed the one trained on all features. However, for small data sets, this did not prove to be true. An earlier work in Cui et al. (2006) described an evaluation using several classification algorithms and high-order n-grams, up to 6-grams. It applied a chi-square-based feature selection algorithm and showed that high-order n-grams help achieve better classification accuracy. High-order n-grams were also utilized successfully in Bespalov et al. (2011), which applied a deep neutral network approach to build a unified discriminative framework for classification. In Abbasi et al. (2008), a genetic-algorithm-based feature selection algorithm was proposed for sentiment classification in different languages. In addition to the usual n-gram features, the authors used stylistic features such as vocabulary richness and function words.

In the context of microblog sentiment classification, Kouloumpis et al. (2011) used four types of features: (1) n-grams; (2) a Multi-Perspective Question Answering (MPQA) subjectivity lexicon (Wilson et al., 2009); (3) counts of the number of verbs, adverbs, adjectives, nouns, and any other parts of speech; and (4) binary features that capture the presence of positive, negative, and neutral emoticons, abbreviations, and intensifiers (e.g., all caps and character repetitions).

Instead of using the full review for classification, Pang and Lee (2004) proposed to apply a machine learning method only to the subjective portions of each review. Such portions are more likely to contain opinions or sentiments. To identify the subjective portions in a review, a simple approach is to use a standard classification algorithm to classify each individual sentence in the review as subjective or objective, treating individual sentences independently. However, neighboring sentences do have some relationships in a document. Considering proximity relations between sentences enables the algorithm to leverage *coherence*: text spans occurring near each other may share the same subjectivity status (subjective or objective), other things being equal. To consider the proximity relation, the authors represented sentences with a graph. Let the sequence of sentences in a review be $x_1,\ldots, x_n$. Each sentence belongs to one of the two classes C_1 (subjective) or C_2 (objective). The algorithm also has access to the following two types of information:

- *Individual score* $ind_j(x_i)$. A nonnegative estimate of each x_i's preference for being in C_j based on just the features of x_i alone
- *Association score* $assoc(x_i, x_k)$. A nonnegative estimate of how important it is that x_i and x_k are in the same class

Using these pieces of information, an undirected flow graph G is constructed with vertices $\{v_1,\ldots, v_n, s, t\}$, where $v_1,\ldots, v_n$ denote the sentences and s and t denote the *source* and the *sink*, respectively. The algorithm then adds n edges (s, v_i) to the graph, each with weight $ind_1(x_i)$, and n edges (v_i, t), each with weight $ind_2(x_i)$. Finally, it adds $\binom{n}{2}$ edges (v_i, v_k), each with weight $assoc(x_i, x_k)$. The optimization problem for the final classification was set up in such a way that the classification result is the outcome of a *minimum cut* of the graph. The individual score $ind_j(x_i)$ is produced based on a sentence-level subjectivity classifier, for example, naïve Bayes, which will give the probabilities for being in each class, and the probabilities are used as $ind_1(x_i)$ and $ind_2(x_i)$ $(= 1 - ind_1(x_i))$. The association score $assoc(x_i, x_k)$ is computed based on the distance between the two sentences. The final review sentiment classification uses only the subjective sentences produced by the minimum cut algorithm. The classification produced this way was shown to be more accurate than that produced by using the whole review.

Related work along the same lines uses annotator rationales to help classification. A rationale is defined as a text span in a document highlighted by human annotators or an automated system as support or evidence for the document's positive or negative sentiment, which is similar to the subjective portion. In Zaidan et al. (2007), human annotators were used to label the rationales, whereas in Yessenalina et al. (2010a), an automated method based on a sentiment lexicon was employed to label rationales. The technique in Yessenalina et al. (2010b) also tries to identify opinionated or subjective sentences for document sentiment classification. It uses a two-level joint model (sentence level and document level) based on structural SVMs (Yu and Joachims, 2009) and directly optimizes the document-level classification. The sentence-level sentiment is treated as latent, and thus no annotations at the sentence level are needed. The work in McDonald et al. (2007) is similar, but it needs sentence-level annotations.

In Liu et al. (2010), different linguistic features were compared for blog and review sentiment classification. It was found that results on blogs were much worse than on reviews because a review usually focuses on evaluating a single entity, whereas a blog can evaluate multiple entities. Opinions on some entities can be positive, but on some others, they can be negative. The authors then studied two methods to improve the classification accuracy on blogs. The first was an information retrieval method that finds relevant sentences to a given topic in each blog and discards the irrelevant sentences before classification. The second method was a simple domain adaption technique that first trains several classifiers from some review domains and then incorporates the hypotheses of the classifiers on the blog data as additional features for training on the blog data. These argumentations resulted in higher classification accuracy for the blog data.

Becker and Aharonson (2010) showed that sentiment classification should focus on the final portion of the text (e.g., the last sentence in a review) based on psycholinguistic and psychophysical experiments using human subjects. However, no computational studies were carried out to verify the claim.

All existing methods use n-gram (usually unigram) features and assign values to features using various term weighting schemes in information retrieval. In Kim et al. (2009), various combinations of term weighting schemes were tested: PRESENCE (binary indicator for presence), TF (term frequency), VS.TF (normalized TF as in vector space model (VS)), BM25.TF (normalized TF as in BM25; Robertson and Zaragoza, 2009), IDF (inverse document frequency), VS.IDF (normalized IDF as in VS), and BM25.IDF (normalized IDF as in BM25). The results showed that PRESENCE did very well. The best combination was BM25.TF·VS.IDF, which needs quite a bit of parameter tuning, and the improvement over PRESENCE is minor (about 1.5%).

In Martineau and Finin (2009), a new term weighting scheme called Delta TFIDF was proposed, which produced quite good results. In the scheme, the feature value ($V_{t,d}$) for a term/word t in a document d is the difference of that term's TFIDF scores in the positive and negative training corpora:

$$V_{t,d} = tf_{t,d} \times \log_2 \frac{N^+}{df_{t,+}} - tf_{t,d} \times \log_2 \frac{N^-}{df_{t,-}} = tf_{t,d} \times \log_2 \frac{N^+}{df_{t,+}} \frac{df_{t,-}}{N^-}, \tag{3.1}$$

where $tf_{t,d}$ is the number of times term t occurs in document d (term frequency), $df_{t,+}$ is the number of positive documents in the training set containing term t, N^+ is the total number positive documents in the training set, $df_{t,-}$ is the number of negative documents in the training set containing term t, and N^- is the total number of negative documents. This term frequency transformation boosts the importance of words that are unevenly distributed between the positive and negative classes and discounts evenly distributed words. This better represents their true importance within the document for sentiment classification.

A comprehensive set of experiments was carried out in Paltoglou and Thelwall (2010) to evaluate the effectiveness of a large number of term weighting schemes. These include those TF and IDF variants in the SMART system (Salton, 1971) and also those variants in BM25 (Robertson and Zaragoza, 2009), their SMART Delta TFIDF versions, and their BM25 Delta TFIDF variants. Smoothing was also applied. The results show that the Delta versions with smoothing performed significantly better than other variants.

In Li et al. (2010), personal (*I*, *we*) and impersonal (*it*, *this product*) sentences were exploited to help classification. Specifically, the authors defined a sentence as *personal* if the subject of the sentence is (or represents) a person and *impersonal* if the subject of the sentence is not (does not represent) a person. Three classifiers, f_1, f_2, and f_3, were then constructed by using only the personal sentences, only the impersonal sentences, and all sentences in each review, respectively. The three base classifiers were then combined by multiplying their posterior possibilities, and the multiplied probability was finally used for classification.

Li et al. (2010) explored negations and some other sentiment shifters to help improve document-level sentiment classification. Unlike the lexicon-based approach used in Kennedy and Inkpen (2006), which we discuss in Section 3.2.2, the authors took a supervised learning approach, which does not explicitly identify individual words or phrases that are sentiment shifters. Instead, it separates sentences in a document into sentiment-shifted sentences and sentence-unshifted sentences using classification. This classification required no manually labeled data. It simply exploited the original document-level sentiment labels and a feature selection method. The two types of sentences were then used to build two independent sentiment classifiers, which were combined to produce the final results. Xia et al. (2013) also proposed a method to make good use of negation words in classification.

In Qiu et al. (2009), an integrated approach of lexicon-based and self-learning methods was proposed (the lexicon-based approach is discussed in Section 3.2.2). Briefly, a lexicon-based method uses sentiment words and phrases to determine the sentiment of a document or sentence. The algorithm in Qiu et al. (2009) consists of two phases. The first phase uses a lexicon-based iterative method, in which some reviews are initially classified based on a sentiment lexicon, and then more reviews are classified through an iterative process with a negative/positive ratio control. In the second phase, a supervised classifier is learned by taking some reviews classified in the first phase as training data. The learned classifier is then applied to other reviews to revise the classifications produced in the first phase. The advantage of this approach is that it needs no manually labeled data, so it is essentially an unsupervised method using a supervised technique and can be applied to any domain, unlike the corpus-based classification methods, which need manually labeled positive and negative reviews from every domain to which the algorithm is applied.

Li and Zong (2008) showed how to perform sentiment classification by exploiting training data from multiple domains. Two approaches were proposed. The first approach combines features from multiple training domains. The second approach combines classifiers built from individual domains. Their results showed that the classifier-level combination performed better than single domain classification (using the training data from only its own domain).

In Li et al. (2009), a nonnegative matrix trifactorization model was proposed for sentiment classification. In this model, an $m \times n$ term-document matrix X is approximated by three factors that specify soft membership of terms and documents in one of k classes, that is, $X \approx FSG^T$. F is an $m \times k$ nonnegative matrix representing knowledge in the word space, that is, the ith row of F represents the posterior probabilities of word i belonging to the k classes. G is an $n \times k$ nonnegative matrix representing knowledge in the document space; that is, the ith row of G represents the posterior probabilities of document i belonging to the k classes, and S is a $k \times k$ nonnegative matrix providing a condensed view of X. In the case of two-class classification, $k = 2$. We can obtain G and F matrices through factorization. G gives us the sentiment classification of each document, and F gives us the sentiment association of each term (or word). Without any initial knowledge, this is an unsupervised model. The authors also experimented with some supervision, for example, using a small set of sentiment words and a small set of document labels, to constrain the factorization model. If word i is a positive word, the model sets $(F_0)_{i1} = 1$, and if it is negative, the model sets $(F_0)_{i2} = 1$. Here F_0 is the initial F matrix. The factorization process is iterative, based on three updating rules. Some known document labels can also be used in the same way. That is, $(G_0)_{i1} = 1$ if the ith document expresses a positive sentiment, and $(G_0)_{i2} = 1$ if the ith document expresses a negative sentiment. These semi-supervised options perform classification quite well.

In Bickerstaffe and Zukerman (2010), the authors considered the more general problem of multiway sentiment classification for discrete, ordinal rating scales, focusing on the document level, that is, the problem of predicting the “star” rating associated with each review. Because the classes are ordinal, the algorithm considered interclass similarity in its classification.

Other work on document-level sentiment classification includes using semi-supervised learning and/or active learning (Dasgupta and Ng, 2009; Zhou et al., 2010; Li et al., 2011), labeling features rather than documents (He, 2010), using word vectors to capture latent aspects of words to help classification (Maas et al., 2011), classifying tonality of news article statements (Scholz and Conrad, 2013), and performing word clustering first to reduce feature sparsity and then building models and classifying using the word clusters as features (Popat et al., 2013). In Li et al. (2012), active learning was applied for imbalanced sentiment classification. In Tokuhisa et al. (2008), emotion classification of dialogue utterances was also investigated. It first performed sentiment classification of three classes (positive, negative, and neutral) and then classified positive and negative utterances into ten emotion categories. Aly and Atiya (2013) crawled and prepared a large set of Arabic book reviews (63,257). Some initial experiments of sentiment classification and rating prediction were performed on them.

3.1.2 Classification Using a Custom Score Function

Instead of using a standard machine learning method, researchers have proposed customized techniques specifically for sentiment classification of reviews. The score function in Dave et al. (2003) is one such technique. It is based on words in positive and negative reviews. The algorithm consists of two steps:

> **Step 1.** Score each term (unigram or n-gram) in the training set using the following equation:

$$\text{score}(t_i) = \frac{\Pr(t_i|C) - \Pr(t_i|C')}{\Pr(t_i|C) + \Pr(t_i|C')}, \tag{3.2}$$

where t_i is a term, C is a class, C' is its complement, that is, not C, and $\Pr(t_i|C)$ is the conditional probability of term t_i in class C, which is computed by taking the number of times that a term t_i occurs in class C reviews and dividing it by the total number of terms in the reviews of class C. A term score is thus a measure of the term's bias toward either class ranging from −1 to 1.

> **Step 2.** Classify a new document $d_i = t_1 \ldots t_n$ by summing up the scores of all terms and using the sign of the total to determine the class:

$$\text{class}(d_i) = \begin{cases} C & \text{eval}(d_i) > 0 \\ C' & \text{otherwise,} \end{cases} \tag{3.3}$$

where

$$\text{eval}(d_i) = \sum_j \text{score}(t_j). \tag{3.4}$$

Experiments were conducted based on more than thirteen thousand reviews of seven types of products. The results showed that bigrams (two consecutive words) and trigrams (three consecutive words) as terms gave (similar) best accuracies (84.6−88.3%). No stemming or stopword removal was applied.

The authors also experimented with many alternative classification techniques, for example, naïve Bayes, SVM, and several variant score functions, and word substitution strategies to improve generalization, for example,

- replace product names with a token ("_productname")
- replace rare words with a token ("_unique")
- replace category-specific words with a token ("_producttypeword")

· replace numeric tokens with NUMBER

Some linguistic modifications using WordNet, stemming, negation, and collocation were tested too. However, these were not helpful and actually degraded the classification accuracy.

3.2 Unsupervised Sentiment Classification

Because sentiment words and phrases are often the dominating factor for sentiment classification, it is not hard to imagine using them for sentiment classification in an unsupervised manner. We discuss two methods here. One, based on the method in Turney (2002), performs classification using some fixed syntactic patterns that are likely to express opinions. The other is based on a sentiment lexicon, which is a list of positive and negative sentiment words and phrases.

Table 3.2. Patterns of POS tags for extracting two-word phrases

	First word	**Second word**	Third word (not extracted)
1	JJ	NN or NNS	anything
2	RB, RBR, or RBS	JJ	not NN nor NNS
3	JJ	JJ	not NN nor NNS
4	NN or NNS	JJ	not NN nor NNS
5	RB, RBR, or RBS	VB, VBD, VBN, or VBG	anything

3.2.1 Classification Using Syntactic Patterns and Web Search

In Turney (2002), each syntactic pattern is a sequence of POS tags with some constraints (Table 3.2). The algorithm consists of three steps:

> **Step 1.** Two consecutive words are extracted if their POS tags conform to any of the patterns in Table 3.2. For example, pattern 2 means that two consecutive words are extracted if the first word is an adverb, the second word is an adjective, and the third word (not extracted) is not a noun. For example, in the sentence "*This piano produces beautiful sounds*," *beautiful sounds* will be extracted because it satisfies the first pattern. The reason these patterns are used is that JJ, RB, RBR, and RBS words often express opinions or sentiments. The nouns or verbs act as the contexts because in different contexts, a JJ, RB, RBR, and RBS word may express different sentiments. For example, the adjective (JJ) *unpredictable* may indicate a negative sentiment in a car review, as in "*unpredictable steering*," but a positive sentiment in a movie review, as in "*unpredictable plot*."

> **Step 2.** The sentiment orientation (SO) of the extracted phrases is estimated using the PMI (Pointwise Mutual Information) measure:

$$\mathrm{PMI}(term_1, term_2) = \log_2\left(\frac{\Pr(term_1 \wedge term_2)}{\Pr(term_1)\Pr(term_2)}\right). \tag{3.5}$$

PMI measures the degree of statistical dependence between two terms. Here $\Pr(\mathrm{term}_1 \wedge \mathrm{term}_2)$ is the actual co-occurrence probability of $term_1$ and $term_2$, and $\Pr(\mathrm{term}_1)\Pr(\mathrm{term}_2)$ is the co-occurrence probability of the two terms if they are statistically independent. The SO of a phrase is computed based on its association with the positive reference word *excellent* and the negative reference word *poor*:

$$\mathrm{SO(phrase)} = \mathrm{PMI(phrase, \text{“excellent”})} - \mathrm{PMI(phrase, \text{“poor”})}. \tag{3.6}$$

The probabilities are calculated by issuing queries to a search engine and collecting the number of *hits*. For each search query, a search engine usually gives the number of relevant documents to the query, called hits. Thus, by searching the two terms together and separately, the probabilities in Equation (3.5) can be estimated. In Turney (2002), the AltaVista search engine was used because it had a NEAR operator to constrain the search to return documents that contain the words within ten words of one another in either order. Let *hits*(*query*) be the number of hits returned. Equation (3.6) can be rewritten as

$$\mathrm{SO}(\text{phrase}) = \log_2 \left(\frac{\text{hits}(\text{phrase } NEAR \text{ "excellent"})\text{hits}(\text{"poor"})}{\text{hits}(\text{phrase } NEAR \text{ "poor"})\text{hits}(\text{"excellent"})} \right). \tag{3.7}$$

> **Step 3.** Given a review, the average SO score of all phrases in the review is computed, and the review is classified as positive if the average SO value is positive and negative otherwise.

Final classification accuracies on reviews from various domains range from 84% for automobile reviews to 66% for movie reviews.

Feng et al. (2013) compared PMI with three other association measures using different corpora. The three new measures are Jaccard, Dice, and Normalized Google Distance. The corpora are Google indexed pages, Google Web IT 5-grams, Wikipedia, and Twitter. Their experimental results show that PMI with the Twitter corpus produces the best results.

3.2.2 Classification Using Sentiment Lexicons

Another unsupervised approach is based on sentiment lexicons and is called the *lexicon-based approach*. The key characteristic of this approach is that it performs classification based on a dictionary of sentiment words and phrases, called a *sentiment lexicon* or *opinion lexicon*, with their associated sentiment orientations and strengths. It may also incorporate intensification and negation to compute a sentiment score for each document (Kennedy and Inkpen, 2006; Taboada et al., 2006, 2011). This approach was used earlier for aspect-level sentiment classification (Hu and Liu, 2004) and for sentence-level sentiment classification (Kim and Hovy, 2004). In the approach, each positive expression (a word or phrase) is assigned a positive SO value, and each negative expression is assigned a negative SO value.

In its base form, to classify a document, the SO values of all sentiment expressions in the document are summed up. The SO of the document is classified positive if the sum is positive, negative if the sum is negative, and neutral if the final sum is 0. There are many variations of this approach, which mainly differ in what value is assigned to each sentiment expression, how negations are handled, and whether additional information is considered. In Hu and Liu (2004) and Kim and Hovy (2004), each positive sentiment expression is given the SO value of +1, and each negative sentiment expression is given the SO value of −1. Negation words (also called *negators*), such as *not* and *never*, reverse the SO value. For example, *good* is +1 and *not good* is −1. It was shown in Polanyi and Zaenen (2004) that other factors in addition to negation words can affect whether a particular expression is positive or negative. These factors are called *sentiment shifters* (or *valence shifters*, as in Polanyi and Zaenen, 2004). Sentiment shifters are expressions that can change the SO value of another expression. There are, in fact, many more sentiment shifters than those identified in Polanyi and Zaenen (2004). We describe them and also additional ways that sentiments may be expressed or implied beyond just sentiment expressions in Sections 5.2, 5.3, and 5.4.

The work in Kennedy and Inkpen (2006) implemented some of the ideas in Polanyi and Zaenen (2004). In addition to negations, which switch or reverse the sentiment of positive or negative expressions, as previously, they considered intensifiers and diminishers, which can alter the SO values of sentiment expressions. Intensifiers and diminishers are expressions that change the degree of the expressed sentiment. An intensifier increases the intensity of a positive or negative expression, whereas a diminisher decreases the intensity of that expression. For example, in the sentence "*This movie is very good*," the phrase *very good* is more positive than just *good*, whereas in the sentence "*This movie is barely any good*," the word *barely* is a diminisher that makes this statement less positive. To allow for intensifiers and diminishers, the paper gives all positive sentiment expressions the value of 2. If they are preceded by an intensifier in the same clause, then they are given the value of 3. If the expressions are preceded by a diminisher in the same clause, then they are given the value of 1. Negative sentiment expressions are given the value of −2 by default and −1 or −3 if preceded by a diminisher or an intensifier, respectively.

Taboada et al. (2011) extended this method further by considering finer cases. The SO value for each sentiment expression is assigned a value from the range of −5 (extremely negative) to +5 (extremely positive). The value of 0 is not used. Each intensifier or diminisher is associated with a positive or negative percentage weight respectively. For example, *slightly* is −50, *somewhat* is −30, *pretty* is −10, *really* is +15, *very* is +25, *extraordinarily* is +50, and (*the*) *most* is +100. If *excellent* has an SO value of 5, *most excellent* would have an SO value of 5 × (100% + 100%) = 10. Intensifiers and diminishers are applied recursively starting from the closest to the SO-valued expression: if *good* has a SO value of 3, then *really very good* has a SO value of (3 × [100% + 25%]) × (100% + 15%) = 4.3. There are two main types of intensifying and diminishing cases: a SO-valued adjective with an adverbial modifier (e.g., *very good*) and a SO-valued noun with an adjectival modifier (e.g., *total failure*). In addition to adverbs and adjectives, other intensifiers and diminishers used in Taboada et al. (2011) are quantifiers (*a great deal of*), all capital letters, exclamation marks, and discourse-connective *but* (to indicate more salient information).

Simply reversing the SO value to handle negation can be problematic in some cases. Consider *excellent*, a +5 adjective: if we negate it, we get *not excellent*, which is a far cry from *atrocious*, a −5 adjective. In fact, *not excellent* seems more positive than *not good*, which would negate to a −3. To capture these pragmatic intuitions, instead of changing the sign, the SO value is shifted toward the opposite polarity by a fixed amount (e.g., 4). Thus a +2 adjective is negated to a −2, but the negation of a −3 adjective (e.g., *sleazy*) is only slightly positive (i.e., +1). Following are a few examples:

a. It’s not terrific (5 − 4 = 1) but not terrible (−5 + 4 = −1) either.

b. I have to admit it’s not bad (−3 + 4 = 1).

c. This CD is not horrid (−5 + 4 = −1).

The idea is that it is difficult to negate a strongly positive word without implying that a less positive one is to some extent true, and thus the negator becomes a diminisher.

As noticed in Kennedy and Inkpen (2006), lexicon-based sentiment classifiers generally show a positive bias. To compensate for this bias, negative expressions, being relatively rare, are given more weight in Taboada et al. (2011) by increasing the final SO value of any negative expression (after other modifiers have been applied) by 50%.

There are also a number of markers indicating that the words appearing in a sentence might not be reliable for the purpose of sentiment analysis. These usually indicate nonfactual contexts and are referred to as *irrealis* moods. The list of irrealis markers includes modals, conditional markers (*if*), negative polarity items like *any* and *anything*, certain (mostly intensional) verbs (*expect*, *doubt*), questions, and words enclosed in quotation marks (which may not be factual but not necessarily reflective of the author's opinion). The SO value of any word in the scope of an *irrealis* marker (i.e., within the same clause) is ignored. This strategy is called *irrealis blocking*. This does not mean that such sentences or clauses express no sentiment. In fact, many such sentences do bear sentiments, for example, "*Anyone know how to repair this lousy car*?" However, it is hard to reliably determine when such sentences express sentiment and when they do not. They are thus ignored. We discuss these issues further when we deal with sentence-level and aspect-level sentiment classification.

In addition to the preceding methods, there are also manual approaches for specific applications. For example, Tong (2001) reported a system that generates sentiment timelines. The system tracked online discussions about movies and displayed a plot of the number of positive and negative messages (*Y*-axis) over time (*X*-axis). Messages were classified by matching specific phrases that indicate the sentiment of the author toward a movie, for example, *great acting*, *wonderful visuals*, *uneven editing*, and *highly recommend it*. The phrases were manually compiled as indicating positive or negative sentiments in the application. The lexicon is thus specific to the domain and needs to be compiled anew for each new domain.

We note that if a large amount of labeled training data for a particular domain is available, supervised learning usually gives superior classification accuracy because it can consider domain-dependent sentiment expressions automatically. Lexicon-based methods cannot easily consider domain-dependent sentiment expressions unless there is an algorithm that is able to discover such expressions and determine their orientations automatically. There is already some work on this (Zhang and Liu, 2011a, 2011b), but it is still immature. Supervised learning also has its weaknesses. The main one is that the classifier trained from one domain usually does not work in another domain (see Section 3.4). Thus, for effective classification, training data are required for each application domain. Lexicon-based methods do not need training data and thus have an edge when no training data are available.

3.3 Sentiment Rating Prediction

Classifying opinion documents only as positive or negative may not be sufficient in some applications, where the user may need the degree of positivity or negativity. For this purpose, researchers have studied the problem of predicting rating scores (e.g., 1–5 stars) of reviews (Pang and Lee, 2005). In this case, the problem is typically formulated as a regression problem because the rating scores are ordinal, although not all researchers solve the problem using regression techniques. Pang and Lee (2005) experimented with SVM regression, SVM multiclass classification using the one-versus-all (OVA) strategy, and a meta-learning method called metric labeling and showed that OVA-based classification is significantly poorer than the other two approaches. This is understandable as numerical ratings are not categorical values. Goldberg and Zhu (2006) improved this approach by modeling rating prediction as a graph-based semi-supervised learning problem with both labeled (with ratings) and unlabeled (without ratings) reviews. The unlabeled reviews were the test reviews whose ratings needed to be predicted. In the graph, each node is a document (review), and the link between two nodes is the similarity value between the two documents. A large similarity weight implies that two documents tend to have the same sentiment rating. The authors experimented with several different similarity schemes. They also assumed that, initially, a separate learner had already predicted the numerical ratings of the unlabeled documents. The graph-based method simply improves the initial predictions by revising the ratings through solving an optimization problem to force ratings to be smooth throughout the graph with regard to both the ratings and the link weights.

Qu et al. (2010) modified the traditional bag-of-words representation to introduce a bag-of-opinions representation of documents to capture the strength of n-grams with opinions. Each of the opinions is a triple, a sentiment word, a modifier, and a negator. For example, in "*not very good*," *good* is the sentiment word, *very* is the modifier, and *not* is the negator. For sentiment classification of two classes (positive and negative), opinion modifiers are not crucial, but for rating prediction, they are very important, and so is the impact of negation words. A constrained ridge regression method was developed to learn the sentiment score or strength of each opinion from domain-independent corpora (of multiple domains) of rated reviews. The key idea was to exploit an available opinion lexicon and the review ratings. To transfer the regression model to a newly given domain-dependent application, the algorithm derives a set of statistics over the opinion scores and then uses them as additional features together with the standard unigrams for rating prediction. Prior to this work, Liu and Seneff (2009) proposed an approach to extracting adverb-adjective-noun phrases (e.g., "*very nice car*") based on the clause structure obtained by parsing sentences into a hierarchical representation. Rather than using learning, they assigned sentiment scores based on a heuristic method that computes the contribution of adjectives, adverbials, and negations to the sentiment degree based on the ratings of reviews where these words occurred.

Snyder and Barzilay (2007) studied the problem of predicting the rating for each aspect instead of predicting the rating of each review. A simple approach to this task would be to use a standard regression or classification technique. However, this approach does not exploit the dependencies between users' judgments across different aspects, which are useful for accurate prediction. Thus this article proposed two models: an aspect model (which works on individual aspects) and an agreement model (which models the rating agreement among aspects). Both models were combined in learning. The features used for training were lexical features such as unigram and bigrams from each review.

Long et al. (2010) used a similar approach to that in Pang and Lee (2005) but employed a Bayesian network classifier for rating prediction of each aspect in a review. For good accuracy, instead of predicting for every review, they focused on predicting only aspect ratings for a selected subset of reviews that comprehensively evaluated the aspects because the other reviews did not have sufficient information. The review selection method used an information measure based on Kolmogorov complexity. The aspect rating prediction for the selected reviews used machine learning. The features for training were only from those aspect-related sentences. The aspect extraction was done using a similar method to that in Hu and Liu (2004).

3.4 Cross-Domain Sentiment Classification

It has been shown that sentiment classification is highly sensitive to the domain from which the training data are extracted. A classifier trained using opinion documents from one domain often performs poorly on test data from another domain because words and even language constructs used for expressing opinions in different domains can be quite different. To make matters worse, the same word may be positive in one domain but negative in another. Thus domain adaptation or transfer learning is needed. Existing research is mainly based on two settings. The first setting needs a small amount of labeled training data for the new domain (Aue and Gamon, 2005). The second needs no labeled data for the new domain (Blitzer et al., 2007; Tan et al., 2007). The original domain with labeled training data are often called the *source domain*, and the new domain used for testing is called the *target domain*.

In Aue and Gamon (2005), the authors proposed to transfer sentiment classifiers to new domains in the absence of large amounts of labeled data in these domains. They experimented with four strategies: (1) training on a mixture of labeled reviews from other domains where such data are available and testing on the target domain; (2) training a classifier, as in strategy 1, but limiting the set of features only to those observed in the target domain; (3) using ensembles of classifiers from domains with available labeled data and testing on the target domain; (4) combining small amounts of labeled data with large amounts of unlabeled data in the target domain (this is the traditional semi-supervised learning setting). SVM was used for the first three strategies, and expectation maximization (EM) for semi-supervised learning (Nigam et al., 2000) was used for the fourth strategy. Their experiments showed that strategy 4 performed the best because it was able to make use of both the labeled and unlabeled data in the target domain.

In Yang et al. (2006), a simple strategy based on feature selection was proposed for transfer learning for sentence-level classification. Their method first used two fully labeled training sets from two domains to select features that were highly ranked in both domains. These selected features were considered to be domain-independent features. A classifier built using these features was then applied to any target or test domains. Another simple strategy was proposed in Tan et al. (2007), which first trains a base classifier using the labeled data from the source domain and then uses the classifier to label some informative examples in the target domain. On the basis of the selected examples in the target domain, a new classifier is learned, which is finally applied to classify the test cases in the target domain.

Blitzer et al. (2007) used a method called structural correspondence learning (SCL) for domain adaptation, which was proposed earlier in Blitzer et al. (2006). Given labeled reviews from a source domain and unlabeled reviews from both the source and target domains, SCL first chooses a set of m features that occur frequently in both domains and are also good predictors of the source labels (in the article, these were the features with the highest mutual information (MI) values with the source labels). These *pivot features* represent the shared feature space of the two domains. SCL then computes the correlations of each pivot feature with other nonpivot features in both domains. This produces a correlation matrix **W**, where row i is a vector of correlation values of nonpivot features with the ith pivot feature. Intuitively, positive values indicate that those nonpivot features are positively correlated with the ith pivot feature in the source domain or in the new domain. This establishes a feature correspondence between the two domains. After that, singular value decomposition (SVD) is employed to compute a low-dimensional linear approximation θ (the top k left singular vectors, transposed) of **W**. The final set of features for training and for testing is the original set of features $\mathbf{x}$ combined with $\theta\mathbf{x}$, which produces k real-valued features. The classifier built using the combined features and labeled data in the source domain should work in both the source and target domains.

Pan et al. (2010) proposed a method similar to SCL at the high level. The algorithm works in the setting where there are only labeled examples in the source domain and unlabeled examples in the target domain. It bridges the gap between the domains by using a spectral feature alignment (SFA) algorithm to *align* domain-specific words from different domains into unified clusters, with domain-independent words as the bridge. Domain-independent words are like pivot words in Blitzer et al. (2007) and can be selected similarly. SFA works by first constructing a bipartite graph with the domain-independent words as one set of nodes and the domain-specific words as the other set of nodes. A domain-specific word is linked to a domain-independent word if the words co-occur either in the same document or within a window. The link weight is the frequency of their co-occurrence. A spectral clustering algorithm is then applied on the bipartite graph to co-align domain-specific and domain-independent words into a set of feature clusters. The idea is that if two domain-specific words have connections to more common domain-independent words in the graph, they tend to be aligned or clustered together with a higher probability. Similarly, if two domain-independent words have connections to more common domain-specific words in the graph, they have a higher probability of alignment. For the final cross-domain training and testing, all data examples are represented with the combination of these clusters and the original set of features.

Along the same lines, He et al. (2011) used joint topic modeling to identify opinion topics (which are similar to the earlier clusters) from both domains to bridge them. The resulting topics, which cover both domains, are used as additional features to augment the original set of features for classification. In Gao and Li (2011), topic modeling was used, too, to find a common semantic space based on domain term correspondences and term co-occurrences in the two domains. This common semantic space was then used to learn a classifier, which was applied to the target domain. Bollegala et al. (2011) reported a method to automatically create a sentiment-sensitive thesaurus using both labeled and unlabeled data from multiple source domains to find the association between words that express similar sentiments in different domains. The thesaurus is then used to expand the original feature vectors to train a binary sentiment classifier. Yoshida et al. (2011) devised a method to transfer from multiple source domains to multiple target domains by identifying domain-dependent and -independent word sentiments. Andreevskaia and Bergler (2008) used an ensemble of two classifiers. The first classifier was built using a dictionary, and the second was built using a small amount of in-domain training data.

In Wu et al. (2009), a graph-based method was presented that uses the idea of label propagation on a similarity graph (Zhu and Ghahramani, 2002) to perform the transfer. In the graph, each document is a node and each link between two nodes is a weight computed using the cosine similarity of the two documents. Initially, every document in the old domain has a label score of +1 (positive) or −1 (negative), and each document in the new domain is assigned a label score based a normal sentiment classifier, which can be learned from the old domain. The algorithm then iteratively updates the label score of each new domain document i by finding k nearest neighbors in the old domain and k nearest neighbors in the new domain. A linear combination of the neighbor label scores and link weights is used to assign a new score to node i. The iterative process stops when the label scores converge. The sentiment orientations of the new domain documents are determined by their label scores. Ponomareva and Thelwall (2012) compared graph-based methods with several other state-of-the-art methods and concluded that graph-based representations offer a competitive solution to the domain adaptation problem.

Xia and Zong (2011) found that across different domains, features of some types of POS tags are usually domain dependent, whereas others are domain free. On the basis of this observation, they presented a POS-based ensemble model to integrate features with different types of POS tags to improve the classification performance.

3.5 Cross-Language Sentiment Classification

Cross-language sentiment classification is sentiment classification of opinion documents in multiple languages. There are two main motivations for cross-language classification. First, researchers from different countries want to build sentiment analysis systems in their own languages. However, much of the research has been done in English. There are not many resources or tools in other languages that can be used to build good sentiment classifiers quickly in these languages. The natural question is whether it is possible to leverage the automated machine translation capability and existing sentiment analysis resources and tools available in English to help build sentiment analysis systems in other languages. The second motivation is that in many applications, companies want to know and compare consumer opinions about their products and services in different countries. If they have a sentiment analysis system in English, they want to quickly build sentiment analysis systems in other languages through translation.

Several researchers have studied this problem. Much of the current work focuses on sentiment classification at the document level and subjectivity and sentiment classification at the sentence level. Limited work has been done at the aspect level, except that in Guo et al. (2010). In this section, we focus on cross-language document-level sentiment classification. Section 4.6 focuses on the sentence level.

In Wan (2008), sentiment resources in English were exploited to perform classification of Chinese reviews. The first step of the algorithm translates each Chinese review into English using multiple translators, which produce different English versions. It then uses a lexicon-based approach to classify each translated English version. The lexicon consists of a set of positive expressions (words or phrases), a set of negative expressions, a set of negation expressions, and a set of intensifiers. The algorithm then sums up the sentiment scores of the expressions in the review considering negations and intensifiers. If the final score is less than 0, the review is negative; otherwise, it is positive. For the final classification of each review, it combines the scores of different translated versions using various ensemble methods (average, max, weighted average, voting, etc.). If a Chinese lexicon is also available, the same technique can be applied to the Chinese version. Its result may also be combined with the results of those English translations. The results show that the ensemble technique is effective. Brooke et al. (2009) also experimented with translation (using only one translator) from the source language (English) to the target language (Spanish) and then used a lexicon-based approach or machine learning for target language document sentiment classification.

In Wan (2009), the author reported a co-training method that uses an annotated English corpus for classification of Chinese reviews in a supervised manner. No Chinese resources were used. In training, the input consisted of a set of labeled English reviews and a set of unlabeled Chinese reviews. The labeled English reviews were translated into labeled Chinese reviews, and the unlabeled Chinese reviews were translated into unlabeled English reviews. Each review was thus associated with an English version and a Chinese version. English features and Chinese features for each review were considered as two independent and redundant views of the review. A co-training algorithm using SVM was then applied to learn two classifiers, which were then combined into a single classifier. In the classification phase, each unlabeled Chinese review for testing was first translated into an English review, and then the learned classifier was applied to classify the review as either positive or negative. In Wan (2013), a co-regression method was presented for cross-language review rating prediction. The method is again based on the co-training idea.

Wei and Pal (2010) used a transfer learning method for cross-language sentiment classification. Because machine translation is still far from perfect, to minimize the noise introduced in translation, they proposed to use the SCL method (Blitzer et al., 2007) to find a small set of core features shared by both languages (English and Chinese). To alleviate the problem of data and feature sparseness, they issued queries to a search engine to find other highly correlated features to those in the core feature set and then used the newly discovered features to create extra pseudo-examples for training.

Boyd-Graber and Resnik (2010) extended the topic modeling method Supervised Latent Dirichlet Allocation (SLDA) (Blei and McAuliffe, 2007) to work on reviews from multiple languages for review rating prediction. SLDA is able to consider the user rating of each review in topic modeling. The extended model MLSLDA creates topics using documents from multiple languages at the same time. The resulting multilanguage topics are globally consistent across languages. To bridge topic terms in different languages in topic modeling, the model used the aligned WordNets of different languages or dictionaries.

In Guo et al. (2010), a topic model–based method was employed to group a set of given aspect expressions in different languages into aspect clusters (categories) for aspect-based sentiment comparison of opinions from different countries (see also Section 9.1).

In Duh et al. (2011), the authors presented their opinions about the research of cross-language sentiment classification. On the basis of their analysis, they claimed that domain mismatch was not caused by machine translation (MT) errors, and accuracy degradation would occur even with perfect MT. They also argued that the cross-language adaptation problem was qualitatively different from other (monolingual) adaptation problems in NLP; thus new adaptation algorithms should be considered.

3.6 Emotion Classification of Documents

Let us now turn to classification of emotion and mood, which is a considerably harder task because (1) there are many more classes, that is, types of emotions and moods and (2) different types of emotions or moods have many similarities, which makes it difficult to separate them. Note that because in writing, it is not easy to distinguish emotion and mood (Alm, 2008), we will not distinguish them in this section.

Existing approaches to emotion or mood classification at the document level are mainly based on supervised learning. For example, Mishne and de Rijke (2006) performed mood classification on a collection of blog posts from LiveJournal.com. On LiveJournal.com, authors can tag each of their posts with a mood type. Thus its blog posts can be naturally used for supervised classification. The main features used in learning are a set of discriminative terms (words or n-grams) for each mood. These terms are computed as follows: for each mood *m*, two probability distributions, θ_m and $\theta_{\neg m}$, are produced; θ_m is the distribution of all words in the blog posts tagged with mood *m*, and $\theta_{\neg m}$ is the distribution of all words in the rest of the blog posts. All words in θ_m are ranked according to their log-likelihood measure, as compared with $\theta_{\neg m}$: this produces a ranked list of "characteristic terms" for mood *m*. Once this process has been carried out for all moods, a single feature set of "discriminating terms" was created by selecting the terms that appear in the top-N position of the separate rank lists for individual moods. Several other features were also used, for example, the hour of the day when the blog was posted or whether the posting date was a weekend or not. For model building, pace regression (Wang and Witten, 1999) was applied.

Lin et al. (2007) classified news articles provided by Yahoo! Chinese news. Readers had voted on the articles based on the readers' perceived emotions. The algorithm used supervised learning with SVM. Four feature sets were employed. The first set consisted of all Chinese character bigrams. The second set contained all words produced by a Chinese word segmentation tool. The third set was the meta-data of the articles, for example, news reporter, news category, location of the news event, publication time, and name of the news agency. The fourth set was the emotion categories of words, which were obtained from an emotion lexicon that has been previously constructed by the authors (Yang et al., 2007).

Supervised learning was also employed in Strapparava and Mihalcea (2008), which used naïve Bayes classification. Another supervised method is based on manifold (Kim et al., 2013). The learning algorithm is different from those used in the preceding articles in that those methods treated mood prediction as a multiclass classification problem with discrete labels. This article assumes a continuous mood manifold and thus involves an inherently different learning paradigm.

Several other studies related to emotions are mainly about emotion lexicon constructions, for example, WordNet-Affect (Strapparava and Valitutti, 2004), which was constructed in the context of WordNet, and the lexicon of Mohammad and Turney (2010), which was constructed using crowdsourcing. Yet, some emotion analysis work (no classification) using different kinds of online texts was also performed in Mihalcea and Liu (2006) and Mohammad (2011).

3.7 Summary

Sentiment classification at the document level detects the overall opinion or sentiment expressed in a document. The problem has been studied extensively by a large number of researchers. However, this level of classification has two main shortcomings:

- It is not concerned with sentiment or opinion targets. Although it is generally applicable to reviews because each review usually evaluates a single entity, it is not easily applicable to nonreviews, such as forum discussions, blogs, and news articles, because many such posts evaluate multiple entities and compare the entities using comparative sentences. In many cases, it is hard to determine whether a post actually evaluates the entity in which the user is interested and whether the post expresses any opinion at all because, unlike reviews, a forum post may only give some product descriptions, let alone determine the sentiment about the entity. Document-level sentiment classification does not perform such fine-grained tasks, which require in-depth NLP rather than just text classification. In fact, online reviews do not need sentiment classification because almost every review on the web has a user-assigned star rating. In practice, it is the forum discussions and blogs that really need sentiment classification to determine people's opinions.
- Even if it is known that a document evaluates a single entity, in most applications, the user wants to know additional details, for example, what aspects of the entity are liked and disliked by consumers. In a typical opinion document, such details are provided, but document-level sentiment classification does not extract them for the user. These details can be very important for decision making. For example, a particular camera got all positive reviews (4 or 5 stars), but some reviewers mentioned the short battery life in their reviews. If a potential buyer wants long battery life, he probably will not buy the camera, although every review is positive about the camera.

4

Sentence Subjectivity and Sentiment Classification

As discussed in the previous chapter, document-level sentiment classification is too coarse for practical applications. We now move to the sentence level and look at methods that classify sentiment expressed in each sentence. The goal is to classify each sentence in an opinion document (e.g., a product review) as expressing a positive, negative, or neutral opinion. This gets us closer to real-life sentiment analysis applications, which require opinions on sentiment targets. Sentence-level classification is about the same as document-level classification because sentences can be regarded as short documents. Sentence-level classification, however, is often harder because the information contained in a typical sentence is much less than that contained in a typical document because of their length difference. Most document-level sentiment classification research papers ignore the neutral class mainly because it is more difficult to perform three-class classification (positive, neutral, and negative) accurately. However, for sentence-level classification, the neutral class cannot be ignored because an opinion document can contain many sentences that express no opinion or sentiment. Note that neutral opinion often means no opinion or sentiment expressed.

One implicit assumption that researchers make about sentence-level classification is that a sentence expresses a single sentiment. Let us start our discussion with an example review:

> *I bought a Lenovo Ultrabook T431s two weeks ago. It is really light, quiet and cool. The new touchpad is great too. It is the best laptop that I have ever had although it is a bit expensive.*

The first sentence expresses no sentiment or opinion as it simply states a fact. It is thus neutral. All other sentences express some sentiment. Sentence-level sentiment classification is defined as follows:

> **Definition 4.1 (Sentence sentiment classification):** Given a sentence x, determine whether x expresses a positive, negative, or neutral (or no) opinion.

As we can see, like document-level sentiment classification, sentence-level sentiment classification also does not consider opinion or sentiment targets. However, in most cases, if the system is given a set of entities and their aspects, the sentiment about them in a sentence can just take the sentiment of the sentence. Of course, this is not always the case. For example, there is no opinion on Chrome in the sentence "*Trying out Chrome because Firefox keeps crashing*." This definition also cannot handle sentences with opposite opinions, for example, "*Apple is doing well in this bad economy*." This sentence is often regarded as containing a mixed opinion. Thus, like document sentiment classification, the problem of sentence sentiment classification is also somewhat restrictive because it is not applicable to many types of sentences owing to its ignorance of sentiment (or opinion) targets. It can still be useful, however, because most sentences in practice express a single opinion or sentiment.

Definition 4.1 does not use the quintuple (e, a, s, h, t) notation because sentence-level classification is an intermediate step in the overall sentiment analysis task and is not concerned with the opinion target (entity or aspect), the opinion holder, or the time when the opinion is posted.

Sentence sentiment classification can be solved either as a three-class classification problem or as two separate two-class classification problems. In the latter case, the first problem (also called the first step) is to classify whether a sentence expresses an opinion. The second problem (also called the second step) classifies those opinion sentences into positive and negative classes. The first problem is often called the *subjectivity classification* in the research literature, which determines whether a sentence expresses a piece of subjective information or objective (or factual) information (Hatzivassiloglou and Wiebe, 2000; Riloff and Wiebe, 2003; Yu and Hatzivassiloglou, 2003; Wiebe et al., 2004; Wilson et al., 2004; Riloff et al., 2006; Wilson et al., 2006). Many researchers regard subjectivity and sentiment as the same concept. This is problematic, as we discussed in Section 2.4.2, because many objective sentences can imply opinions, and many subjective sentences contain no positive or negative opinions. Thus, it is more appropriate for the first step to classify each sentence as *opinionated* or *not-opinionated* (Liu, 2010), regardless of whether it is a subjective or an objective sentence.

> **Definition 4.2 (Opinionated):** A sentence is opinionated if it expresses or implies a positive or negative sentiment.

> **Definition 4.3 (Not-opinionated):** A sentence is not-opinionated if it expresses or implies no positive or negative sentiment.

However, the common practice is still to use the term *subjectivity classification*. In the following, we first discuss the concept of subjectivity (Section 4.1) and then the existing work on sentence-level subjectivity classification (Section 4.2) and sentiment classification (Section 4.3).

Like Chapter 3, this chapter is written in a survey style owing to there being a large number of published papers, and most of them use supervised machine learning and thus focus on feature engineering. There is still no independent and comprehensive experimental evaluation of the existing techniques and feature sets to assess their effectiveness.

4.1 Subjectivity

Subjectivity is a concept that has been widely used in sentiment analysis. It has also caused some confusion among researchers. In many papers, being subjective and being sentiment-bearing are regarded as equivalent, but they are not the same. Let us define sentence subjectivity here. Because the concept depends on the definitions of both subjective and objective, we give the dictionary definitions of these two terms first:[2]

> **Definition 4.4 (Subjective):** Proceeding from or taking place in a person's mind rather than the external world.

> **Definition 4.5 (Objective):** Having actual existence or reality.

On the basis of these definitions, we can define sentence subjectivity as follows:

> **Definition 4.6 (Sentence subjectivity):** An *objective sentence* states some factual information, whereas a *subjective sentence* expresses some personal feelings, views, judgments, or beliefs.

An example of an objective sentence is "*The iPhone is an Apple product*." An example of a subjective sentence is "*I like the iPhone*." The task of determining whether a sentence is subjective or objective is called *subjectivity classification* (Wiebe and Riloff, 2005). However, we should note the following:

- A subjective sentence may not express any positive or negative sentiment. Subjective expressions can express opinions, appraisals, evaluations, allegations, desires, beliefs, suspicions, speculations, and stances (Wiebe, 2000; Riloff et al., 2006). Some of these concepts indicate positive or negative sentiments, and some of them do not. For example, "*I think he went home*" is a subjective sentence as it expresses a belief but it does not express or imply any positive or negative sentiment. The sentence "*I want to buy a camera that can take good photos*" is also subjective and even contains a sentiment word *good*, but again it does not give a positive or negative sentiment about anything. It actually expresses a desire or intention (we discuss intention mining in Chapter 11).
- Objective sentences can imply opinions or sentiments due to desirable and undesirable facts (Zhang and Liu, 2011b). For example, the following two sentences, which state some facts, clearly imply negative sentiments about the respective products because the facts are undesirable:
  - "*The earphone broke in two days.*"
  - "*I bought the mattress a week ago and a valley has formed in the middle.*"

Apart from positive and negative sentiment, many other types of subjectivity have also been studied in various communities, although not as extensively as sentiment, for example, affect, emotion, mood, judgment, appreciation, speculation, hedge, perspective, arguing, agreement and disagreement, and political stances (Lin et al., 2006; Medlock and Briscoe, 2007; Alm, 2008; Ganter and Strube, 2009; Greene and Resnik, 2009; Somasundaran and Wiebe, 2009; Hardisty et al., 2010; Murakami and Raymond, 2010; Neviarouskaya et al., 2010; Mukherjee and Liu, 2012). Many of them may also imply opinions or sentiments. We have discussed affect, emotion, and mood in Section 2.3. We discuss arguing, agreement, disagreement, and stance in Chapter 10.

In summary, the concepts of subjectivity and sentiment are not equivalent, although they have a large intersection. Most people would agree that, psychologically, sentiment is a kind of subjective feeling and that subjectivity is a superconcept of sentiment and sentiment is a subconcept of subjectivity. However, one does not always need to use subjective sentences to express sentiment because our commonsense knowledge and pragmatics in communication can tell us what facts are desirable and what facts are undesirable in a particular context.

4.2 Sentence Subjectivity Classification

Subjectivity classification classifies sentences into two classes, subjective and objective (Wiebe et al., 1999). Early research solved subjectivity classification as a standalone problem, rather than for the purpose of sentiment classification. More recently, researchers and practitioners have treated it as the first step of sentence-level sentiment classification by using it to remove objective sentences that are assumed to express or imply no opinion or sentiment. In this case, as we discussed earlier, *subjective* and *objective* should really mean *opinionated* and *not-opinionated*, respectively.

Most existing approaches to subjectivity classification are based on supervised learning. For example, the early work reported in Wiebe et al. (1999) performed subjectivity classification using the naïve Bayes classifier with a set of binary features, for example, the presence in the sentence of a pronoun, an adjective, a cardinal number, a modal other than *will*, and an adverb other than *not*. Subsequent research used other learning algorithms and more sophisticated features.

In Wiebe (2000), an unsupervised method for subjectivity classification was proposed that simply used the presence of subjective expressions in a sentence to determine the subjectivity of a sentence. Because there was not a complete set of such expressions, it provided some seeds and then used distributional similarity (Lin, 1998) to find similar words, which were also likely to be subjectivity indicators. However, words found this way had low precision and high recall. Then, the method in Hatzivassiloglou and McKeown (1997) and the concept of gradability in Hatzivassiloglou and Wiebe (2000) were applied to filter wrong subjective expressions. We discuss the method in Hatzivassiloglou and McKeown (1997) in Section 7.2. *Gradability* is a semantic property that enables a word to appear in a comparative construct and to accept modifying expressions that act as intensifiers or diminishers. Gradable adjectives express properties in varying degrees of strength, relative to a norm either explicitly mentioned or implicitly supplied by the modified noun (for example, a *small planet* is usually much larger than a *large house*). Gradable adjectives were found using a seed list of manually compiled adverbs and noun phrases (such as *a little*, *exceedingly*, *somewhat*, and *very*) that are frequently used as grading modifiers. Such gradable adjectives are good indicators of subjectivity.

In Yu and Hatzivassiloglou (2003), Yu and Hatzivassiloglou performed subjectivity classifications using sentence similarity and a naïve Bayes classifier. The sentence similarity method is based on the assumption that subjective or opinion sentences are more similar to other opinion sentences than to factual sentences. They used the SIMFINDER system in Hatzivassiloglou et al. (2001) to measure sentence similarity based on shared words, phrases, and WordNet synsets. For naïve Bayes classification, they used features such as words (unigram), bigrams, trigrams, parts of speech, the presence of sentiment words, the counts of the polarities (or orientations) of sequences of sentiment words (e.g., “++” for two consecutive positively oriented words), and the counts of parts of speech combined with sentiment information (e.g., “JJ+” for positive adjective), as well as features encoding the sentiment (if any) of the head verb, the main subject, and their immediate modifiers. They also performed sentiment classification to determine whether a subjective sentence is positive or negative, as we discuss in the next section.

One of the bottlenecks in applying supervised learning is the manual effort involved in annotating a large number of training examples. To save the manual labeling effort, a bootstrapping approach to label training data automatically was proposed in Riloff and Wiebe (2003). The algorithm works by first using two high-precision classifiers (HP-Subj and HP-Obj) to automatically identify some subjective and objective sentences. The high-precision classifiers use lists of lexical items (single words or n-grams) that are good subjectivity clues. HP-Subj classifies a sentence as subjective if it contains two or more strong subjective clues. HP-Obj classifies a sentence as objective if there are no strong subjective clues. These classifiers give very high precision but low recall. The extracted sentences are then added to the training data to learn patterns. The patterns (which form the subjectivity classifiers in the next iteration) are then used to automatically identify more subjective and objective sentences, which are then added to the training set, and the next iteration of the algorithm begins.

For pattern learning, a set of syntactic templates is used to restrict the kinds of patterns to be learned. Some example syntactic templates and example patterns are as follows:

Syntactic template	Example pattern
<subj> passive-verb	<subj> was satisfied
<subj> active-verb	<subj> complained
active-verb <dobj>	endorsed <dobj>
noun aux <dobj>	fact is <dobj>
passive-verb prep <np>	was worried about <np>

Wiebe and Riloff (2005) used the discovered patterns to generate a rule-based method that produces training data for subjectivity classification. The rule-based subjective classifier classifies a sentence as subjective if it contains two or more strong subjective clues; otherwise, it does not label the sentence. In contrast, the rule-based objective classifier looks for the absence of clues: it classifies a sentence as objective if there are no strong subjective clues in the sentence and it meets several other conditions. The system also learns new patterns about objective sentences using the information extraction system AutoSlog-TS (Riloff, 1996), which finds patterns based on some fixed syntactic templates. The data produced by the rule-based classifiers were used to train a naïve Bayes classifier. A related study was also reported in Wiebe et al. (2004), which used a more comprehensive set of features or subjectivity clues for subjectivity classification.

Riloff et al. (2006) studied relationships among different features. They defined subsumption relationships among unigrams, n-grams, and lexico-syntactic patterns. If a feature is subsumed by another, the subsumed feature is not needed. This can remove many redundant features.

In Pang and Lee (2004), a mincut-based algorithm was proposed to classify each sentence as being subjective or objective. The algorithm works on a sentence graph of an opinion document, for example, a review. The graph is first built based on local labeling consistencies (which produces an association score of two sentences) and an individual sentence subjectivity score computed based on the probability produced by a traditional classification method (which produces a score for each sentence). Local labeling consistency means that sentences close to each other are more likely to have the same class label (subjective or objective). The mincut approach is able to improve individual sentence-based subjectivity classification because of the local labeling consistencies. The purpose of this work was to remove objective sentences from reviews to improve document-level sentiment classification. In Scheible and Schütze (2013), a similar approach was employed. However, it does not classify based on *subjective* and *objective* classes but *opinionated* and *not-opinionated*, where they are called *sentiment relevance* and *sentiment irrelevance*, respectively. The set of features used is also different.

Barbosa and Feng (2010) classified the subjectivity of tweets (posts on Twitter) based on traditional features with the inclusion of some Twitter-specific clues such as retweets, hashtags, links, uppercase words, emoticons, and exclamation and question marks. For sentiment classification of subjective tweets, the same set of features was used.

Interestingly, in Raaijmakers and Kraaij (2008), it was found that character n-grams of subwords rather than word n-grams can also be used to perform sentiment and subjectivity classification well. For example, for the sentence “*This car rocks*,” subword character bigrams are th, hi, is, ca, ar, ro, oc, ck, ks. In Raaijmakers et al. (2008) and Wilson and Raaijmakers (2008), word n-grams, character n-grams, and phoneme n-grams were all compared for subjectivity classification. BoosTexter (Schapire and Singer, 2000) was used as the learning algorithm. Surprisingly, they showed that character n-grams performed the best and that phoneme n-grams performed similarly to word n-grams.

Wilson et al. (2004) pointed out that a single sentence may contain both subjective and objective clauses. It is useful to pinpoint such clauses. It is also useful to identify the strength of subjectivity. A study of automatic subjectivity classification was presented to classify clauses of a sentence into four levels of strength of subjectivity expressed in individual clauses (*neutral*, *low*, *medium*, and *high*). Strength classification thus subsumes the task of classifying a sentence as subjective or objective. For classification, the authors used supervised learning. Their features included subjectivity indicating words and phrases and syntactic clues generated from the dependency parse tree.

Benamara et al. (2011) performed subjectivity classification with four classes, *S*, *OO*, *O*, and *SN*, where *S* means subjective and evaluative (their sentiment can be positive or negative), *OO* means positive or negative opinion implied in an objective sentence or sentence segment, *O* means objective with no opinion, and *SN* means subjective but not evaluative (no positive or negative sentiment). This classification conforms to our discussion in Sections 4.1 and 2.4, which showed that a subjective sentence may not necessarily be evaluative (with positive or negative sentiment) and that an objective sentence can imply sentiment as well.

Additional works on subjectivity classification of sentences have also been done in Arabic (Abdul-Mageed et al., 2011) and Urdu languages (Mukund and Srihari, 2010) based on different machine learning algorithms using general and language-specific features.

4.3 Sentence Sentiment Classification

We now turn to sentence sentiment classification. That is, if a sentence is classified as subjective, or, rather, opinionated, we determine whether it expresses a positive or negative opinion. Supervised learning again can be applied to solve the problem similarly to document-level sentiment classification, and so can lexicon-based methods. If an application needs opinions about some desired target entities or entity aspects, the system can simply assign the overall sentiment of each sentence to the target entities and aspects in the sentences. This assignment, however, can be problematic, as we discuss in Section 4.3.1.

4.3.1 Assumption of Sentence Sentiment Classification

As discussed at the beginning of the chapter, sentence-level sentiment classification makes the following important assumption, which is often not explicitly stated in research papers:

> **Assumption 4.7**: A sentence expresses a single opinion or sentiment.

As with document-level analysis, sentence-level analysis does not consider the opinion (or sentiment) target. This assumption also imposes several other restrictions, which make it difficult for sentence-level sentiment classification to be applied to several types of complex sentences:

1. The assumption is only appropriate for simple sentences (subject-verb-object) with one sentiment, for example, "*The picture quality of this camera is amazing*." It is not appropriate for simple sentences with more than one sentiment, for example, "*Lenovo is doing quite well in this poor PC market*." It is often not applicable to compound or complex sentences because they often express more than one sentiment in a sentence. For example, the sentence "*The picture quality of this camera is amazing and so is the battery life, but the viewfinder is a little small for such a great camera*" expresses both positive and negative sentiments. For '*picture quality*' and '*battery life*,' the sentence is positive, but for *viewfinder*, it is negative. It is also positive about the *camera* as a whole (the GENERAL aspect described in Section 2.1). Because of this multiple-sentiment problem, some researchers regard such sentences as having a mixed sentiment and use a separate class called MIXED to represent or label this type of sentences. However, mixed-class sentences are not easy to use in practice.

2. It may detect an overall positive or negative tone from a sentence but ignore the details, which causes problems in applications. For example, many researchers regard the following sentence as positive and expect a sentiment classifier to classify it as such (Neviarouskaya et al., 2010; Zhou et al., 2011): "*Despite the high unemployment rate, the economy is doing well*." It is true that the overall tone of this sentence is positive, as the author emphasizes her positive sentiment on *the economy*, but it does not mean that the sentence is positive about everything mentioned in the sentence. It is actually negative about the *unemployment rate*, which we must not ignore because practical applications often need opinions and their targets. If in an application we simply assign *unemployment rate* the same positive sentiment as the whole sentence, it is clearly wrong. However, if we go to the aspect-level sentiment analysis and consider the opinion target explicitly for each opinion, the problem is solved (see Chapter 5).

3. Sentence-level sentiment classification can only be applied to sentences expressing regular opinions but not to sentences expressing comparative opinions, for example, "*Coke tastes better than Pepsi*." This example sentence clearly expresses an opinion, but we cannot simply classify the sentence as being positive, negative, or neutral. We need different methods to extract and analyze comparative opinions as they have different semantic meanings (see Chapter 8).

4.3.2 Classification Methods

For sentiment classification of subjective sentences, Yu and Hatzivassiloglou (2003) used a method similar to that in Turney (2002), which we discussed in Section 3.2. Instead of using one seed word for positive and one for negative, as in Turney (2002), this work used a large set of seed adjectives. Furthermore, instead of using PMI, this work used a modified log-likelihood ratio to determine the positive or negative orientation for each adjective, adverb, noun, or verb. To assign an orientation to each sentence, it used the average log-likelihood scores of its words. Two thresholds were chosen using the training data and applied to determine whether the sentence has a positive, negative, or neutral orientation. The same problem was also studied in Hatzivassiloglou and Wiebe (2000), considering gradable adjectives.

In Hu and Liu (2004), a lexicon-based algorithm was proposed for aspect-level sentiment classification, but the method can determine the sentiment orientation of a sentence as well. It was based on a sentiment lexicon generated using a bootstrapping strategy with some given positive and negative sentiment word seeds and the synonyms and antonyms relations in WordNet. We discuss various methods for generating sentiment lexicons in Chapter 7. The sentiment orientation of a sentence was determined by summing up the orientation scores of all sentiment words in the sentence. A positive word was given the sentiment score of +1 and a negative word was given the sentiment score of −1. Negation words and contrary words (e.g., *but* and *however*) were also considered. In Kim and Hovy (2004), a similar approach was used. Their method for compiling a sentiment lexicon was also similar. However, the sentiment orientation of a sentence was determined by multiplying the scores of the sentiment words in the sentence. The authors also experimented with two other methods of aggregating sentiment scores, but they were inferior. In Kim and Hovy (2004, 2007) and Kim et al. (2006), supervised learning was used to identify several specific types of opinions. In Nigam and Hurst (2004), a domain-specific lexicon and a shallow NLP approach to assessing the sentence sentiment orientation was applied.

In Gamon et al. (2005), a semi-supervised learning algorithm was used to learn from a small set of labeled sentences and a large set of unlabeled sentences. The learning algorithm was based on EM using the naïve Bayes as the base classifier (Nigam et al., 2000). This work performed a three-class classification, positive, negative, and “other” (no opinion or mixed opinion).

In McDonald et al. (2007), a hierarchical sequence learning model similar to conditional random fields (CRF) (Lafferty et al., 2001) was proposed to jointly learn and infer sentiment at both the sentence level and the document level. In the training data, each sentence was labeled with a sentiment, and each whole review was also labeled with a sentiment. They showed that learning both levels jointly improved accuracy for both levels of classification. Täckström and McDonald (2011a) further reported a method that learns only from the document-level labeling but performs both sentence-level and document-level sentiment classifications. In Täckström and McDonald (2011b), the authors integrated a fully supervised model and a partially supervised model to perform multilevel sentiment classification.

In Hassan et al. (2010), an algorithm was proposed to identify attitudes about participants in online discussions. Because the authors were only interested in the discussion recipient, the algorithm only used sentence segments with second person pronouns. Its first step finds sentences with attitudes using supervised learning. The features were generated using Markov models. Its second step determines the orientation (positive or negative) of the attitudes, for which it used a lexicon-based method similar to that in Ding et al. (2008), except that the shortest path in the dependence tree was utilized to determine the orientation when there were conflicting sentiment words in a sentence, whereas Ding et al. (2008) used word distance (see Section 5.1).

In Socher et al. (2013), a deep learning method called Recursive Neural Tensor Network was proposed to perform sentence- and phrase-level sentiment classification. The network basically produces a composition function for phrases represented in parse trees. The training uses the given sentiment label and output of a softmax classifier taking as input the vector generated from the neural network composition function. The softmax classifier is also trained based on the vector of the parse tree node and the given label of the node. The work also produced a labeled movie review data set at the sentence and phrase levels using the review corpus from Pang and Lee (2005). It was shown that the proposed method produces more accurate results than other supervised methods because of its compositionality. For example, it can handle negation of opinions, which is hard to handle based on bag-of-word models.

Finally, many researchers have also studied Twitter post (or tweet) sentiment classification as each tweet is quite short and can be regarded as a sentence. For example, Davidov et al. (2010) performed sentiment classification of tweets using the traditional n-gram features and also hashtags, smileys, punctuations, and their frequent patterns. These additional features were shown to be quite effective. Volkova et al. (2013) investigated gender differences in the use of subjective or opinionated languages, emoticons, and hashtags for male and female users. Their experiments showed that gender-aware or gender-dependent classification gives better results than gender-independent classification. Hu et al. (2013) presented a supervised approach to sentiment classification of microblogs by taking advantage of social relations, which are mainly used to tackle the high level of noise in microblogs.

Other interesting recent work includes the study of character-character sentiments toward each other in Shakespeare's plays using a sentiment lexicon (Nalisnick and Baird, 2013) and multimodal sentiment classification of utterances extracted from video reviews of products (Perez-Rosas et al., 2013). Features used in classification include transcribed text of utterances, acoustic signals, and facial expressions.

4.4 Dealing with Conditional Sentences

Much of the existing research on sentence-level subjectivity classification or sentiment classification focuses on solving the general problem without considering that different types of sentences may need different treatments. Narayanan et al. (2009) argued that it is unlikely to have a one-technique-fits-all solution because different types of sentences express sentiments in very different ways. A divide-and-conquer approach may be needed, that is, focused studies on different types of sentences. Their paper focused on conditional sentences, which have some unique characteristics that make it hard for a system to determine sentiment orientations.

Conditional sentences are sentences that describe implications or hypothetical situations and their consequences. Such a sentence typically contains two clauses that are dependent on each other: the condition clause and the consequent clause. Their relationship has significant impact on whether the sentence expresses a positive or negative sentiment. A simple observation is that sentiment words (e.g., *great*, *beautiful*, *bad*) alone cannot distinguish an opinion sentence from a non-opinion one, for example, "*If someone makes a reliable car, I will buy it*" and "*If your Nokia phone is not good, buy this Samsung phone*." The first sentence expresses no sentiment toward any particular car, although "*reliable*" is a positive sentiment word, but the second sentence is positive about the Samsung phone and it does not express an opinion about the Nokia phone (although the owner of the Nokia phone may be negative about it). Hence, a method for determining sentiments in nonconditional sentences will not work for conditional sentences. In Narayanan et al. (2009), a supervised learning approach was proposed to deal with the problem using a set of linguistic features, for example, sentiment words or phrases and their locations, POS tags of sentiment words, tense patterns, and conditional connectives.

Here we list a set of interesting patterns in conditional sentences that often indicate sentiment. This set of patterns is particularly useful for reviews, online discussions, and blogs about products. They are not frequently used in other types of domains. Each of these patterns must appear in the consequent clause. The conditional clause often expresses a conditional intent to buy a particular type of product, for example, "*If you are looking for a great car*," "*If you are in the market for a good car*," and "*If you like fast cars*." The patterns are as follows:

POSITIVE	:: =	ENTITY is for you
	|	ENTITY is it
	|	ENTITY is the one

	|	ENTITY is your baby
	|	go (with | for) ENTITY
	|	ENTITY is the way to go
	|	this is it
	|	(search | look) no more
	|	CHOOSE ENTITY
	|	check ENTITY out
NEGATIVE	:: =	forget (this | it | ENTITY)
	|	keep looking
	|	look elsewhere
	|	CHOOSE (another one | something else)
CHOOSE	:: =	select | grab | choose | get | buy | purchase | pick | check |
		check out
ENTITY	: =	this | this ENTITY_TYPE | ENTITY_NAME

POSITIVE and NEGATIVE are the sentiments. ENTITY_TYPE is a product type, for example, car or phone. ENTITY_NAME is a named entity, for example, iPhone or Motorola. Here negation is not included, which should be handled in standard ways, to be discussed in Section 5.3. In most cases, the entity names are not mentioned in such sentences; that is, they are either mentioned in earlier sentences or they are actually the product being reviewed. However, the target aspects of opinions are frequently mentioned in the conditional clause, for example, "*If you want a beautiful and reliable car, look no further*," which give positive opinions to both the *appearance* and the *reliability* aspects of the car.

Although these patterns are quite useful for recognizing sentiments in conditional sentences, they can be unsafe for nonconditional sentences. Thus they should not be used for nonconditional sentences. Clearly there are other types of conditional sentences that can express opinions or sentiments, for example, "*If you do not mind the price, this is a great car*." This sentence expressed two opinions, one negative for the *price* and one positive for the *car*. However, most conditional sentences containing sentiment words express no opinions. To recognize them is still very challenging. Incidentally, sentences expressing uncertainty using *if* and *whether* usually express no positive or negative sentiment either, for example, "*I wonder if the new phone from Motorola is good or not*." Here, *wonder* can be replaced by many other words or phrases, for example, *am not sure*, *am unsure*, *am not certain*, *am uncertain*, *am not clear*, *am unclear*.

Another type of difficult sentence is the interrogative sentence, that is, the question. For example, "*Can anyone tell me where I can find a good Nokia phone*?" clearly has no opinion about any particular phone. However, "*Can anyone tell me how to fix this lousy Nokia phone*?" has a negative opinion about the Nokia phone. Many rhetorical questions are also opinionated, for example, "*Aren't HP Minis pretty*?" and "*Who on earth wants to live in this building*?" To my knowledge, little work has been done in this area.

To summarize, I believe that for more accurate sentiment analysis, we need to handle different types of sentences differently. Much further research is needed in this direction.

4.5 Dealing with Sarcastic Sentences

Sarcasm is a sophisticated form of speech act in which the speakers or the writers say or write the opposite of what they mean. Sarcasm has been studied in linguistics, psychology, and cognitive science (Gibbs, 1986; Kreuz and Glucksberg, 1989; Utsumi, 2000; Gibbs and Colston, 2007; Kreuz and Caucci, 2007). In the context of sentiment analysis, it means that when one says something positive, one actually means negative, and vice versa. Sarcastic sentences are very difficult to deal with in sentiment analysis because commonsense knowledge and discourse analysis are often required to recognize them. Some initial attempts have been made to handle sarcasm in recent years (Tsur et al., 2010; González-Ibáñez et al., 2011), but our knowledge about it is still very limited. On the basis of my own experiences, sarcastic sentences are not common in reviews of products and services, but they can be quite frequent in online discussions and commentaries about politics.

In Tsur et al. (2010), a semi-supervised learning approach was proposed to identify sarcasms. The paper also gives a number of nice examples of sarcastic titles of reviews, for example,

1. "[I] Love The Cover" (book)
2. "*Where am I*?" (GPS device)
3. "Be sure to save your purchase receipt" (smart phone)
4. "Are these iPods designed to die after two years?" (music player)
5. "Great for insomniacs" (book)
6. "All the features you want. Too bad they don't work!" (smart phone)
7. "Great idea, now try again with a real product development team" (e-reader)

Example 1 is sarcastic because of the expression *don't judge a book by its cover*. Choosing it as the title of the review reveals that the author is negative about the book. Example 2 requires knowledge of the context (review of a GPS device). Example 3 might seem borderline between suggesting a good practice and a sarcastic utterance, however, like example 1, placing it as the title of the review leaves no doubt about its sarcastic meaning. It implies poor quality of the phone and that one needs to be prepared to return it. In example 4, the sarcasm emerges from the naïve-like question that assumes the general expectation that goods should last. In example 5, the sarcasm requires commonsense knowledge (insomnia → boredom), and in examples 6 and 7, the sarcasm is conveyed by the explicit contradiction. Note that example 7 contains an explicit positive sentiment (*great idea*), whereas the positive sentiment in example 6 is not explicit. From these sentences, we can clearly see the difficulty of dealing with sarcasm.

The sarcasm detection algorithm proposed in Tsur et al. (2010) uses a small set of labeled sentences (seeds) but does not use unlabeled examples. Instead, it expands the seed set automatically through web search. The authors posited that sarcastic sentences frequently co-occur in texts with other sarcastic sentences. An automated web search using each sentence in the seed training set as a query was performed. The system then collected up to fifty search engine snippets for each seed example and added the collected sentences to the training set. This enriched training set was then used for learning and classification. For learning, it used two types of features: pattern-based features and punctuation-based features. A pattern is an ordered sequence of high-frequency words similar to sequential patterns in data mining (Liu, 2006, 2011). Two criteria were also designed to remove too general and too specific patterns. Punctuation-based features include the number of "!," "?," and quotation marks and the number of capitalized or all capital words in the sentence. For classification, a *k*NN-based method was employed. This work, however, did not perform sentiment classification. It only separated sarcastic and nonsarcastic sentences.

González-Ibáñez et al. (2011) studied the Twitter data to distinguish sarcastic tweets and nonsarcastic tweets that directly convey positive or negative opinions (neutral utterances were not considered). Again, a supervised learning approach was taken using SVM and logistic regression. As features, they used unigrams and some dictionary-based information. The dictionary-based features include word categories (Pennebaker et al., 2007), WordNet-Affect (WNA) (Strapparava and Valitutti, 2004), and a list of interjections (e.g., ah, oh, yeah) and punctuations (e.g., !, ?). Features like emoticons and *ToUser* (which marks if a tweet is a reply to another tweet, signaled by <@user>) were also used. Experimental results for three-way classification (sarcastic, positive, and negative) showed that the problem is very challenging. The best accuracy was only 57%. Again, this work did not classify sarcastic sentences into positive and negative classes.

Recently, Riloff et al. (2013) proposed a bootstrapping method to identify a specific type of sarcastic tweets characterized by positive sentiment followed by a negative situation. For example, in "*I love waiting forever for a doctor*," *love* indicates a positive sentiment and *waiting forever* indicates a negative situation. It was found that this type of sarcastic tweet is very common on Twitter. The authors further limited their study to positive sentiments that are expressed as verb phrases or as predicative expressions (predicate adjective or predicate nominal) and negative situation phrases that are complements to verb phrases. The bootstrapping learning process relies on the assumption that a positive sentiment phrase usually appears to the left of a negative situation phrase and in close proximity (usually, but not always, adjacent), that is,

[+ VERB PHRASE] [– SITUATION PHRASE].

The proposed bootstrapping algorithm starts with a single seed positive sentiment verb *love*. Using a manually labeled sarcastic and nonsarcastic tweets corpus, it first finds a set of candidate negative situation phrases that are n-grams following *love* (on the right-hand side) and are verb complement phrases of certain forms, which are defined as some bigram POS patterns. It then scores each candidate phrase based on the manually labeled tweets. Those that pass the score threshold are added to the set of negative situation phrases. The set of negative situation phrases is then used to find the two types of positive sentiment phrases in a similar way. The bootstrapping process alternately learns positive sentiments and negative situations until no more phrases can be found. The resulting sets of positive sentiment phrases and negative situation phrases are then used to identify sarcastic tweets.

4.6 Cross-Language Subjectivity and Sentiment Classification

Researchers have also studied cross-language subjectivity classification and sentiment classification at the sentence level as well as the document level. Again, the area of research focuses on using the extensive resources and tools available in English and automated translations to help build sentiment analysis systems in other languages that have few resources or tools. Current research proposed three main strategies:

1. Translate test sentences in the target language into the source language and classify them using a source language classifier.
2. Translate a source language training corpus into the target language and build a corpus-based classifier in the target language.
3. Translate a sentiment or subjectivity lexicon in the source language to the target language and build a lexicon-based classifier in the target language.

Kim and Hovy (2006) experimented with strategy 1, translating German e-mails to English and applying English sentiment words to determine sentiment orientation, and with strategy 3, translating English sentiment words into German sentiment words and analyzing German e-mails using German sentiment words. Mihalcea et al. (2007) also experimented with translating English subjectivity words and phrases into the target language. They actually tried two translation strategies for cross-language subjectivity classification. First, they derived a subjectivity lexicon for the target language (in their case, Romanian) using an English subjectivity lexicon through translation. A rule-based subjectivity classifier similar to that in Riloff and Wiebe (2003) was then applied to classify Romanian sentences into subjective and objective classes. The precision was not bad, but the recall was poor. Second, they derived a subjectivity-annotated corpus in the target language using a manually translated parallel corpus. They first automatically classified English sentences in the corpus into subjective and objective classes using some existing tools, and then projected the subjectivity class labels to the Romanian sentences in the parallel corpus using the available sentence-level alignment in the parallel corpus. A subjectivity classifier based on supervised learning was then built in Romanian to classify Romanian sentences. In this case, the result was better than the first approach.

In Banea et al. (2008), the authors reported three sets of experiments. First, a labeled corpus in the source language (English) was automatically translated into the target language (Romanian). The subjectivity labels in the source language were then mapped to the translated version in the target language. Second, the source language text was automatically labeled for subjectivity and then translated into the target language. In both cases, the translated version with subjectivity labels in the target language was used to train a subjectivity classifier in the target language. Third, the target language was translated into the source language, and then a subjectivity classification tool was used to classify the automatically translated source language text. After classification, the labels were mapped back into the target language. The resulting labeled corpus was then used to train a subjectivity classifier in the target language. The final classification results were quite similar for the three strategies.

Banea et al. (2010) conducted extensive experiments for cross-language sentence-level subjectivity classification by translating from a labeled English corpus to five other languages. First, they showed that using the translated corpus for training worked reasonably well and consistently for all five languages. Combining the translated versions in different languages with the original English version to form a single training corpus can also improve the original English subjectivity classification itself. Second, the paper demonstrates that by combining the predictions made by monolingual classifiers using a majority vote, it is possible to generate a high-precision sentence-level subjectivity classifier.

The technique in Bautin et al. (2008) was also to translate documents in the target language into English and use an English lexicon-based method to determine the sentiment orientation for each sentence containing an entity. This technique actually works at the aspect level. The sentiment classification method is similar to that in Hu and Liu (2004).

Kim et al. (2010) introduced a concept called multilingual comparability to evaluate multilingual subjectivity analysis systems. This was defined as the level of agreement in the classification results of a pair of multilingual texts with an identical subjective meaning. Using a parallel corpus, they studied the agreement among the classification results of the source language and the target language using Cohen's kappa. For the target language classification, they tried several existing translation-based cross-language subjectivity classification methods. The results show that classifiers trained on corpora translated from English to the target languages perform well for both subjectivity classification and multilingual comparability.

Lu et al. (2011) attempted a slightly different problem. The paper assumes that there is a certain amount of sentiment-labeled data available for both the source and target languages, and there is also an unlabeled parallel corpus. The method is a maximum entropy-based EM algorithm that jointly learns two monolingual sentiment classifiers by treating the sentiment labels in the unlabeled parallel text as unobserved latent variables and maximizing the regularized joint likelihood of the language-specific labeled data together with the inferred sentiment labels of the parallel text. In learning, it exploits the intuition that two sentences or documents that are parallel (i.e., translations of one another) should exhibit the same sentiment. Their method can thus simultaneously improve sentiment classification for both languages.

4.7 Using Discourse Information for Sentiment Classification

Most existing work on both document-level and sentence-level sentiment classification does not use the discourse information either among sentences or among clauses in the same sentence. However, in many cases, such analysis is necessary. For example, in the segment

> "*I'm not tryna be funny, but I'm scared for this country. Romney is winning*."

if there is no intersentential discourse analysis, we will not be able to find out that the author is negative about *Romney*. Current research on discourse analysis is still primitive and cannot handle this kind of cases.

Sentiment annotation at the discourse level was studied in Asher et al. (2008) and Somasundaran et al. (2008). Asher et al. (2008) used five types of rhetorical relations: *contrast*, *correction*, *support*, *result*, and *continuation*, with attached sentiment information for annotation. Somasundaran et al. (2008) proposed a concept called *opinion frames*. The components of opinion frames are opinions and the relationships with their targets.

In Somasundaran et al. (2009), the authors performed sentiment classification based on the opinion frame annotation using the *collective classification* algorithm in Bilgic et al. (2007), which is also described in detail in Section 6.4. Collective classification performs classification on a graph, in which the nodes are sentences (or other expressions) that need to be classified and the links are relations. In the discourse context, they are sentiment-related discourse relations. These relations can be used to generate a set of relational features for learning. Each node itself also generates a set of local features. The relational features allow the classification of one node to affect the classification of other nodes in the collective classification scheme. In Zhou et al. (2011), the discourse information within a single compound sentence was used to perform sentiment classification of the sentence. For example, the sentence "*Although Fujimori was criticized by the international community, he was loved by the domestic population because people hated the corrupted ruling class*" is a positive sentence, although it has more negative opinion words (see also Section 4.7). This paper used pattern mining to find discourse patterns for classification.

In Zirn et al. (2011), the authors proposed a method to classify discourse segments. Each segment expresses a single (positive or negative) opinion. Markov logic networks were used for classification, which not only can utilize a sentiment lexicon but also the local/neighboring discourse context.

4.8 Emotion Classification of Sentences

Like emotion classification at the document level, sentence-level emotion classification is also considerably harder than sentence-level sentiment classification. The classification accuracy of most published works is less than 50% due to many more classes and similarity or relatedness of different emotion types. Emotions are highly subjective, too, which makes it difficult to even manually label them in sentences. Like sentence-level sentiment classification, both supervised learning and lexicon-based approaches have been applied to emotion classification. We discuss some existing works using supervised learning first.

Alm et al. (2005) classified the emotional affinity of sentences in the narrative domain of children's fairy tales using supervised learning. The classification method used was a variation of the Winnow algorithm. The features are not the traditional word n-grams but fourteen groups of Boolean features about each sentence and its context in the document. The classes are only two: neutral and emotional. Additional work was reported in Alm (2008), which used individual types of emotion as class labels. The work in Aman and Szpakowicz (2007) also classifies at the sentence level using only two classes. It experimented with sentiment words, emotional words, and all words as features. It showed that using all words as features gives the best results with SVM.

In Mohammad (2012), a Twitter data set was annotated with emotion types based on emotion word hashtags in Twitter posts and performed classification using SVM with binary features that capture the presence or absence of unigrams and bigrams. In Chaffar and Inkpen (2011), a few classification methods (i.e., decision trees, naïve Bayes, and SVM) were compared on several document-level and sentence-level classification data sets. It was shown that SVM performed consistently better.

In the lexicon-based approach, Yang et al. (2007) first constructed an emotion lexicon and then performed emotion classification at the sentence level using the lexicon. For constructing the emotion lexicon, the proposed algorithm uses only sentences with a single user-provided emoticon. For a word, it computes a collocation (or association) strength of the word with each emoticon using a measure similar to pointwise mutual information (PMI). Those top-scored words are very likely to indicate different types of emotion. For emotion classification of sentences, it experimented with two approaches. The first approach is similar to the lexicon-based approach to sentiment classification. For each sentence, the algorithm uses the emoticon collocation strength scores of the words in the sentence and several voting strategies to decide the emotion type of the sentence. The second approach uses supervised learning with SVM. The features are only the top *k* emotion words. The results showed that SVM performed better.

A related method is reported in Liu et al. (2003), which proposed a more sophisticated lexicon-based method. The algorithm first uses a small lexicon of emotion words for six emotion types (i.e., *happy*, *sad*, *anger*, *fear*, *disgust*, and *surprise*; from Ekman, 1993) to extract sentences from a commonsense knowledge base called Open Mind Common Sense (OMCS) (Singh, 2002). The lexicon words and their emotion values in the sentences are then propagated to other related words in the sentences based on some commonsense relation rules. The expanded lexicon and the emotion values of its emotion words are then used with a set of rules (called models in the paper) to classify emotions.

Earlier work in Zhe and Boucouvalas (2002) used a lexicon-based method as well, with a set of accompanied rules for special handling of different types of language constructs and different types of sentences. Yet another similar approach was taken in Neviarouskaya et al. (2009), which used a set of more fine-grained rules to handle constructs at various grammatical levels. Specifically, it followed the compositionality principle and developed a rule-based algorithm for emotion classification. At the individual word level, the algorithm uses an emotion lexicon and a list of emotion-indicating items such as emoticons, abbreviations, acronyms, interjections, question and exclamation marks, repeated punctuations, and capital letters. At the phrase level, rules were designed to deal with emotions expressed in adjective phrases, noun phrases, and verb plus adverbial phrases, verb plus noun phrases, and verb plus adjective phrases. At the sentence level, rules are designed to deal with sentence clues indicating no emotions, such as those involving think, believe, may, and conditional statements. To classify a sentence into an emotion type, another set of rules was applied to aggregate the emotion scores from the components of the sentence following certain precedence. This technique gave good accuracy in classification of emotions expressed in sentences extracted from blog posts.

4.9 Discussion

Sentence-level subjectivity classification, sentiment classification, and emotion classification go further than document-level classification as they move closer to opinion targets and sentiments about the targets. However, because they are still not concerned with opinion targets, there are several shortcomings for real-life applications, as we mentioned earlier:

- In most applications, the user needs to know what the opinions are about, that is, what entities or aspects of entities are liked and disliked. As at the document level, the sentence-level analysis also does not identify entities and their aspects and opinions about them, which are key to applications.
- Although we might say that if we know the opinion targets (e.g., entities and aspects, or topics), we can simply assign the sentiment orientation of the sentence to the targets in the sentence. However, this is problematic, as we discussed in Section 4.3.1. Sentence-level classification is only suitable for simple sentences with a single opinion in each sentence. It is not applicable to compound and complex sentences such as "*Trying out Chrome because Firefox keeps crashing*" and "*Apple is doing very well in this poor economy*" because in these sentences, the opinions are different for different targets. Even for sentences with a single overall tone, different parts of the sentence can still express different opinions. For example, the sentence "*Despite the high unemployment rate*, *the economy is doing well*" has an overall positive tone, but it does not have a positive opinion about the *unemployment rate*.
- Sentence-level classification cannot deal with opinions or sentiment in comparative sentences, for example, "*Coke tastes better than Pepsi*." Although this sentence clearly expresses an opinion, we cannot simply classify the sentence as being positive, negative, or neutral. We need different methods to deal with them as they have quite different semantic meanings from regular opinions.

To solve all these problems, we need aspect-level analysis, that is, to perform sentiment analysis following the full definition given in Section 2.1. We discuss aspect-level sentiment analysis in the next two chapters and the analysis of comparative opinions in Chapter 8.

2 http://www.thefreedictionary.com/.

5

Aspect Sentiment Classification

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Following the natural progression of chapters, this chapter should focus on expression-level (word or phrase) sentiment classification as the last two chapters were about document-level and sentence-level classifications. However, we leave that topic to Chapter 7. In this and the next chapter, we focus on *aspect-based sentiment analysis* (or opinion mining) to deal with the full sentiment analysis problem as defined in Section 2.1, that is, classifying sentiments and extracting sentiment or opinion targets (entities and aspects).

As we discussed in Chapters 3 and 4, classifying opinion text at the document level or at the sentence level as positive or negative is insufficient for most applications because these classifications do not identify sentiment or opinion targets or assign sentiments to the targets. Even if we know that each document evaluates a single entity, a positive opinion document about an entity does not mean that the author is positive about every aspect of the entity. Likewise, a negative opinion document does not mean that the author is negative about everything. For a more complete analysis, we need to discover aspects and determine whether the sentiment is positive, negative, or neutral about each aspect. To obtain such details, we need aspect-based sentiment analysis, which is the full model defined in Section 2.1. Aspect-based sentiment analysis was earlier called *feature-based opinion mining* in Hu and Liu (2004).

In the general case (Definition 2.1 in Section 2.1.1), an opinion is defined as a quadruple (g, s, h, t), where g is the opinion target, s is the sentiment on the target, h is the opinion holder, and t is the time when the opinion is given. However, in many cases, it is useful to decompose an opinion target to an entity and one of its aspects. This gives the quintuple definition of (e, a, s, h, t), where e is an entity and a is one of its aspects (Definition 2.7 in Section 2.1.4). When the opinion is only about the entity e and not any of its aspects, we assign the GENERAL to the aspect component in the quintuple to indicate the fact. For example, for the opinion in the sentence "*I love the iPhone*," the entity is *iPhone* and the aspect is GENERAL because the opinion is about *iPhone* in general or as a whole. However, for the sentence "*iPhone's voice quality is great*," the entity is still *iPhone* but the aspect is *voice quality*, because in this case, the opinion is not about the *iPhone* as a whole but about its voice quality.

In different application domains, aspect-based sentiment analysis may be named differently because there is not a single term that sounds natural in every application domain. For example, in some applications, the term *topic-based sentiment analysis* is used, where a topic means an aspect. In some other applications, because the users are interested only in sentiment on entities, they may also use the term *entity-based sentiment analysis*, which is actually covered by aspect-based sentiment analysis because the quintuple definition includes both entities and aspects. Some researchers even use the term *target-based sentiment analysis*. In this book, we use aspect-based sentiment analysis throughout.

To achieve the goal of aspect-based sentiment analysis, we need to perform six basic tasks (Section 2.1.6), which are all highly challenging and require deep NLP capabilities. Among them, two tasks have received the most research attention: aspect extraction and aspect sentiment classification.

1. *Aspect extraction.* This task is to extract aspects and entities that have been evaluated. For example, in the sentence "*The voice quality of this phone is amazing*," we should extract *voice quality* as an aspect of the entity represented by *this phone*. For simplicity of presentation, we often omit entities in our discussions and focus only on aspects. But do bear in mind that whenever we talk about an aspect, we must know the entity to which it belongs; otherwise, the aspect is not meaningful. Hence aspect extraction covers entity extraction. Note that *this phone* here does not indicate the aspect GENERAL because the evaluation is not about the phone as a whole but about its voice quality. The sentence "*I love this phone*" evaluates the whole phone, that is, the GENERAL aspect of the entity indicated by *this phone*.

2. *Aspect sentiment classification.* This task determines whether the opinions on different aspects are positive, negative, or neutral. In the first example sentence, the opinion about the *voice quality* aspect is positive. In the second (i.e., "*I love this phone*"), the opinion about the aspect GENERAL (the entire entity) is also positive.

This chapter focuses on the second task. The next chapter discusses aspect extraction, where we will also cover the existing research on other extraction tasks in Section 2.1.6.

5.1 Aspect Sentiment Classification

As with sentiment classification at the sentence and document levels, aspect-level sentiment classification also has two main approaches: the supervised learning approach and the unsupervised lexicon-based approach. However, these approaches are not the same as their counterparts at the sentence level or the document level because we now need to consider opinion targets in the classification. In the next three subsections, we first describe the two approaches and then their advantages and disadvantages.

5.1.1 Supervised Learning

Although we still use the same machine learning algorithms such as SVM and naïve Bayes classification, the kinds of features used for sentence-level and clause-level sentiment classification are no longer sufficient or appropriate. The key reason is that those features do not consider (or are independent of) opinion target (entity and/or aspect) and are thus unable to determine to which target an opinion refers. To remedy this problem, we need to add the ability to consider opinion target in learning, which is quite challenging. There are two main approaches to this. The first approach is to generate a set of features that are dependent on the target entity or aspect in the sentence. Clearly these features are not used in sentence- or document-level classifications because their features are *target independent*. The second approach is to determine the application scope of each sentiment expression to determine whether it covers the target entity or aspect in the sentence. For example, in the sentence "*Apple is doing very well in this bad economy*," the sentiment word *bad*'s application scope covers only *economy* but not *Apple* (i.e., *bad* does not modify *Apple*). This approach assumes that the system knows each sentiment expression.

The current supervised learning methods mainly use the first approach but also have a flavor of the second approach. For example, Jiang et al. (2011) uses a syntactic parse tree to generate a set of target-dependent features that represent some syntactic relationships of the target entity or aspect words and other words. It assumes that the target entity or aspect is already given or has been discovered beforehand. Let w_i be a word and T be the target entity or aspect. Some example target-dependent features used in Jiang et al. (2011) are as follows: if w_i is a transitive verb and T is its object, the feature w_i_*arg*2 is generated, where *arg* means argument. For example, if *iPhone* is the target entity, for the sentence "*I love the iPhone*," the feature *love_arg*2 is generated. If w_i is a transitive verb and T is its subject, the feature w_i_*arg*1 is generated. If w_i is an intransitive verb and T is its subject, the feature w_i_*it_arg*1 is generated. If w_i is an adjective or noun and T is its head, the feature w_i_*arg*1 is generated. Apart from these and other target-dependent features, the technique also employed conventional target-independent features used in sentence-level or document-level classifications.

A related approach in Boiy and Moens (2009) computed the feature weight (value) for each word feature based on the distance between the word feature and the target entity or aspect. Three alternative weights were defined using the following:

1. *Depth difference*. The feature weight is inversely proportional to the difference in depth between the word feature and the entity of interest in the parse tree.

2. *Path distance*. If the parse tree is seen as a graph, the weight of a word feature is inversely proportional to the length of the path between the feature and the entity of interest using a breadth-first search.

3. *Simple distance*. The weight of a word feature is inversely proportional to its distance to the entity of interest in the sentence. In this case, no parse tree is used.

5.1.2 Lexicon-Based Approach

Although we still use the terminology of lexicon-based approach, the approach here is not the same as that of document-level or sentence-level sentiment classification. Again, the key difference is that we now need to explicitly consider the opinion target, which is absent at the document level or sentence level. To consider the opinion target, both approaches mentioned previously can be used. That is, we can compute the sentiment orientation on a target in a sentence by using a sentiment aggregation function that is able to take into account the distances of the sentiment expressions (words or phrases) and the target entity or aspect in the sentence. We can also find the application scope of each sentiment expression to determine whether it covers the target entity or aspect in the sentence. This is typically done by exploiting the syntactic relationships of sentiment expressions and opinion targets. Clearly one can also combine the two approaches.

The lexicon-based approach to aspect sentiment classification can be stated as follows: it uses (1) a lexicon of sentiment expressions including sentiment words, phases, idioms, and composition rules (Section 5.2); (2) a set of rules for handling different language constructs (e.g., *sentiment shifters* and *but-clauses*) and types of sentences; and (3) a sentiment aggregation function or a set of sentiment and target relationships derived from the parse tree to determine the sentiment orientation on each target in a sentence (Ding et al., 2008; Liu, 2010). Extension and adaptation of the approach to analyzing comparative sentences will be given in Section 8.3.

Here we introduce a simple lexicon-based method (Ding et al., 2008) (which improves the method in Hu and Liu, 2004) to give a flavor of this approach. We assume that the target entities and aspects are known, either given or have been extracted beforehand. Aspect extraction is discussed in the next chapter. The method consists of four steps:

1. *Mark sentiment expressions (words and phrases).* This step marks all sentiment expressions in each sentence that contains one or more aspects (including entities). Each positive expression is assigned the sentiment score of +1 and each negative expression is assigned the sentiment score of −1. For example, after this step, the sentence "*The voice quality of this phone is not good, but the battery life is long*" becomes "The *voice quality* of this phone is not **good** [+1], but the *battery life* is long" because *good* is a positive sentiment word (the aspects in the sentence are italicized). Note that *long* here is not a sentiment word, but we can infer its sentiment in this context shortly. In fact, we can regard *long* as a context-dependent sentiment word, which we discuss in Chapter 7.

2. *Apply sentiment shifters.* Sentiment shifters (also called *valence shifters* in Polanyi and Zaenen, 2004) are words and phrases that can change sentiment orientations. There are several types of such shifters. Negation words like *not*, *never*, *none*, *nobody*, *nowhere*, *neither*, and *cannot* are the most common type. This step turns our sentence into "The *voice quality* of this phone is **not good** [−1], but the *battery life* is long" owing to the negation word *not*. We discuss several other types of sentiment shifters in Section 5.3. Note that not every appearance of a sentiment shifter changes the sentiment orientation, for example, "*not only…but also*." Such phrases need to be identified beforehand based on a precompiled lexicon and skipped in sentiment classification.

3. *Handle but-clauses.* Words or phrases that indicate *contrary* need special handling because they often change sentiment orientations. The most commonly used contrary word in English is *but*. A sentence containing a contrary word or phrase is handled by applying the following rule: the sentiment orientations before the contrary word (e.g., *but*) and after the contrary word are opposite to each other if the opinion on one side cannot be determined. The if-condition in the rule is used because contrary words and phrases do not always indicate an opinion change, for example, "*Car-x is great, but Car-y is better*." After this step, our sentence is turned into "The *voice quality* of this phone is **not good** [−1], **but** the *battery life* is *long* [+1]," where [+1] is added at the end of the but-clause. Here we can infer that *long* is positive for *battery life*. In addition to *but*, words or phrases such as '*however*,' '*with the exception of*,' '*except that*,' and '*except for*' also have the meaning of contrary and are handled in the same way. As in the case of negation, not every *but* means contrary, for example, "*not only . . . but also*." Such non-but phrases containing *but* also need to be identified beforehand based on a precompiled lexicon and should be skipped.

4. *Aggregate sentiment scores.* In this last step, a sentiment or opinion aggregation function is applied to the resulting sentiment scores to determine the final orientation of the sentiment on each aspect in the sentence. Given a sentence s containing a set of aspects $\{a_1, \ldots, a_m\}$ and a set of sentiment expressions $\{se_1, \ldots, se_n\}$ with their sentiment scores obtained from steps 1–3, the sentiment orientation for each aspect a_i in sentence s is determined by the following aggregation function:

$$\text{score}(a_i, s) = \sum_{se_j \in s} \frac{se_j.ss}{\text{dist}(se_j, a_i)}, \tag{5.1}$$

where se_j is a sentiment expression in sentence s, dist(se_j, a_i) is the word distance between aspect a_i and sentiment expression se_j in s, and $se_j.ss$ is the sentiment score of se_i. Multiplicative inverse is used to give lower weights to sentiment expressions that are far away from aspect a_i. If the final score is positive, then the opinion on aspect a_i in s is positive. If the final score is negative, then the sentiment on the aspect is negative. It is neutral otherwise.

This simple algorithm performs quite well in practice. It can handle the sentence “*Apple is doing very well in this bad economy*” without any problem. There are also other aggregation functions. For example, Hu and Liu (2004) simply summed up the sentiment scores of all sentiment expressions in a sentence or sentence segment. However, Equation (5.1) seems to work better in general. Similar methods are also employed later in Wan (2008) and Zhu et al. (2009).

To make this method more effective, we can determine the scope of each individual sentiment expression rather than using word distance to ensure that sentiments and their targets are matched more accurately. One obvious method is to exploit the relationships of sentiment expressions and their targets. There are many such relationships, which can be grouped into three categories.

1. *Syntactic dependencies*. This type mainly involves *adjective-noun* dependency relations and *verb-adverb* dependency relations. For example, for the sentence “*This camera takes great pictures*,” we can use the dependency relation of adjective *great* and noun *picture* to identify the target (*picture*) of the opinion or sentiment indicated by *great*. Another example of adjective-noun relations is “*The picture quality is great*.” Here *picture quality* is the aspect expression or the target of the opinion indicated by *great*. An example of verb-adverb relations is “*I can install this software easily*.” Incidentally, the dependency relation of the adverb *easily* and the verb *install* can also be utilized to identify the target of the opinion (the *installation* aspect of the software). The aspect is indicated by the verb *install*. We discuss these relations in Section 6.2 when we study how to use them to extract aspects.

2. *Sentiment word itself as target aspect*. In many cases, a sentiment word serves two roles, as a sentiment word and also as an aspect indicator. Many adjective sentiment words are such words. Apart from some general adjective sentiment words such as *great*, *good*, *amazing*, and *bad*, which can modify anything, most adjectives describe some specific attributes or properties of entities: for example, *expensive* describes *price*, and *beautiful* describes *appearance*. *Price* and *appearance* are called the *attribute nouns* of the adjectives *expensive* and *beautiful*, respectively. For example, in the sentence “*BMW is expensive*,” the sentiment is indicated by *expensive*, which also implies the aspect *price*, the target aspect of the sentiment or opinion. *BMW* is the target entity, which has a syntactic dependency with *expensive*, as discussed earlier (see also Section 6.2). Adjectives and their attribute nouns are discussed further in Section 6.4.

3. *Semantic relations*. This category of relations is hard to recognize in general, except for a small subset, because they are based on the meaning and/or usage patterns of individual words or phrases. For example, in "*John admires Jean*," the positive opinion indicated by *admires* has the target of *Jean*. There is no sentiment about *John*, who is actually the opinion holder. However, if we change the word *admires* to *murdered*, the opinion target becomes *John*. Notice that this is a fact-implied opinion. Many sentiment composition rules discussed in Section 5.2 fall into this semantic relation category. In general, semantic relations indicating opinions and targets can be arbitrarily complex.

To make use of these relations (except the second category), a syntactic parse tree is typically needed to first identify them. Of course, in a practical implementation, one can also employ a shallow parser to help identify the relations approximately. Apart from parsing-based methods, Liu et al. (2012) proposed a word alignment method to align or to pair sentiment expressions and sentiment targets (see Section 6.2.1), and Yang and Cardie (2013) proposed a supervised learning method to link sentiment and target (see Section 6.3.2).

Another way to improve the preceding lexicon-based sentiment classification method is to automatically discover the sentiment orientation of context-dependent (sentiment) words such as *long*. The algorithm in Ding et al. (2008) has a technique for this. More details about this topic are given in Chapter 7.

Other related work includes that of Blair-Goldensohn et al. (2008), who integrated a lexicon-based method with supervised learning. Kessler and Nicolov (2009) experimented with four different strategies for determining the sentiment on each aspect or target and also showed several interesting statistics on why it is so hard to link sentiment words to their targets. Although the preceding methods were not developed for comparative sentences, it is not hard to adapt them for comparative sentences. In fact, that has been done in Ganapathibhotla and Liu (2008) and Ding et al. (2009). We discuss this adaption in Chapter 8.

Along with aspect-level sentiment classification, researchers have also studied aspect sentiment rating prediction. However, this thread of work is mainly done in conjunction with aspect extraction in the context of topic modeling, which we cover in Section 6.6.

5.1.3 Pros and Cons of the Two Approaches

We now shed some light on the advantages and disadvantages of the supervised learning approach and the lexicon-based approach. The key advantage of the learning-based approach is that a learning algorithm can automatically learn from all kinds of features for classification through optimization. Most such features are difficult to use by a lexicon-based method because people do not know how to apply them without an algorithm to figure it out. Supervised learning is, however, dependent on the training data, which need to be manually labeled for each domain. As discussed in Section 3.4, a sentiment classifier trained from the labeled data in one domain often does not work in another domain. Although researchers have studied domain adaptation (or transfer learning), existing techniques are still far from mature for practical use. The current domain adaptation methods are also mainly for document-level sentiment classification as documents are long and contain more features for classification than individual sentences or clauses. Supervised learning is thus difficult to scale up to a large number of application domains. Another shortcoming is that it is hard to learn things that do not occur frequently.

The lexicon-based approach is able to avoid some of these issues partially and has been shown to perform well in a large number of applications. Most industrial systems are based on this approach. The key advantage of the lexicon-based approach is its domain independence, which means that it can be applied to any domain. It does not need the user to manually label a large number of sentences for each application domain, as required in the supervised learning approach. The lexicon-based method is also flexible in the sense that the system can be easily extended and improved. If an error occurs, the user can simply correct some existing rules and/or add new rules to the system's rule base. Supervised learning is harder to extend or improve because the problem sentences have to appear frequently for a learning algorithm to pick up the right patterns.

The lexicon-based approach also has its disadvantages. It needs a heavy investment in time and effort to build the initial knowledge base of lexicon, patterns, and rules. The next few sections present some of these, which I have accumulated over the years, and should help a programmer to build an initial sentiment analysis system fairly easily. Furthermore, although the lexicon-based approach claims to be domain independent, some additional work is still needed to take care of the idiosyncrasies of each domain. However, after one has worked on a large number of domains, there is less and less additional work required for each new domain. The main idiosyncrasy that is hard to deal with is domain- or context-dependent sentiment words and phrases. For example, the word *suck* usually indicates a negative opinion, but in the domain of vacuum cleaner reviews, it often expresses a positive opinion about the suction power. Although some data mining techniques have been proposed to discover such words and their orientations, current methods are still not accurate. This, however, presents a very promising research direction. If one can make good progress in attacking this problem, sentiment classification accuracy can be improved dramatically.

All this being said, I believe that machine learning has a greater potential for the future, although a great deal of research is still needed. By machine learning, I do not mean just the existing supervised classification or unsupervised clustering approaches. In fact, I feel that the current approaches are not likely to be sufficient for making major progresses in the field. With a huge number of data sets available, more sophisticated or even new kinds of machine learning algorithms should be designed to make major breakthroughs in learning domain–independent and domain-specific knowledge needed for sentiment analysis.

5.2 Rules of Sentiment Composition

As indicated earlier, in addition to sentiment words and phrases, there are many other types of language constructs that can convey or imply sentiments. Most of them are also harder to deal with. This section lists and studies some of them, which were called *rules of opinion* in Liu (2010). In this book, we call them *sentiment composition rules* to stress the complexity and compositionality of sentiment expressions. We also add a large number of new rules to the list in Liu (2010). For completeness, individual sentiment words and phrases are covered as well.

As for the usage of these rules, they can be utilized by both the lexicon-based approach and the supervised learning-based approach:

1. These composition rules, together with a sentiment lexicon, form the core of the lexicon-based approach for aspect-based sentiment classification. As mentioned earlier, this approach is widely used in commercial sentiment analysis systems (although their levels of sophistication and algorithmic details may vary) because of its flexibility and domain-independent nature.

2. They can serve as effective features for supervised learning. Some commercial systems also use supervised learning with manually labeled data for training.

In a nutshell, a sentiment composition rule represents a scenario that implies a positive or negative sentiment. It can be as simple as a sentiment word with a given orientation or as complex as a composite expression that may need domain knowledge to determine its sentiment orientation. From these rules, we can see why sentiment analysis is a difficult problem and why simply using a sentiment lexicon for analysis is far from sufficient.

Here we present the rules at the conceptual level, meaning that the rules are meant to be language independent. However, because this book is written in English, I also list the English constructs that are often used to express the concepts, which not only help reader understanding but also can be employed directly in building an actual sentiment analysis system in English. For other languages, these rules can be adapted and instantiated with words and phrases in those languages. For example, I have tried to map each of these rules to Chinese with no difficulty. However, the actual expressions used in different languages are obviously very different.

One way to represent these rules is to use the idea of compositional semantics (Montague, 1974; Dowty et al., 1981), which states that the meaning of a compound expression is a function of the meaning of its constituents and of the syntactic rules by which they are combined. Several researchers also studied compositionality in the context sentiment analysis. However, the representation schemes used in existing research (see Section 5.2.6) are far from sufficient for handling the sophistication required to represent most, if not all, sentiment composition rules listed in this section. I still do not have a good way to represent them formally in a grammar framework because of their diversity and complexity. In what follows, I first describe the rules conceptually without considering how they may be represented in an actual system. After studying the impact of negation, modality, and coordination conjunction *but* on sentiment, a representation scheme is offered in Section 5.7 to code these rules at the expression level so that they can be used in an actual sentiment analysis system.

Besides the sentiment that these rules introduce, many of the rules also give good indications where the opinion targets (entities and aspects) are. This information is extremely valuable for two reasons: first, it allows us to perform opinion target (entity and aspect) extraction based on sentiment rules, which we discuss in Chapter 6; second, it enables the system to find the right targets for opinions. For example, in the sentence "*This doctor forced me to take the medicine*," the negative opinion is not about *the medicine* but about *this doctor*. We discuss target specification in Section 5.7 when we describe rule representation at the expression level, which can be directly used in a sentiment analysis system.

5.2.1 Sentiment Composition Rules

We present the rules using a specification language similar to the Backus-Naur form (BNF). But the use of this pseudo-BNF is mainly for convenience as it is easy to represent alternative concepts. It allows us to get the gist of the ideas and avoid details, which we discuss in Section 5.7. Because there are a large number of rules, we only discuss a subset of them here to facilitate reading. The rest are given in the appendix. To aid in understanding, we also group the rules into categories. To save space, we generally list only lexemes in the rules. *Lexemes* are words that can act as dictionary entries. Words that perform different particular grammatical roles (e.g., past tense) are called *inflectional forms*. For example, for the lexeme *solve*, its inflectional forms include *solve*, *solves*, *solving*, and *solved*. However, these rules almost always apply to inflectional forms as well as to the lexemes.

1. *General sentiment rules*. These are the top-level or the most general rules. They decide the final assignment of positive (POSITIVE) or negative (NEGATIVE) sentiment to each expression. They are expanded by subsequent rules and discussed in more detail in the next few sections. Some of the rules are highly involved, and their applications can be context dependent.

POSITIVE	:: =	PO
	|	NEGATION NE
	|	MODAL NE
	|	# BUT NE
	|	NE BUT #
NEGATIVE	:: =	NE
	|	NEGATION PO
	|	MODAL PO
	|	# BUT PO
	|	PO BUT #
NE	:: =	N

PO	:: =	P

POSITIVE and NEGATIVE. These are the final sentiments used to determine the sentiment orientations on the targets in a sentence.

P and PO. These two nonterminals represent two types of *positive sentiment expressions*. P represents an atomic positive sentiment expression, which can be a sentiment word, phrase, or idiom in a sentiment lexicon. PO can be P or a compound positive sentiment expression to be defined in subsequent rules. The positive sentiment lexicon is defined as

P	:: =	amazing | beautiful | excellent | expensive feel | expressive look | good | make someone special | stand above the rest | stand out |…

N and NE. These are analogous to P and PO, respectively, but represent two types of *negative sentiment expressions*. Additional expressions for NE are defined in subsequent rules. The negative sentiment lexicon is defined as

N	:: =	bad | cheap feel | cheap look | cost an arm and a leg | pain | painful | poor | smell a rat | take a beating | terrible | ugly |…

NEGATION NE (or PO). This pattern represents the negation of a negative (or positive) sentiment expression. Negation is an involved topic. We dedicate Section 5.3 to it.

MODAL NE (or PO). This pattern represents the composition of a modal auxiliary verb and a negative (or positive) expression, for example, "*This car should have a better engine*." Modality and sentiment also form a complex topic, which is studied in Section 5.4.

 # BUT NE (or PO). This pattern is about sentiment related to coordinating conjunction *but*, which is also called a *contrary word*. The # symbol represents the sentence segment before *but*. That is, the POSITIVE sentiment of the rule POSITIVE ::- # BUT NE is only applicable to the sentence segment before *but*. However, the interaction between *but* and sentiment is more complicated than this, and we detail it in Sec- tion 5.5.

NE (or PO) BUT #. This pattern is similar to the preceding one, but here the implied sentiment is only applicable to the sentence segment after *but*.

The rest of the rules in this subsection, including those in the appendix, define PO and NE. Note that we use words of all uppercase letters to denote nonterminals and words of all lowercase letters to denote terminals.

2. *Decreasing or increasing the quantity of a sentiment item (PO or NE).* This set of rules says that decreasing or increasing the quantity of a sentiment item (often expressed as nouns and noun phrases) can change the sentiment orientation. For example, in the sentence "*This drug reduced my pain significantly*," *pain* is a negative sentiment word and the *reduction* of *pain* indicates a desirable or positive effect of the drug.

PO	:: =	DECREASE NE | INCREASE PO
NE	:: =	DECREASE PO | INCREASE NE

The actual words or phrases representing the concepts of DECREASE and INCREASE are highly diverse and numerous. We discuss them in Section 5.2.2.

Note that INCREASE PO and INCREASE NE do not change sentiment orientations, but they can increase the sentiment intensity. Also, expressions with a decreasing or increasing meaning in a sentence may appear before or after PO/NE, for example,

"*My pain has subsided after taking the drug*."

"*This drug has reduced my pain*."

"*This earphone can isolate noise*."

Sentences of this type usually use verbs to express the meaning of decreasing or increasing, but they can use words of other parts of speech too. The concept of *decreasing* also extends to verbs such as *disappeared* and *removed*, for example,

"*My pain disappeared after taking the drug*."

"*My pain has gone after taking the drug*."

"*After taking the drug, I am now pain free*."

"*After taking the drug, I am now free from pain completely*."

In these example sentences, we can see where the opinion targets or aspects are, that is, those nouns and noun phrases in the NE and PO expressions. These sentences all represent indirect opinions and the aspect in each sentence is indicated by *pain*.

3. *Decreasing or increasing the quantity of a positive potential item (PPI) or a negative potential item (NPI)*. For some items, increasing (or decreasing) their quantities is positive (or negative), for example,

"*Lenovo has cut their revenue forecast*."

"*Lenovo has increased the battery life of their laptops*."

"*This song has climbed the chart by several places*."

Here *revenue*, *battery life*, *chart places* are called *PPI* because increasing them is desirable. However, for some other items, increasing (or decreasing) their values/quantities is negative (or positive), for example,

"*Sony has increased the price of the camera*."

Here *price* is called a *NPI* because a large value for it is not desirable (to consumers). These example sentences are factual statements and have fact-implied opinions (see Section 2.4.2).

The following rules represent these concepts:

PO	:: =	DECREASE NPI | INCREASE PPI
NE	:: =	DECREASE PPI | INCREASE NPI
PPI	:: =	access | answer | budget | benefit | choice | class | color | connection | credit | diversity | developed | dividend | durability | economy | efficiency | feature | functionality | GDP | growth | help | insurance | opportunity | option | profit | quality | revenue | yield | reliability | security | selection | solution | spirit | strength | usefulness | standard |…
NPI	:: =	charge | cost | duplicate | effort | expense | fee | hesitation | jobless | maintenance | price | repair | spender | the need | tax | unemployment |…

Again, the concept of decreasing extends to disappearing, removing, for example,

"*My hope has gone*."

"*The fee has been waived*."

"*After the action, all duplicates disappeared*."

The difference between PO/NE and PPI/NPI is that PPI and NPI items do not possess sentiment themselves, whereas PO and NE items do. The example PPI and NPI expressions were extracted from many different domains. In a specific application, they need to be discovered from the domain corpus. For example, in the economy domain, *growth* and *budget* are PPIs, and in the mortgage domain, *interest rate* and *down payment* are NPIs for borrowers.

PPIs and NPIs can be discovered automatically or semi-automatically, or compiled manually. Wen and Wu (2011) published a bootstrapping *cum* classification algorithm for this purpose using Chinese text with some success.

4. *Less or more quantity of a sentiment item (PO or NE)*. Similar to rule sets (or categories) 2 and 3, less quantity of a positive (or negative) item is negative (or positive) and more quantity of a positive (or negative) item is positive (or negative). Some example sentences follow:

"*This production line produces fewer defects*."

"*This drug has reduced more pain than my previous drug*."

We have the following composition rules:

PO	:: =	LESS NE | MORE PO
NE	:: =	LESS PO | MORE NE

Note that MORE PO and MORE NE do not change sentiment orientations. We include them for completeness. We also want to highlight two other issues. First, for these rules, the sentiment words are usually nouns or noun phrases. Second, there may be an additional level of composition in an actual sentence. For example, the second example sentence involves another level of composition, that is, *more pain* is negative, but reducing negative becomes positive. Note that the aspect or the opinion target in this case is *pain* (not *more pain*).

Because there are many expressions that can describe the general concepts of LESS and MORE, we study them in detail in Section 5.2.3. This set of rules is closely related to comparative opinions, which we study in Chapter 8.

5. *Small or less and large or more quantity of a PPI or NPI*. This is similar to the case of rule set 4, as shown in the following example sentences:

"*The battery life is short*."

"*This phone gives me more battery life*."

"*The price of the car is high*."

"*I won't buy this phone due to the high cost*."

Battery life is a PPI, and *price* and *cost* are NPIs.

PO	:: =	SMALL_OR_LESS NPI | LARGE_OR_MORE PPI
NE	:: =	SMALL_OR_LESS PPI | LARGE_OR_MORE NPI

Because there are many expressions that can express the concepts of SMALL_OR_LESS and LARGE_OR_MORE, we study these expressions in Section 5.2.3. This set of rules is also related to comparative opinions, discussed in Chapter 8.

6. *Producing and consuming resource and waste*. If an entity produces a large quantity of resources, it is desirable or positive. If it consumes a large quantity of resources, it is undesirable or negative. For example, *electricity* is a resource, and the sentence "*This computer uses a lot of electricity*" gives a negative opinion about the power consumption of the computer. Likewise, if an entity produces a large quantity of waste, it is negative. If it consumes a large quantity of wastes, it is positive:

PO	:: =	PRODUCE LARGE_MORE RESOURCE
	|	PRODUCE SMALL_LESS WASTE
	|	CONSUME LARGE_MORE WASTE
	|	CONSUME SMALL_LESS RESOURCE
NE	:: =	PRODUCE SMALL_LESS RESOURCE
	|	PRODUCE LARGE_MORE WASTE

	|	CONSUME SMALL_LESS WASTE
	|	CONSUME LARGE_MORE RESOURCE
PRODUCE	:: =	generate | produce |…
CONSUME	:: =	consume | need | require | spend | use | take | …
RESOURCE	:: =	attention | effort | energy | gas | oil | money | power | resource | room | space | electricity | service | water | opportunity |…
WASTE	:: =	waste | dust | rubbish |…

Resources are also a kind of PPI and waste is a kind of NPI (rule 3). They thus can be governed by other rules concerning PPI and NPI, for example, "*This device reduces the gas consumption by 20%*."

In a particular domain, there may be other resources and wastes, which need to be discovered. For example, in the washer domain, detergent is a resource, and in the printer domain, ink is a resource. We discuss resource term discovery in Section 6.2.1.

7. *Desirable or undesirable fact*. As we have mentioned several times earlier, there are many objective or factual expressions that can imply positive or negative sentiment because they describe desirable and undesirable facts. Such sentences may use no sentiment words, for example, "*After sleeping on the mattress for two weeks, I saw a valley in the middle*" and "*After taking the drug, my blood pressure went up to* 410." The first sentence implies a negative opinion about the mattress, even though there is no sentiment word in the sentence, because a *valley in the middle* is not desirable. The second sentence is also negative because of the very high blood pressure. Thus we have the following composition rules:

PO	:: =	DESIRABLE_FACT
NE	:: =	UNDESIRABLE_FACT

Desirable and undesirable facts are very hard to deal with because they are different in different domains. For example, in the mattress domain, the following words often indicate undesirable facts: *mountain*, *hill*, *valley*, *hole*, and *body impression*. For an application, such words have to be either discovered automatically or compiled manually. Zhang and Liu (2011b) proposed an initial automated method to discover aspect nouns that also indicate sentiment.

8. *Performing desirable or undesirable action*. Similar to desirable and undesirable facts, if an entity performs a desirable action or function, it is positive, and if it performs an undesirable action, it is negative. Then we have

PO	:: =	DESIRABLE_ACTION
NE	:: =	UNDESIRABLE_ACTION

Desirable and undesirable actions are also hard to deal with as they too are domain dependent. In a domain, some verbs and verb phrases usually indicate desirable or undesirable actions. For example, the first of the following sentences is positive due to *hiring*, and the rest are negative due to *laying off*, *buy my votes*, and *skips frames*, respectively:

"*HP is hiring*."

"*Motorola is planning to lay off more people*."

"*She wants to buy my vote*."

"*This player skips frames*."

9. *Meeting expectation*. In many cases, people have expectations about an entity. If the entity meets or exceeds their expectations, it is positive; otherwise, it is negative.

PO	:: =	MEET EXPECTATION
MEET	:: =	above | beyond | exceed | live up to | meet | satisfy | surpass |…
EXPECTATION	:: =	expectation | my need | my requirement |…

The following are some example sentences:

“*It meets my need/requirement*”

“*It lives up to my expectations*.”

“*The performance of this product is above/beyond my expectation*.”

“*I find them work as advertised/expected*.”

“*It works exactly the way that I wanted*.”

“*It provides everything you need*.”

“*It gives what you look for*.”

“*Everything is going as planned*.”

10. *Part and overall sentiment*. Sentences that satisfy this set of rules are usually compound sentences with different sentiments in different parts of the sentence. The second part often serves to summarize the overall sentiment on an entity, but we should not ignore the sentiment in the first part, for example,

“*Despite the high price, I still like this phone very much*.”

“*Although there are some minuses with the seats, this is still my car of choice*.”

“*The price of this phone is high, but overall it is a great phone*.”

“*Although the car has great engine, I do not like it as it has so many other issues*.”

We single out this type of sentence and treat it as special because it often gives an overall sentiment to the entity being evaluated. This is useful because in some applications, the user is only interested in the entity-level analysis (e.g., in brand management) and not in sentiment about entity aspects:

NE	: =	PO* BUT_OVERALL_IS NE
PO	: =	NE* BUT_OVERALL_IS PO

“BUT_OVERALL_IS NE (PO)” means it is overall negative (NE) or positive (PO). To recognize “BUT_OVERALL_IS NE (PO),” the system needs to detect some special kinds of sentences such as the preceding. One strong clue is that the dominant clause usually mentions the entity type (e.g., *car*) or even the entity name. We should also note the following: first, although each such sentence focuses on the dominant sentiment, it does not mean that the sentiment expressed in the secondary clause should be ignored. We use * to indicate that. Second, it is not always true that the second part of the sentence signifies the dominant sentiment. In fact, the reverse order occurs, too, for example, “*This is my car of choice despite some minuses with the seats*.”

To improve reading and avoid unnecessary details, additional rules are given in the appendix. This does not mean that the additional rules are less important. In fact, they are all very important in building a sentiment analysis system. We should note that these conceptual rules can appear in many forms and expressed using different words and phrases. Moreover, they may also manifest differently in different domains. Most of them are hard to recognize and hence are not easy to apply. Furthermore, by no means do we claim that this set of rules is the complete set that governs opinion or sentiment. In fact, there are many others, and with further research, more rules will be discovered.

Like individual sentiment words, an occurrence of an opinion rule in a sentence does not always indicate opinion or sentiment. For example, the sentence “*I want a car with high reliability*” does not express a positive or negative opinion on any specific car as it expresses a desire of the author, although *high reliability* is positive and covered by our rules. Another class of sentences that contains sentiment expressions but expresses no evaluation or sentiment is the class that describes purposes, for example,

“*We used the system to solve the formatting problem*.”

“*This drug is for treating stomach pain*.”

“*This drug is for the treatment of stomach pain*.”

Yet another class comprises the how-to sentences, for example,

“*How to solve this problem is a difficult question*.”

“*How to win a game is hard to know*.”

My Opinion Parser system has mechanisms to detect such cases using rules specified in the specification language described in Section 5.7.

5.2.2 DECREASE and INCREASE Expressions

As we have discussed in rule sets 2 and 3, decreasing (DECREASE) and increasing (INCREASE) expressions (words and phrases) are crucial for sentiment analysis. This subsection studies them and lists some of the commonly used such English words and phrases. We study DECREASE expressions first, and then INCREASE expressions. The following is a list of commonly used DECREASE expressions that act as verbs:

> *alleviate, attenuate, block, cancel, cease, combat, come down, crackdown, crack down, cut, cut back, cut down, cut off, cut out, die off, die out, decrease, deduct, diminish, disappear, discontinue, discount, downgrade, drop, dwindle, eliminate, fade, fall, filter, get around, get off, get over, go away, go down, halt, have gone, improve, isolate, lack, lessen, limit, lock, lose, minimize, miss, mitigate, omit, pay off, pass off, plunge, prevent, quit, reduce, relieve, remove, resolve, shut out, shrink, slide, slip, smooth, soothe, stop, subside, suppress, take away, take off, to be down, undo, vanish, weed out, waive, wipe out, wither*, and so on.

These words can appear either before or after a PO/NE/PPI/NPI expression. They can be further grouped based on their usage characteristics.

DECREASE expressions that mainly decrease NPI and NE items (DECREASE-N). These DECREASE expressions are used almost exclusively with negative sentiment items. Commonly used DECREASE-N expressions (or words) include *alleviate*, *avoid*, *handle*, *lessen*, *mitigate*, *relieve*, *resolve, soothe, subside, waive*, and so on. The following are some example sentences:

"*The noise level has subsided*."

"*The school waived my tuition fees*."

"*This device can mitigate the impact of the crash*."

"*This drug relieved my shoulder pain*."

DECREASE expressions that mainly decrease PPI and PO items (DECREASE-P). These DECREASE expressions are used almost only with positive sentiment items. DECREASE-P expressions (or words) include *lack, lose, omit, miss*, and so on. The following are some example sentences:

"*This phone lacks magic*."

"*The company has missed a great opportunity*."

"*This phone omitted one important detail*."

"*I really miss the smoothing capability of the old version*."

"*He lost our trust*."

"*The company loses a good customer*."

DECREASE expressions that mainly appear after PO/NE/PPI/NPI items (DECREASE-after). These DECREASE expressions are mainly used in active sentences with PO/NE/PPI/NPI items appearing before such expressions. Examples of DECREASE-after expressions include *die off, die out, disappear, dwindle, fade, fall, go away, pass off, slide, slip, to be down, vanish, wither*, and so on. Some example sentences follow:

"*The unemployment rate has fallen*."

"*My neck pain has disappeared*."

"*The noise problem went away*."

"*All their profits have vanished*."

"*The economy is down*."

When these verbs and verb phrases are used in the gerund form to form a phrase, the PO/NE/PPI/NPI expression can occur after the DECREASE expressions, for example,

"*The company is experiencing a period of dwindling profits*."

DECREASE expressions that mainly appear before PO/NE/PPI/NPI items (DECREASE-before). These DECREASE expressions are mainly used in active sentences with PO/NE/PPI/NPI items appearing after such expressions. Examples of after-DECREASE expressions include *quit* and *stop*:

"*This machine quit working on the second day*."

Most DECREASE expressions can act on both PO/PPI and NE/NPI and can also appear before or after PO/NE/PPI/NPI items, which is mostly determined by active or passive voices of sentences.

Active and passive voice. If a sentence is in active voice, then the DECREASE verb normally occurs before the PO/NE/PPI/NPI expressions, for example,

"*The earphone can block surrounding noise*."

If a sentence is in passive voice, the situation is the opposite, for example,

"*The surrounding noise is blocked by the earphone effectively*."

Thus, knowing whether a sentence is active or passive is important because the system will know where to look for PO/NE/PPI/NPI expressions, which usually are also the opinion targets, for example,

"*Standard and Poor's downgraded Greece's credit rating*."

Because this is an active voice sentence, we know that the opinion target is after *downgrade*. The sentence does not express any opinion about *Standard and Poor's*, but only a negative opinion about *Greece's credit rating*. *Standard and Poor's* is actually the opinion holder.

Detecting active and passive voice requires accurate parsing. This can be challenging because of the poor grammar of social media posts, inaccuracy of parsers, and the fact that most verbs in English have the same past simple and past participle forms.

Noun DECREASE expressions. The DECREASE expressions (words of phrases) discussed so far are verbs and phrases acting as verbs, but DECREASE expressions can be nouns, too, usually noun forms of verbs, for example, *remove* (verb) and *removal* (noun), and *reduce* (verb) and *reduction* (noun). Here are two example sentences using noun DECREASE expressions:

"*This drug resulted in a decrease in my stomach pain*."

"*This promotion offers a big price reduction*."

In the first sentence, the NE word *pain* is after the DECREASE word *decrease*, whereas in the second, the NPI word *price* is before the DECREASE word *reduction*.

We now turn to INCREASE verbs. INCREASE verbs behave similarly to DECREASE verbs. Commonly used verbs and verb phrases in the category include the following:

build up, burst, climb, come back, elevate, enlarge, escalate, expand, extend, go up, grow, increase, intensify, mark up, pile up, progress, raise, return, rise, soar, surge, to be up, and so on.

Some example sentences are as follows:

"*The pain comes back*."

"*My pain has returned within two days*."

"*The profit of the company surged last month*."

"*The price of this car has been marked up by two thousand dollars*."

"*Google's stock price soared yesterday*."

The types of INCREASE expressions are also similar to the types of DECREASE expressions. Like DECREASE expressions, INCREASE expressions can be nouns too (e.g., *increase* and *upsurge*). However, there are fewer INCREASE expressions.

5.2.3 SMALL_OR_LESS and LARGE_OR_MORE Expressions

Adjectival expressions (words and phrases) about quantity, size, length, weight, and speed are important for determining or implying sentiment when they are combined with PO/NE/PPI/NPI items, resources, and wastes. They form the LESS, MORE, SMALL_OR_LESS, and LARGE_OR_MORE expressions used in rule sets 4 and 5 in Section 5.2.1. In this subsection, we list some of the commonly used such expressions.

Adjectival expressions of quantify. These are also called quantifiers, and they consist of *small* quantity quantifiers (denoted by SMALL-Qs), *neutral* quantifiers (denoted by NEUTRAL-Qs), and *large* quantity quantifiers (denoted by LARGE-Qs). We extend the meaning by also including expressions like *no*, *free of*, and *free from*, as they function similarly.

SMALL-Qs. These words and phrases include *few, only a few, little, only a little, a/one little bit, a small number of, a fraction of, free, free of, free from, no, nonexistent, not many, not much, rare, a small amount of, a small quantity of, a tiny amount of,* and *tight*. Small quantity also includes zero quantity. The following are some example sentences that use such expressions and express or imply positive or negative sentiment:

"*This bank is very tight on credit*."

"*This vacuum cleaner uses no bag*."

"*After taking the drug, I am now pain free*."

"*This washer uses a tiny amount of water*."

In some cases, fractions are also employed to express small quantities, for example,

"*The price is only one third of what it was two years ago*."

"*The price is only 40% of what it was two years ago*."

"*The price is only a small fraction of what it was two years ago*."

Such sentences can be recognized by some fixed patterns used to express fractions.

NEUTRAL-Qs. These words and phrases of quantity include expressions like *some, any, several, a fair amount of, a number of,* and *enough*. These expressions are not commonly used to compose sentiment expressions, except the word *enough*, for example,

"*They provide enough space for kids to play around*."

Here *space* is a resource as well as a PPI.

LARGE-Qs. These expressions include *an awful lot of, a bundle of, a great/good deal of, a great/good many of, a huge amount of, a large amount of, a large quantity of, a load of, loads of, a lot of, lots of, many, much, a plenty of, a ton of*, and *tons of*. Some example sentences with explicit or implicit/implied sentiment are

"*This machine uses a lot of electricity*."

"*This program needs a huge amount of disk space*."

In some cases, multiples are also employed to express a large quantity, for example,

"*The price now is 3 times that of two years ago*."

In comparative sentences, comparative quantifiers, denoted by MORE-Qs and LESS-Qs, are used in a similar way.

MORE-Qs. These words and phrases include *more, most, a larger number of, a lot more, plenty more, a larger amount of, a larger quantity of*, and so on.

LESS-Qs. These words and phrases include *fewer, least, fewest, less, a smaller number of, a smaller amount of, a smaller quantity of*, and so on.

Adjectival expressions of size. We use two concepts to represent size, LARGE and SMALL, which can be expressed with many words and phrases:

LARGE:
big, enormous, hefty, huge, large, massive, and so on.

SMALL:
meager, minimum, small, tiny, and so on.

For their comparative forms, LARGER and SMALLER, we have:

LARGER:
bigger, greater, larger, and so on.

SMALLER:
smaller, lesser, tinier, and so on.

Adjectival expressions of weight.

HEAVY:

heavy, *weighted*, *weighty*, and so on.

LIGHT:

light, *featherweight*, *lightweight*, *weightless*, and so on.

For their comparative forms, HEAVIER and LIGHTER, we have:

HEAVIER:

heavier.

LIGHTER:

lighter.

Adjectival expressions of length.

LONG:

long.

SHORT:

short.

For their comparative forms, LONGER and SHORTER, we have:

LONGER:

longer.

SHORTER:

shorter.

Adjectival expressions of degree.

HIGH:

high.

LOW:

low.

For the comparative forms, HIGHER and LOWER, we have:

HIGHER:

higher.

LOWER:

lower.

Adjectival expressions of speed.

FAST:

fast, immediate, quick, swift, and rapid.

SLOW:

crawling, like a snail, like a tortoise, lagging, slow, slow-moving, snaillike, tortoise-like, and so on.

For their comparative forms, FASTER and SLOWER, we have:

FASTER:

faster.

SLOWER:

slower.

Finally, the concepts of LESS, MORE, SMALL_OR_LESS, and LARGE_OR_MORE are defined as follows:

SMALL_OR_LESS	:: =	SMALL_SPEC | LESS
LARGE_OR_MORE	:: =	LARGE_SPEC | MORE

SMALL_SPEC	:: =	SMALL-Q | SMALL | LOW | LONG | LIGHT | SLOW
LARGE_SPEC	:: =	LARGE-Q | LARGE | LONG | HIGH | HEAVY | FAST
LESS	:: =	LESS-Q | SMALLER | LOWER | LONGER | LIGHTER | SLOWER
MORE	:: =	LARGER-Q | LARGER | LONGER | HIGHER | HEAVIER | FASTER

So far, we have only discussed words and phrases that function as adjectives modifying nouns. Their corresponding adverbials can be used as well, to modify verbs. In this case, verbs are PO/NE items or PPI/NPI items. The following examples illustrate their use:

"*This phone is highly priced*."

"*This phone costs a lot*."

"*This printer prints very fast*."

We will not discuss them further because the ideas are similar.

5.2.4 Emotion and Sentiment Intensity

As discussed in Section 2.3, there are many basic human emotions. Analyzing these is an important part of sentiment analysis. On the basis of my experience, emotions can be handled in the same way as normal sentiments, except that an additional lexicon is required for each emotion, and sentiment intensity also needs to be accounted for.

For example, for the emotions *anger*, *joy*, and *sad*, we have the following indicating words:

Anger:
absurd, awful, crap, crappy, disgraceful, disgusted, disgusting, furious, garbage, gruesome, hate, horrible, horrid, horrify, horrific, and so on.

Joy:
adorable, amazed, attractive, awesome, breathtaking, brilliance, brilliant, charm, delight, elegant, elegance, excited, exciting, and so on.

Sad:
bitter, despair, despondent, disconsolate, dismal, distress, doleful, downcast, dreary, gloomy, sad, unhappy, and so on.

Given these lexicons (there are also many phrases), any lexicon-based sentiment analysis system can mine emotions.

If we want to reflect different intensities of emotions and rational sentiments or opinions using multiple ratings, intensifiers and diminishers should be considered. The ideas in Sections 2.1.3, 2.3.2, and 3.2.2 are applicable. For example, the sentence “*This product is very bad*” is more negative than the sentence “*This product is bad*,” and the emotion in the sentence “*I am somewhat unhappy with their service*” is weaker than that in the sentence “*I am unhappy about their service*,” where *very* is an intensifier and *somewhat* is a diminisher. Because the topic has been covered in Sections 2.1.3, 2.3.2, and 3.2.2, we will not discuss it further, except to stress that when a rational sentiment expression is modified by an intensifier, the rational sentiment can be turned to an emotional sentiment (see Section 2.3.2).

Distinguishing rational and emotional sentiments, however, is subjective. There is still no standard methodology for their separation. In a practical system, the system designer is free to design his own scheme. In Opinion Parser, I used sentiment and emotion words and phrases to decide five rating scales in sentiment classification, that is, emotional positive, rational positive, neutral, rational negative, and emotional negative. My experience is that the five ratings are sufficient for most practical applications. Of course, one can design finer-grained ratings.

5.2.5 Senses of Sentiment Words

Sentiment words and phrases are instrumental for sentiment analysis. However, few such sentiment words, if any, actually express sentiment in all possible contexts. A word can have multiple meanings or senses, in some of which it may not have any sentiment. For example, *great* is a positive sentiment word, but *great* as in *great grandfather* does not express any sentiment. Because word sense disambiguation is still a very difficult problem in NLP, we cannot depend on it to solve our problem. In fact, we may have to ignore word sense disambiguation entirely and use some other clues to determine whether a sentiment word actually expresses sentiment in a particular context. Although the POS of a word can tell whether a sentiment word expresses sentiment in some cases, in other cases, the same POS may imply sentiment in some senses and not in others. In the rest of this section, we use some common sentiment words to further illustrate the point and describe how they may be suitably used in a sentiment analysis system.

> ***Pretty* and *terribly*.** When *pretty* is used as an adjective, verb, or noun, it has a positive orientation, except when it appears in some special phrases or idioms, for example, *cost a pretty penny*, which means something costs a lot of money (i.e., it has the same meaning as *cost an arm and a leg* and *cost the earth*). However, when it is used as an adverb modifying an adjective, it does not indicate a positive or negative sentiment but only qualifies the sentiment of the adjective, for example, *pretty good*, *pretty bad*, *pretty sure*. In this case, it has the meaning of *to a fairly or moderately high degree*. Specifically, when it is followed by an adjective or adverb, its own default sentiment should be ignored. However, owing to POS tag errors, we cannot completely depend on POS tags produced by a tagger. The system may need to see the POS tag of the word after it and whether the word after it expresses sentiment. The adverb *terribly* functions in a similar way, although it is not as frequently used as *pretty*. In *terribly bad* and *terribly good*, it has the sense or meaning of *very* or *extremely*. However, when it is not modifying an adjective, it is a strong negative sentiment word with the meaning of *very badly*, for example, "*This car is terribly built*."

> ***Easily*, *clearly*, and *well*.** These three words usually have a positive orientation, but in some senses they may not indicate sentiment. However, it is difficult to determine in which sense each of the words is used in an actual sentence. We often have to use some other clues to make the decision. *Easily* and *clearly* are often positive when they are used with verbs that have no sentiment. However, when they are used with sentiment verbs, they no longer exhibit sentiment themselves but instead only intensify the context sentiment. Furthermore, when they modify a *be*

verb in an active voice, they also do not exhibit sentiment. The following sentences give some examples:

"*This software can be installed easily*."

"*This machine gets damaged easily*."

"*He explains everything clearly*."

"*This is clearly a bad phone*."

Many other words in English have similar usage, such as *fast* and *quickly*. Sometimes the positions where such words appear in a sentence can give a good indication of whether they express sentiment. For example, when *clearly* appears as the first word in a sentence, it just means *obviously*, and the sentiment of the sentence should usually be found from the rest of the sentence. The word *well* as an adverb functions similarly:

"*Clearly, this is a problem for the car*."

"*Clearly, this is not my car*."

"*Well, I do not think this is a good car*."

Incredible. *Incredible* is a hard case. It is mostly positive in informal text meaning *astonishing* and *amazing*, but in a negative context it means *unbelievable* and can even be negative, for example,

"*This car is incredible*."

"*It is incredible that this guy murdered so many people*."

"*It is incredible that Apple sold so many iPhones*."

Incredible in the first sentence expresses a positive opinion by default, but in the second and the third sentences, it means *beyond belief*. The second sentence is negative and the third sentence is positive. Thus *incredible* can be handled in a sentiment analysis as follows: when the sentence has other sentiment-bearing words or phrases, *incredible* only reinforces the sentiment, and its default positive sentiment should be ignored. However, in some cases, it can be hard to detect the meaning of *incredible* because its context may appear in a previous sentence, for example,

"*He murdered ten people*. *This is an incredible case*."

Smell. *Smell* can be either a verb or a noun. It is an interesting word in English as far as sentiment is concerned:

“*This car smells*.”

“*This perfume smells good*.”

“*This room smells bad*.”

“*This room has a smell*.”

“*This room has a foul smell*.”

“*This room has a nice smell*.”

When there is no associated positive or negative sentiment word, *smell* is often negative regardless of whether it acts as a verb or a noun. But when there is, *smell* does not have a sentiment. That is, the sentiment of the sentence or clause depends on the sentiment of the adjective before or after *smell*. There is also an idiom involving *smell*, *smell a rat*, which should overwrite the sentiment of *smell*.

5.2.6 Survey of Other Approaches

Early work on sentiment or opinion rules is mainly about sentiment word and negation word combinations (Hu and Liu, 2004; Kim and Hovy, 2004). This later led to the general concept of *sentiment reversal* resulting from the compositions of sentiment shifters and positive or negative sentiment words, for example, "*not*" & POS("*good*") => NEG("*not good*") and "*fail to*" & POS("*impress*") => NEG("*fail to impress*"). An extension to sentiment reversal is the one similar to rule set 3 in Section 5.2.1, for example, "*reduced*" & NEG("*pain*") => POS("*reduced pain*"). Moilanen and Pulman (2007) also introduced *sentiment conflict*, which is used when multiple-sentiment words occur together, for example, "*terribly good*." Conflict resolution is achieved by ranking the constituents on the basis of relative weights assigned to them dictating which constituent is more important with respect to sentiment. In Neviarouskaya et al. (2010), six types of composition rules were introduced: *sentiment reversal*, *aggregation*, *propagation*, *domination*, *neutralization*, and *intensification*. *Aggregation* is similar to *sentiment conflict* but is defined differently. If the sentiments of words in adjective-noun, noun-noun, adverb-adjective, adverb-verb phrases have opposite orientations or polarities, mixed polarity with the dominant polarity of the pre-modifier is assigned to the phrase, for example, POS('*beautiful*') & NEG('*fight*') = > POSneg('*beautiful fight*'). The rule of *propagation* is applied when a verb of *propagation* or *transfer* type is used in a phrase/clause and the sentiment of an argument that has prior neutral polarity needs to be determined, for example, PROP-POS("*to admire*") & "*his behavior*" = > POS("*his behavior*"); "*Mr. X*" & TRANS("*supports*") & NEG("*crime business*") = > NEG("*Mr. X*"). We can see this covers the opinion target. The rules of *domination* are as follows: (1) if polarities of a verb and an object in a clause have opposite directions, the polarity of verb prevails (e.g., NEG("*to deceive*") & POS("*hopes*") = > NEG("*to deceive hopes*")); (2) if a compound sentence joins clauses using the coordinate connector "*but*," the attitude features of the clause following the connector are dominant (e.g., 'NEG("*It was hard to climb a mountain all night long*"), *but* POS("*a magnificent view rewarded the traveler in the morning*").' = > POS(whole sentence)). The rule of *neutralization* is applied when a preposition-modifier or condition operator relates to a sentiment statement, for example, "*despite*" & NEG('*worries*') = > NEUT("*despite worries*"). The rule of *intensification* strengthens or weakens a sentiment score (intensity), for example, Positive_score("*happy*") < Positive_score("*extremely happy*")). Additional related works can be found in the literature (Nasukawa and Yi, 2003; Polanyi and Zaenen, 2004; Choi and Cardie, 2008; Ganapathibhotla and Liu, 2008; Neviarouskaya et al., 2009; Nakagawa et al., 2010; Min and Park, 2011; Socher et al., 2011; Yessenalina and Cardie, 2011).

As we can see, many of the sentiment composition rules discussed in Section 5.2.1 and the appendix have not been expressed with compositions in the literature, for example, those about resource usage and about desirable and undesirable facts. Existing rules are also too restrictive for practical use because we need to deal with the potential problem of there being other words in between the component words in a rule. For example, in "*The drug reduced a lot of my shoulder pain*," the words *reduced* and *pain* in the rule, "*reduced*" & NEG("*pain*") = > POS("*reduced pain*"), are not next to each other in the sentence. The rule is thus not easy to apply. We need to know what expression is allowed in between and whether the application scope of *reduced* actually covers *pain*. In fact, we need a more sophisticated and yet flexible representation language to code the rules, which we discuss in Section 5.7. By flexible, I mean that the representation language should not depend too much on correct grammar or correct parse trees because much of the opinion text from social media is informal, containing numerous grammatical and other types of errors.

5.3 Negation and Sentiment

Sentiment shifters (or valence shifters, as they are called in Polanyi and Zaenen, 2004) often change sentiments in the opposite directions. Negation words like *no*, *not*, *never*, *none*, *nobody*, *nowhere*, *neither*-*nor*, *nothing*, and *cannot* are the most common type of sentiment shifters. However, as we have seen in Section 5.2, sentiment change can be achieved in many ways. In Section 5.4, we will also see that modality can have a major impact on sentiment too.

In this section, we will not use rules as in Section 5.2.1 to represent the applications of negations, as they can be largely described using the dependency grammar. The dependency parse tree of a sentence can also help us determine the application scope of each negation word or phrase in the sentence, which we will discuss in Section 5.3.5. However, knowing the application scope of each negation word or phrase does not mean that we can easily determine whether the negated expression implies a positive or negative sentiment. This is beyond the traditional study of negation or modality in the literature. We will see this point shortly.

5.3.1 Negation Words

A negation word can affect the sentiment expressed in a sentence in many ways. The following three ways are very common:

1. It directly negates a positive or negative sentiment expression, for example,

"*This car is not good*."

"*This Sony camera is not as bad as people think it is*."

"*Nobody likes this car*."

"*No race could John win*."

"*John cannot win any race*."

"*Nothing works on this computer.*"

"*The fridge is small enough not to take up a lot of space*."

In these sentences, the negation words simply reverse the sentiments indicated by the sentiment words or phrases in the sentences. Note that "*take up a lot of space*" is a negative sentiment expression by the resource usage rule set 6 in Section 5.2.

However, this sentiment reversal should not be treated as a general rule. In many cases, simply reversing the sentiment orientation is problematic. For example, "*I am not angry*" does not mean "*I am happy*," and "*This is not the best car*" does not mean "*This is a bad car*." We discussed this issue in Section 3.2.2, where one method was described to deal with the problem. However, there is still no standard way to solve the problem.

2. It indicates that some expected or desirable functions or actions cannot be performed. Such sentences often do not use any sentiment words.

"*When I click the start button, the program does not launch*."

"*My car does not start in a few occasions*."

"*The fridge door cannot be opened.*"

"*Nowhere can I find out how to use the display function*."

"*You can do nothing on iPad*."

Sentiments in these sentences can be quite hard to recognize because it is very difficult to know what the expected or desirable functions or actions are for a particular entity or aspect in a domain. The negation words here do not function as sentiment shifters, as they do in case 1, because there is no sentiment from a sentiment word to shift in any of the preceding sentences.

Hard to, difficult to, have difficulty in: These phrases function similarly to negation words in this context, but with a weaker strength or intensity.

3. It negates a desirable or undesirable state expressed without using a sentiment word:

"*The water that comes out the fridge is not cold*."

"*No bag is used on this vacuum cleaner anymore*."

Sentiments in such sentences are also hard to determine because it is difficult to decide what the desirable or undesirable state is or what is expected in a particular domain without an explicit sentiment word or phrase present in the sentence. For example, in the second sentence, without the knowledge that older vacuum cleaners hold dust in bags, one needs to change them frequently, and changing bags is very troublesome, it is hard to know whether the sentence is positive or negative.

In what follows, we discuss a few other issues about negation expressions.

Negation in comparative sentences. Negating a comparative or superlative opinion word can be tricky in some cases, for example,

"*This car is not better than my previous car*."

"*This car is not the best car in the market*."

The first sentence may not have a negative opinion on *this car* because the two cars could be equally good. The situation in the second sentence is similar. However, on the basis of my experience, treating both of them as negative for *this car* is acceptable in practice, although in some cases, their meanings can be affected by the context, for example,

"*This car is not the best car in the market, but it is quite good*."

When an equative comparison is negated, the orientation usually reverses, for example, "*This car is not as good as my previous car*." For definitions of different types of comparisons, please refer to Chapter 8.

In some cases, negating a comparative does not change sentiment orientation, for example,

"*It does not get better/worse than this*."

"*Nothing I have seen could rival the pyramids*."

"*Nothing is better than an iPhone*."

These sentences are usually easy to deal with because *than* (or *rival*, which signifies a comparison here) splits a sentence into two segments with one side positive and the other negative. Note that the first sentence does not mention the target entity, which should have been mentioned in a previous sentence.

Double negation. Sentences involving double negation are often difficult to deal with, for example,

"*This is not the reason for not providing a good service*."

"*It is not that I do not like it*."

"*There is nothing that it cannot do*."

***Not* followed by a noun phrase.** In this case, *not* usually does not change or introduce sentiment on the entity or aspect represented by the noun phrase unless the noun phrase is a sentiment word or phrase, for example,

"*I hate Audi not Mini*."

"*It is not a Sony, but a Samsung*."

"*Evo runs Android not the Windows mobile software*."

"*She is not a beauty*."

"*She is not a nice person*."

Not in the first three sentences does not change or introduce any sentiment as there is no sentiment to be changed in the application scope of *not*. *Not* in the last two sentences does change their sentiment orientations because the noun phrases express desirable states. There are also some rather complex cases, for example,

"*Evo runs Android and not the creaky Windows mobile software*."

"*Well, Touchpad is not an iPad*."

For the first sentence, it is easy to know that the opinion (or sentiment) target of *creaky* is the *Windows mobile software*. But the hard part is to realize that *not* does not change the orientation of *creaky*, which is a negative sentiment word. The second sentence is even harder to deal with because it depends on the general impression of people about *iPad*. In this case, the opinion on

Touchpad is negative because the impression among consumers is that *iPad* is a very good product.

Negation words in imperative sentences. Because imperative sentences give commands or make requests, they usually do not express sentiment. Thus, negation words in them also do not change sentiment:

“*No bigotry please*.”

“*Do not bring a calculator*.”

But such sentences can express sentiment in some cases, for example,

“*Do not waste time on this movie*.”

The author of this sentence is negative about the movie.

Negation words in idioms or phrases. Negation words in idioms and phrases should be treated as integral parts of the idioms or phrases rather than independent negation words. Here is a list of some commonly used idioms and phrases containing negation words:

believe it or not, by no means, can stand no more, cannot wait to, do not apply, do not get me started, do not get me wrong, do not mind, do not push too hard, for no reason, have nothing to do with, if not better, if not impossible, if not the best/worst, last but not (the) least, look no further, never ending story, no avail, no bearing, no big deal, no brainer, no change, no comparison, no difference, no doubt, no end, no exception, no exaggeration, no fun, no idea, no issue, no matter, no question, no question asked, no stranger, no time, no way, no soul, no luck, not looking back, no problem, no rush, no stake, no substitute, no such thing as, no use, no wonder, not alone, not a big deal, not a deal breaker, not a fan of, not huge on something, not just, not least of, not only, not possible without, not the least, not the only, not to mention, not until, nothing to do, second to none, why not, and so on.

As we can see, sentences involving negation words may or may not express any explicit or implied sentiment. But it should be safe to say that if a sentence does not use a sentiment word or an expression of a desirable or undesirable state or action, it usually does not have a clear sentiment. The problem is that it is often hard to identify whether there is an expression stating a desirable or undesirable state or action and what is expected in a domain.

5.3.2 Never

The negation word *never* is special. Although it is mainly used as a negation word to express a strong positive or negative opinion, it can also function in other ways. The following examples show its base use as a strong negation word:

"*This vacuum never loses suction*."

"*I will never buy another product from eBay*."

"*This printer never worked properly*."

"*I never liked any Apple products*."

"*I have never heard a good thing about this car*."

However, *never* can function in diverse ways, many of which do not change sentiment orientations at all. It thus needs special treatments. In the following, we study several cases.

1. Express a positive opinion on a single entity by dismissing all others.

"*I will never buy anything else*."

"*I will never buy any other brand of vacuum*."

"*I will never switch back to another brand*."

The target of the opinion is not given in any of the sentences, but it usually can be inferred easily from the previous sentences. Of course, one may explicitly mention the opinion target sometimes using *except*, *besides*, and *but*, for example,

"*I have never liked any other smart phone except iPhone*."

"*Once you buy this phone you will never want another phone*."

Expressions like *anything else*, *any other*, and *another* are the key here as they do not include the entity in question itself. Any change to them could result in a completely different meaning, for example,

"*I would never spend such an exorbitant amount of money on any phone*."

2. Express an opinion that something has never been *so good*/*bad* (or *this/that good* or *bad*) or *better*/*worse* (using comparatives). In such a sentence, the use of a sentiment word or some desirable or desirable state expression is important, for example,

"*My carpets were never this clean*."

“*I have never had such a clean house*.”

“*I have never owned a car that is so fun to drive*.”

“*I never knew how bad this phone was until I bought a Nokia phone*.”

“*This car has never been better*.”

The first two sentences are from reviews of a vacuum cleaner. They actually express indirect opinions or benefits because the opinion targets in the sentences are the vacuum cleaner, which is not even mentioned. Thus, discourse-level analysis is needed. The words *so*, *this*, and *such* are crucial in the first three sentences, which often express some surprising or unexpected results. Without them, the meaning and the sentiment orientation of these sentences can be completely different, or at least ambiguous. The fourth sentence expresses a contrast (see also Section 5.5). The sentiment on *this phone* is negative but on the *Nokia phone* is positive. The last sentence uses a comparative (*better*) to express the current superior state of the car.

3. Express something desirable or undesirable that has never been experienced before.

“*I never had a vacuum blowing out a clean smell before*.”

Again, in such a sentence, the use of a sentiment word or some expression of a desirable or desirable state is important.

To deal with these special uses of *never*, the first step is to recognize them in the sentences. These cases should not be difficult to recognize using patterns. Once they are recognized, we can just ignore the negation sense of *never*.

5.3.3 Some Other Common Sentiment Shifters

***Hardly, barely, rarely, seldom*.** These are *presuppositional* words. They can also change a sentiment orientation. We can compare "*It works*" with "*It hardly works*." *Works* indicates a positive sentiment, but *hardly works* does not: it presupposes that better was expected.

***Little, few, rare*.** These words change the sentiment orientation in a similar way:

"*The Fed has little room left to revive growth*."

"*Few people like this product*."

"*The problem is rare.*"

We have encountered these words in Section 5.2.3. We discuss them again here for completeness in the context of negation. Note that *a little* and *a few* do not have this meaning, and when *little* or *few* is used with other senses/meanings, they may not express sentiment either, for example,

"*This little machine is great*."

"*I went to Chicago in the past few days*."

"*We had that little house in the South*."

***Fail to, refuse to, omit, neglect*.** These words and phrases often change sentiment orientations too. They function similarly to presuppositional words:

"*This camera fails to impress me*."

"*The fridge door refuses to open*."

"*This camera never failed to impress me*."

The last sentence can be regarded as a double negation case.

***Far from, nowhere* (*even*) *near/close*.** These phrases function just like negation words and indicate sentiment change, for example,

"*This car is nowhere near perfect*."

"*This car is far from perfect*."

5.3.4 Shifted or Transferred Negations

In English, when one expresses negation with verbs like *think*, *believe*, and so on, one prefers to negate the first verb instead of the second. That is, we shift or transfer the negation from the second verb to the first. Take, for example, the following sentences:

"*I do not think this is a good car*."

"*I do not believe that this car is worth the price*."

Interestingly, when modality is used, the opinion may not be reversed in some cases, for example,

"*I did not believe that this car could work so well*."

In fact, modal auxiliary verbs such as *would*, *should*, *could*, *might*, *need*, *must*, and *ought to* are another type of sentiment shifter. We study them in Section 5.4. Sarcasm often changes sentiment orientations, too, for example, "*What a great car, it failed to start the first day*." Although it may not be hard to recognize such shifters manually, spotting them in actual sentences and handling them correctly automatically is very challenging (see Section 4.5).

5.3.5 Scope of Negations

We have discussed many cases where, when there is a negation word and a sentiment word or phrase in a sentence, the sentiment should not be reversed. Besides these cases, there is yet another reason. That is, the sentiment word may not be in the application scope of the negation word. For example, in the following sentence, the negation word *not* does not change the orientation of the sentiment word *horrible* because *horrible* is beyond the scope of *not*:

"*I did not drive my car on that horrible road*."

In the following sentence, *not* applies to *like* but not to *ugly*:

"*I do not like this car because it is ugly*."

In most cases, simple syntactic rules can determine the application scope of a negation word quite well. For example, several rules are proposed in Jia et al. (2009) using a dependency parse tree. It defines the scope to be the word span between the negation expression (word or phrase) and another word or punctuation after it. The key is to determine the end of the span. The main rule basically says that the ending should not cross the independent clause where the negation expression resides or its next subordinate clause. This rule is further refined with four additional rules to restrict the scope or to reduce the span further.

Sentiment verb rule. Whenever a negation expression in a sentence negates a sentiment verb, the word immediately after the verb is the end of the scope.

Sentiment adjective rule. Whenever a sentiment adjective forms a "cop" or "xcomp" typed dependency with the closest preceding copula or verb that is negated by a negation expression, the expression immediately after this adjective is the end of the scope. Here "cop" means copula and "xcomp" means open clausal complement (de Marneffe and Manning, 2008).

Sentiment noun rule. Whenever a sentiment noun acts as the object of a verb negated by a negation expression, the expression immediately after this noun is the end of the scope.

Double object rule. Whenever a negation expression negates a verb taking double objects, only the direct object should be in the scope, and the indirect object should be excluded.

Jia et al. (2009) also described several exceptions, which are cases where negative words should not be treated as such, for example, *not only* and *not just*. We discussed these in the preceding subsections. Note that here the scope does not include shifted negations, which should be handled separately, as discussed previously. In Ikeda et al. (2008) and Li et al. (2010), supervised classification was used to determine whether a negation expression should change the sentiment in a sentence. The scope of negation was also studied in the general NLP context by researchers. For example, in

Rosenberg and Bergler (2012) and Rosenberg et al. (2012), some heuristic rules were proposed also based on syntactic dependency trees.

Although many cases of negation have been covered in this section, there are definitely many more. Even the covered cases in this section are not easy to deal with because a large number of sentences are objective sentences, which require some understanding of the application domain to analyze them correctly. In that sense, I have actually presented many problems but provide few solutions. Much further research is needed.

5.4 Modality and Sentiment

Modal verbs or expressions in sentences can have a significant impact on the sentiment expressed in those sentences. This is quite natural because modality expresses notions such as possibility, probability, necessity and obligation, permission, ability, and intention, which are subjective in nature and closely related to sentiment and feeling. There are three types of modality in English: deontic, epidemic, and dynamic (Aarts, 2011).

> **Deontic modality.** Deontic modality is concerned with getting people to do things or (not) allowing them to do things, that is, with such notations as *obligation* and *permission*, for example,
>
> "*Sony must improve the reliability of their laptops*."
>
> "*This company should reduce the price of their products*."
>
> "*You may return the phone to us*."

Epidemic modality. Epidemic modality expresses some kind of inferencing or judgment about the truth of a proposition, for example,

"*Sony may produce good cameras*."

"*Sony might have solved its picture quality problem*."

Dynamic modality. It is often concerned with *ability* and *volition*, for example,

"*The camera can take great pictures*."

"*I cannot tell whether this is a good car*."

In English, there are nine core modal verbs:

can, could, may, might, will, would, shall, should, must.

Can, *may*, *will*, *shall*, and *must* are in present tense, and *could*, *might*, *would*, and *should* are the past tense forms of *can*, *may*, *will*, and *shall*, respectively. However, *could*, *might*, *would*, and *should* also have specialized meanings in which they do not function as the past tense forms of *can*, *may*, *will*, and *shall*. All of them can be combined with negation to form interesting combinations, which have important impact on sentiment analysis. There are also some *marginal modal verbs*,

dare, need, ought (*to*),

and modal idioms,

have (*got*) *to*, *had better*/*best*, *would rather*, and so on.

So far, little research has been done about how modals influence sentiment, except Liu et al. (2013), which proposes a supervised learning method to perform sentiment classification of sentences with modals. However, owing to the use of supervised learning, it does not help us understand modality's impact on sentiment. Although there are extensive studies of modality in linguistics, they are not for sentiment analysis purposes. Here our focus is only on the use of modals in sentiment or opinion sentences and how they affect sentiment orientations.

On the basis of these definitions, we can see that sentences of epidemic modality using *may* or *might* usually do not express clear sentiment because of the uncertainty involved in such sentences. Deontic modality and dynamic modality are closely related to sentiment. Before we go into details, we make three observations:

- Most modal sentences expressing negative opinions do not use negation words.
- Most modal sentences expressing positive opinions use negation words.
- As a result, in sentences with negative sentiment, modal verbs typically serve as sentiment shifters, and such sentences often involve comparatives (e.g., *-er* words) or words and phrases with comparative meanings.

***Can* and *could*.** In many cases, the ability to do something, that is, dynamic modality, is positive:

"*I can count on Apple*."

"*This device can deal with the connection problem*."

"*This phone can do speed dialing but my previous phone cannot*."

Could and *can* often combine with a comparative (JJR or RBR) to express negative sentiment, but such sentences are not comparative sentences:

"*The touch screen could be better*."

"*I can find a better GPS for this amount of money*."

"*The voice quality could be improved*."

Although *improved* is not a comparative word, it does express a more desirable state. When a negation word is combined with a comparative, the sentence can be either positive or negative, depending on the comparative in the sentence:

"*I cannot be happier with this product*."

“*It cannot be worse than this*.”

“*I cannot praise this product more highly*.”

There are also many other common ways that *cannot* and *could not* are used to express sentiment. In many cases, *cannot* may be replaced with *could not*:

“*Their service agent cannot be bothered to serve me*.”

“*I cannot wait to see this movie*.”

“*This phone cannot compare with my old phone*.”

“*I cannot live without this phone*.”

“*This is a deal that I cannot resist/refuse*.”

“*You cannot beat the price*.”

“*I cannot stand this movie*.”

“*I can stand no more*.”

“*You cannot find anything else for this price/money*.”

“*I cannot find anything in X to compare with Y*.”

Clearly *cannot* and *could not* can also be treated simply as normal negations, as in “*This car cannot do a fast reverse*.” However, in some cases, the negation may not affect sentiment, for example, “*I cannot say whether this camera is good or not*,” because the scope of *cannot* does not go beyond *say* in this sentence.

Will* and *would. *Will* does not seem to have clear patterns that indicate sentiment. However, like *could*, *would* can be used together with positive sentiment words to imply negative sentiment. It can also be combined with a comparative (JJR or RBR) to express a negative sentiment:

“*I would have loved this product*.”

“*It would have been a good car*.”

“*I would like something better than this*.”

“*I would like something prettier*.”

The following examples show some other special uses of *would* to indicate sentiment:

“*I would not buy any other car than this*.”

"*I would not buy this car*."

"*I would not like anything else*."

"*Without Google, I would be failing every exam*."

"*I did not believe that this phone would work so/this well*."

The last sentence, which gives a positive opinion about *the phone*, also shows that the verb tense of the sentence can have a big impact on sentiment. If the sentence is changed to "*I do not believe that the phone will work well*," it becomes negative.

***Shall* and *should*.** Like *will/would*, *shall* does not seem to have clear patterns that indicate sentiment, whereas *should* functions similarly to *could*. *Should* often combines with a comparative (JJR or RBR) to express a negative sentiment. Such sentences are not comparative sentences:

"*This car should be less expensive*."

"*Apple should know better*."

"*Apple should have done better*."

"*iPhone should have a bigger screen*."

"*Sony should improve their products*."

"*Sony should reduce the price of their products*."

Unlike *could*, when negation is used with *should*, it often still expresses negative sentiment:

"*They should not make the screen so big*."

"*They should not have done this terrible thing*."

"*Nobody should buy this product*."

The modal *ought to* functions similarly to *should*.

***Need* and *must*.** The use of *need* for sentiment is similar to *should* when there is no negation word involved. In some cases, *must* can be used in place of *need* with the addition of a verb. For simplicity, we do not distinguish *need*'s use as a modal from its other uses here:

"*This phone needs a good/better screen*."

"*This phone needs work or improvement*."

"*Sony needs to improve their products*."

"*This car needs more gas*."

“*Sony must have a better screen in order to compete in this market*.”

“*Sony must improve their products*.”

“*What they need is a big screen*.”

When negation or a similar word is used, *need* often expresses positive sentiment:

“*Sony needn’t further improve its TV*.”

“*iPhone allows you to make a call without the need of using your figures*.”

“*Touch screens eliminate the need for a mouse*.”

Have to, had better,* and *better. These modal idioms can express or change opinions like *must*, for example,

“*Sony had better improve its products*.”

“*Sony has to reduce the price of its TV in order to sell*.”

“*All you have to do is to press the button and everything will be done*.”

Interestingly, their negations are often used to express positive opinion, for example,

“*With this feature, you no longer have to use your fingers*.”

“*You do not have to use many programs to perform this task anymore*.”

Sometimes such a modal may not indicate any opinion itself, although the other part of the sentence may express opinions, for example,

“*I have to admit/say/confess/agree that this is a great car*.”

Have to can also combine with other modal verbs to express opinions, for example,

“*It is a faulty phone and I should not have to pay to send it back to the dealer*.”

Want, wish, hope,* and *like. These English verbs can express modality but are not modal verbs because they are not auxiliaries. For example, the following sentences all express negative opinions about the screen. They involve some words of comparison:

“*I wish the iPhone had a bigger screen*.”

“*I hope they can improve their screen*.”

“*I want a bigger screen from the iPhone*.”

5.5 Coordinating Conjunction *But*

Conjunctions are words that are used to link other words or larger expressions. There are two types of conjunctions: *coordinating conjunctions* and *subordinating conjunctions*. Coordinating conjunctions are *and*, *or*, *but*, and related words. Subordinating conjunctions are *after*, *because*, *when*, *where*, *that*, *which*, and so on, and are used to introduce subordinate clauses in sentences. Coordinating conjunction *but* is of particular interest to sentiment analysis because its use is very frequent in opinion documents and it usually connects contrasting constituents with opposite opinions. Thus the ability to effectively deal with complex sentences involving *but* can make a major difference for the sentiment analysis accuracy.

In general, *but* has two distinct senses.

> ***But* as a preposition.** In this sense, *but* is used as an alternative to *except* (*for*), *apart from*, and *bar* to introduce the only thing or person that the main part of the sentence does not include:
>
> "*I like all Honda models but the CRV.*"
>
> "*I would not want anything but the iPhone*."
>
> This use of *but* is often after words such as *everyone*, *nobody*, *anything*, *anywhere*, *all*, *no*, *none*, *any*, and *every*. It raises the question of how we should deal with words that represent a set of hidden entities. For example, in the first sentence, the author is positive about every car model of *Honda* except the *CRV* (negative). If the system knows all of the *Honda* car models, each of them can be given a positive opinion. However, in most applications, the system does not know the complete set of entities. Hence, to simplify the analysis in practice, only the explicit entity and opinion are normally used. That is, the first sentence is negative about the *CRV* and the second sentence is positive about the *iPhone*.

> ***But* as a conjunction.** This is the most common use of *but*. It links two contrastive clauses:
>
> "*The picture quality of this camera is great, but the battery life is short*."
>
> "*The voice quality of iPhone is not great, but it sure looks pretty*."
>
> We can see from these examples that the opinions before and after *but* are opposite to each other. This characteristic can be exploited for several purposes. First, if we can determine the sentiment orientation of one side, we can infer the orientation of the other side. For example, in the first sentence, it is easy to discover that the clause before *but* is positive because of the sentiment word *great*. Then, we can infer the negative sentiment for the clause after *but*. Second,

> we can use it to help determine the sentiment orientation of some context-dependent opinion word. For example, from the positive sentiment before *but*, we can infer that *short* is negative for *battery life*.

But here also has the sense of negation. It collates frequently with negative expressions. In such sentences, the contrastive meanings before and after *but* are often quite obvious:

"*The seat is slightly uncomfortable but not too bad*."

"*Fuel economy is very good but not what is stated*."

"*They are not cheap but definitely worth it*."

"*I hate Audi but not Honda*."

"*I'm not a HP fan but that new HP Envy is no joke a full music laptop*."

From these sentences, we can see something quite tricky. For example, the clause after *but* in the first sentence only weakens the negative sentiment about the seat but does not really change it. The second sentence is similar. To get this level of fine detail is challenging. One simple and reasonable strategy is to still give opposite opinions before and after *but* for the same aspect.

There are even more complex cases, which make the rule of thumb (opinions on both sides of *but* are opposite to each other) difficult to apply in practice because contrast does not always mean opposite. Here are some example sentences, which highlight the issue:

"*The phone worked well at first, but after a short while the sound deteriorated quickly*."

"*He promised us work but gave us none*."

"*The phone functions well so far, but we will have to wait and see if it will last*."

"*The engine is very powerful but it is still quiet*."

"*I knew this phone's battery life is not long but not this bad*."

"*This is a great phone, but the iPhone is better*."

"*I thought I needed an SUV, but the Prius has been great*."

The first three sentences involve a sequence of events. To identify the sentiment expressed in them, it is important to know the expressions of time (i.e., *at first* and *so far*), which indicate the sequence of sentiments. The first two sentences are negative, but for the third sentence, the clause after *but* expresses no opinion. The fourth sentence has two positive opinions, one before *but* and one after *but*.

The fifth sentence is similar but with negative opinion on both sides of *but*. The sixth sentence is also similar but expresses a comparative opinion. The last sentence expresses no opinion in the first part.

But can also be used as an adverb, but this is quite rare. The expression *but for* may be used as a preposition and has the meaning of a negated if-clause, for example, "*But for their help, I would not have a phone to use*." *But* is also becoming more commonly used to link two contrastive sentences. In this case, *but* is normally the first word of the second sentence with a similar meaning to *however*: in terms of sentiment analysis, the sentiment orientations in the two sentences are typically different.

Finally, there are many other words and phrases that can have similar meanings or senses as *but*, for example, *although, aside from, despite, except, except for, except that, however, instead of, oddly, on the other hand, other than, otherwise, rather than, until, whereas, with exception of*, and so on. We should be aware that *but* in many idioms and phrases may or may not indicate explicit contrast, for example, *no (other) choice but, no other way but, not only&but also, cannot help but, last but not least,* and *nothing but*. In such cases, one can just ignore *but*.

5.6 Sentiment Words in Non-opinion Contexts

In this section, we highlight several situations where sentiment words indicate no sentiment.

Entity names containing sentiment words. Many businesses choose their names to project a positive image. This causes a problem for sentiment analysis, especially in informal text such as social media, where people may not use capitalization to indicate entity names. For example, an insurance company is called *Progressive*, an electronic store is called *Best Buy*, a Hollywood movie is called *Pretty Woman*, and a salon is called *Elegant Beauty Salon & Spa*. The name of a particular type of business may also contain sentiment words. For example, *beauty salon*, *beauty parlor*, or *beauty shop* are names of a kind of business. The word *beauty* can cause problems for sentiment classification because it is usually regarded as a positive sentiment word, as in "*This car is a beauty*."

Function names containing sentiment words. One should also be mindful of the names of some functions. For example, in video players, there is a button called *fast forward* or *fast rewind*. If *fast*'s default sentiment polarity is positive, a sentence containing *fast forward* may result in a sentiment classification error. Another example is *beauty treatment*, which is the name of a class of procedures that enhance someone's personal beauty. If *beauty* is used as a positive sentiment word by default, it can cause errors. Some functions of software may also include sentiment words, for example, "*I am feeling lucky*" in Google search.

A preprocessing step should be applied to identify such entity and function names. Entity names are slightly easier to identify, but function names are hard to recognize because people never use capitalization to indicate them. Grammar-based methods need to be applied. For example, if a sentiment noun like *beauty* is followed by another noun, it usually does not express any sentiment. However, there are exceptions. For example, when one reads the sentence "*she is a beauty queen*," one would automatically have a positive opinion about her appearance.

Greetings and good wishes. In any language, there are numerous expressions for greetings and good wishes. Such expressions almost always contain sentiment words. For example, English has good morning, good day, happy birthday, happy anniversary, warm regards, best regards, best wishes, good luck, have a great weekend, hope you get well soon, and so on.

These expressions do not express any positive or negative opinion and should thus be ignored in sentiment analysis. One can compile a good set of such expressions fairly easily and mask them in the preprocessing stage. To automatically discover them is also an option because many of them appear at the end of a message.

Authors' self-description. In many cases, authors describe themselves and the descriptions can contain sentiment words. In these sentences, it is natural to mention some entity names and/or their aspects. However, the opinions in the sentences are not about the entities or their aspects but about the authors themselves. Such sentences are hard to recognize. Compare the following two sentences:

"*I know Lenovo laptops very well*."

"*Lenovo knows the needs of their customers very well*."

In the first sentence, the sentiment word *well* describes the author himself. Thus it has nothing to do with Lenovo laptops. However, in the second sentence, the opinion is positive about Lenovo. In product reviews, sentences describing authors themselves and also using sentiment words in the sentences are rare, but in forum discussions, such sentences are common because authors in forums could be experts or experienced users of the discussed products or services and they come to answer questions and provide advice. These sentences are not easy to deal with because when first-person pronouns (*I* and *we*) are used, the sentences often express personal experiences and opinions about the entities involved and not about the authors themselves.

"*I have used several Lenovo laptops and am very happy about their reliability*."

To deal with these sentences, parsing can help identify opinion targets. We discuss the topic in Section 6.2.

Apart from the preceding, there are a large number of other contexts in which sentiment expressions express no opinion. The following are some examples.

- Uncertainty, e.g., "*I am not sure whether the iPhone is the best phone for me or not*."
- Action intention, e.g., "*I am looking for a good iPhone case*."
- General fact, e.g.,"*No insurance means that you have to pay high cost*."
- Commercial advertisement, e.g., "*Buy this great camera and win a trip to Hawaii*."
- Past impression, e.g., "*I thought this car was not good, but after driving it for a few weeks, I simply love it*."

Because little study has been done about these types of sentences or expressions, it is hard to know the percentage of such expressions or sentences that express no sentiment. Furthermore, although we humans can understand these cases fairly easily, spotting them automatically by an algorithm is challenging.

5.7 Rule Representation

We are now ready to discuss how to represent complex sentiment-bearing expressions and rules in a sentiment analysis system. The representation should ideally cover all intrinsic details needed for effective recognition of such expressions and rules and for applying them to arrive at the right sentiment on the right target aspects and/or entities.

Although some research has been done on rule representation, as described in Section 5.2.6, current proposals from the research community are too simplistic for practical use. Systems in industry use much more sophisticated representations. For example, the rule representation or specification language in my Opinion Parser system, which uses a lexicon-based approach, employs regular expressions to represent rules. Each symbol in regular expressions is also attached with a set of constraints and actions.

We now describe a rule specification language based on the language used in Opinion Parser. The language follows a *default-and-exception* scheme. The reason for using this scheme is that, as discussed in Section 5.2.5, almost no sentiment word has a fixed sentiment orientation in all senses and/or contexts. Each word's sentiment orientation is thus represented with a default orientation (the most frequently used orientation or polarity) and a set of exceptions. That is, the default sentiment orientation can be overwritten by exceptions with different orientations or no sentiment at all. The exception rules basically represent different special contexts and their corresponding sentiment orientations. This default-and-exception scheme also applies to sentiment composition rules.

We do not discuss regular expressions further as they are standard. Here we discuss only how each symbol is represented. A symbol, denoted by SYMBOL, can be either a word, denoted by WORD_spec, or a gap in between two important words, denoted by GAP_spec. A gap cannot be the first or the last symbol of a rule in the regular expression. The grammar for SYMBOL is as follows:

SYMBOL	:: =	WORD_spec | GAP_spec
WORD_spec	:: =	"(" word WORD POS VOICE LOC_range TARGET_loc ACTION ")"
WORD	:: =	WORD_set | ("(" not WORD_set ")") | + | − | ASPECT | ENTITY | nil

POS	:: =	POS_set | ("(" not POS_set ")") | nil
VOICE	:: =	active | passive | nil
LOC_range	:: =	"(" (start | end) START END ")" | nil
TARGET_loc	:: =	self | left | right | nil
ACTION	:: =	+ | − | nil
GAP_spec	:: =	"(" gap RANGE POS ")"
RANGE	:: =	("(" MIN MAX ")") | CHUNK | nil
CHUNK	:: =	np | vp | pp | clause | nil

WORD_SPEC represents the specification of a word, and it has seven (7) components.

word: indicator of a word specification.

WORD: a set of possible or alterative words (WORD_list), or not any word of the set indicated by (not WORD_set).

+ and −: positive and negative sentiment respectively.

ASPECT or ENTITY: the word being an aspect or an entity.

nil: nothing to specify.

POS: a set of alternative POS tags (POS_list) for the word, or not any POS tag of the set indicated by (not POS_set).

VOICE: either active or passive voice.

LOC_range: location of the word in the sentence, which should be in the range between the number START and the number END, counting from the first word (indicated by *start*) or the last word (indicated by *end*) of the sentence.

TARGET_loc: indicating where the opinion target should be. *self* means this word, *left* means to the *left* of this word, and *right* means to the *right* of this word.

ACTION: sentiment to be attached to this word. +, −, and *nil* represent negative, positive and neutral (or no) sentiment respectively.

GAP_spec: represents a gap specification. It consists of three (3) components.

gap: a fixed word indicating a gap specification.

RANGE: the range of the gap. MIN means the minimum gap size (e.g., 0, no gap) and MAX means the maximum gap size (e.g., 5, five words gap).

CHUNK: a noun phrase (np), a verb phrase (vb), a prepositional phrase (pp), or a clause (clause).

For example, we want to express the rule that *throwing something away* is negative. We can use the following regular expression rule to represent it:

((word (“throw”) nil active nil right −)

(gap np nil)

(word (“away”) nil nil nil left nil))

The sentence “*I want to throw the iPhone away*” matches this rule. After it is matched, the negative sentiment sign − is attached to *throw* as the rule’s action. The opinion target is between *throw* and *away*. The gap should be a noun phrase; that is, there should be a noun phrase between *throw* and *away*.

Although the language is fairly expressive, there are complex sentiment compositions or contexts that cannot be specified in this languge. For example, it does not allow intersentence discourse-level specifications as required by this segment of two sentences: “*I’m not tryna be funny, but I’m scared for this country. Romney is winning*.” Furthermore, because Opinion Parser uses only shallow parsing, it does not allow specification of rules based on parse trees. The reason is that current syntactic parsers are too slow for practical use unless one has a large number of machines. Additionally, many social media posts, such as tweets and discussions, are full of grammatical errors and other language irregularities, which make parsing highly error-prone. We also note that this specification language does not cover the specification for emotions, but that can be easily added. Sentiment and emotion intensities can be incorporated too.

5.8 Word Sense Disambiguation and Coreference Resolution

So far, we have not studied any core NLP problems and their effects on aspect sentiment classification. Because sentiment analysis works with the natural language text, it naturally encounters all issues and difficulties of NLP. This section highlights the NLP issues in the sentiment analysis context using two popular NLP tasks, *word sense disambiguation* and *coreference resolution*, and presents some existing work on them.

As discussed earlier, whether a word indicates sentiment and what orientation it expresses in a particular sentence context is, to a great extent, determined by the sense of the word in that context. Also, in determining opinion targets, coreference resolution plays a major role because, in many cases, the opinion targets are mentioned, not in the sentences where sentiments are expressed, but in their previous sentences. These targets thus need to be discovered through coreference resolution. Unfortunately, none of the two tasks has received much research attention in the sentiment analysis community.

Akkaya et al. (2009) first studied *subjectivity word sense disambiguation* (SWSD). Their task was to automatically determine which word instances in a corpus are being used with subjective senses and which are being used with objective senses. Currently, most subjectivity or sentiment lexicons are compiled as lists of words without their specific senses (meanings). However, many words have both subjective and objective senses. False hits – subjectivity clues used with objective senses – are a significant source of error in subjectivity and sentiment analysis. The authors of the article built a supervised SWSD model to disambiguate members of a subjectivity lexicon as having a subjective sense or an objective sense in a corpus context. The algorithm relies on common machine learning features for word sense disambiguation (WSD). However, the performance was substantially better than the performance of full WSD on the same data, suggesting that the SWSD task is feasible and that subjectivity provides a natural coarse-grained grouping of senses. They also showed that SWSD can subsequently help subjectivity and sentiment analysis.

Coreference resolution has been studied extensively in the NLP community in general. It refers to the problem of determining multiple expressions in a sentence or document referring to the same thing, that is, they have the same "referent." For example, in "*I bought an iPhone two days ago. It looks very nice. I made many calls in the past two days. They were great*," *it* in the second sentence refers to *iPhone*, which is an entity, and *they* in the fourth sentence refers to *calls*, which is an aspect. Recognizing these coreference relationships is clearly very important for aspect-based sentiment analysis. If we do not resolve them, but only consider the opinion in each sentence in isolation, we lose in recall. Although we know that the second and fourth sentences in this piece of text express opinions, we do not know about what and we thus get no useful opinion, but in fact, the text expresses a positive opinion about the iPhone itself and also a positive opinion about its call quality.

Ding and Liu (2010) proposed a supervised learning approach to the problem of *entity and aspect coreference resolution*, that is, to determine which mentions of entities and/or aspects the pronouns refer to. The interesting point of this paper was the design and testing of two opinion-related features that used sentiment analysis for the purpose of coreference resolution. The two features are semantic features that current general coreference resolution methods do not consider, and they can help improve the coreference resolution accuracy.

The first feature is based on sentiment analysis of regular sentences and comparative sentences and the idea of *sentiment consistency*. Consider these sentences: "*The Nokia phone is better than this Motorola phone. It is cheap too*." Our common sense tells us that *it* means *Nokia phone* because, in the first sentence, the sentiment about *Nokia phone* is positive (comparative positive), but the sentiment is negative (comparative negative) for *Motorola phone*, and the second sentence is positive. Thus we conclude that *it* refers to *Nokia phone* because people usually express sentiments in a consistent way. It is unlikely that *it* refers to *Motorola phone*. However, if we change "*It is cheap too*" to "*It is also expensive*," then *it* probably now refers to *Motorola phone*. To obtain this feature, the system needs to have the ability to determine positive and negative opinions expressed in both regular and comparative sentences.

The second feature considers what entities and aspects are modified by what sentiment words. Consider these sentences: "*I bought a Nokia phone yesterday. The sound quality is good. It is cheap too*." The question is whether *it* refers to *sound quality* or the *Nokia phone*. We know that *it* refers to *Nokia phone* because *sound quality* cannot be cheap. To obtain this feature, the system needs to identify what sentiment words are usually associated with which entities or aspects. Such relationships have to be mined from the corpus.

Stoyanov and Cardie (2006) proposed the problem of *source coreference resolution*, which is the task of determining which mentions of opinion holders (sources) refer to the same entity. The authors used existing coreference resolution features in Ng and Cardie (2002). However, instead of simply employing supervised learning, they used partially supervised clustering.

5.9 Summary

Aspect-level sentiment analysis provides the level of detail required by most practical applications. Although a great deal of work has been done in the research community and many systems have also been built in industry, the problem is still far from solved. Every subproblem remains highly challenging. As one CEO put it, "*our sentiment analysis system is as bad as everyone else's*," which is a nice portrayal of the current situation and the difficulty of the problem.

Two key problems are aspect extraction and aspect sentiment classification. This chapter focused on aspect sentiment classification. In particular, we presented a large number of linguistic patterns that imply opinion and sentiment, which we call rules of sentiment composition or rules of opinions. They can be used in both the supervised learning approach and the lexicon-based approach to aspect sentiment classification. In addition, we also studied negation handling and the influence of modality on sentiment. The classification accuracy of most existing systems, however, is still not high enough for many application domains because existing algorithms are still unable to deal with complex sentences that require more than sentiment words and simple parsing, or to handle factual sentences that imply opinions. Although we have seen a large number of rules, they are still insufficient. First, many rules are hard to recognize in an actual sentence and thus are not easy to apply. Second, there are still many other rules that are not easily described. Third, identifying targets of opinions is also very challenging, which results in opinions being given to wrong entities and/or aspects.

On the whole, we seem to have witnessed a long-tail situation. While sentiment words can handle about 60% of the cases (more in some domains and less in others), the rest are highly diverse, numerous, and infrequent, which makes it hard for statistical machine learning algorithms to learn patterns because there are simply not enough training data. There seems to be an unlimited number of ways that people use to express positive and negative opinions. Every domain appears to have something special. In Wu et al. (2011), a more complex graph-based representation of opinions was proposed, which requires even more sophisticated solution methods.

So far, the research community has mainly focused on opinions about electronic products, hotels, and restaurants. These domains are easier (although not easy) to analyze, and reasonable accuracy can be achieved if one can focus on each domain and take care of its special cases. When one moves to other domains, for example, mattresses or paint, the situations get considerably harder, because in these domains, many factual statements imply opinions. One may need to compile a different lexicon for each domain. Political and social domains are another can of worms. Political sentiments are particularly hard to determine because of the complex mixture of factual reporting and subjective opinions, sarcasm, and the need for background knowledge.

In terms of the type of social media, researchers working on aspect-based sentiment analysis have focused mainly on reviews and tweets from Twitter. These forms of data are also easier (again, not easy) to handle because reviews are opinion rich and have little irrelevant information, whereas tweets are very short and often straight to the point. Other forms of opinion text, such as forum discussions and commentaries, are much harder to deal with because sentiments are mixed with all kinds of non-opinion content, and texts often talk about multiple entities and even involve user interactions. This leads us to another major issue that we have not discussed so far as there is limited research on it: data noise. Almost all forms of social media are very noisy (except reviews) and full of all kinds of spelling, grammatical, and punctuation errors. Most NLP tools, such as POS taggers and parsers, need clean data to perform accurately. Thus a significant amount of preprocessing is needed before any analysis. See Dey and Haque (2008) for some preprocessing tasks and methods.

To make significant progress, I believe that we still need novel ideas to study opinion text in a wide range of domains. Successful algorithms are likely to require a good integration of machine learning and domain linguistic knowledge.

6

Aspect and Entity Extraction

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This is the second chapter about aspect-based sentiment analysis. In Section 2.1, we defined each opinion as a quintuple (e, a, s, h, t), where e is an entity and a is one of its aspects, s is the sentiment on the aspect a, h is the opinion holder and t is the time when the opinion is expressed. Chapter 5 focused on aspect-based sentiment classification, which determines s. This chapter focuses on extraction of entities and aspects on which sentiments or opinions have been expressed.

Entity and aspect extractions are often regarded as two separate tasks because the methods and features used for their recognition are usually different due to their individual specific characteristics. Entities commonly refer to names of products, services, individuals, events, and organizations, and aspects commonly refer to the attributes and components of entities. The two tasks are also collectively called *opinion target extraction* in sentiment analysis because they together form the targets of opinions. After their extraction, a resolution step is also performed to group synonymous entities and aspects together to facilitate opinion summarization. Let us use two example sentences to ground the tasks:

"*I brought a Motorola X phone yesterday, and its voice quality is great*."

"*The sound from this Moto X phone is great*."

The entities in the two sentences are *Motorola X* and *Moto X*, and the aspects are *voice quality* and *sound*. The entity and aspect extraction tasks aim to find these entities and aspects. The resolution step should group *Motorola X* and *Moto X* together as they refer to the same entity, and *voice quality* and *sound* together as they refer to the same aspect. This chapter will not discuss how to determine sentiments on entities or aspects as it has been studied in Chapter 5.

In general, both aspect extraction and entity extraction are information extraction tasks. However, in the context of sentiment analysis, some specific characteristics of the problem can facilitate their extractions. A key characteristic is that an opinion always has a target. The target is an aspect or an entity. We can exploit some syntactic structures often used to depict opinion and target relationships to help extraction. In this chapter, we first focus on extracting explicit aspects, which are nouns or noun phrases (see Section 2.1.6), and we then discuss implicit aspects in Section 6.4. There are four main approaches to extracting explicit aspects:

1. Extraction by finding frequent nouns and noun phrases.

2. Extraction by exploiting syntactic relations. There are two main types of relations:

i. Syntactic dependencies depicting opinion and target relations.

ii. Lexico-syntactic patterns encoding entity and part/attribute relations.

3. Extraction using supervised learning.

4. Extraction using topic models.

The chapter is divided into two main parts, *aspect extraction* and *entity extraction*. Although the preceding approaches can be used for both tasks, focused work on entity extraction in the context of sentiment analysis is limited because it has been researched extensively in other communities. In the second part of the chapter, we review those existing work from other communities about entity extraction. Along with these two main tasks, this chapter also discusses the existing research of opinion holder and time extraction.

Throughout the chapter, I use product reviews to develop the ideas and to illustrate the concepts because entities and aspects are clearly identifiable, and entities and aspects are often easily separable. In some other domains the boundary between entities and aspects is fuzzy. For example, in the political domain, individual candidates are clearly entities and we can mine public opinions about them and their aspects such as their experiences, personal attributes, and families. For political issues, however, it is often hard to distinguish entities and aspects unless there is a clear hierarchical relationship between issues. For example, we may regard *tax increase* as an entity and *tax increase for the rich* and *tax increase for the poor* as two aspects of the entity. When such hierarchical relationships are not clear or it is unnecessary to distinguish entities and aspects, we can simply treat all issues as entities or aspects.

6.1 Frequency-Based Aspect Extraction

Frequency-based aspect extraction finds *explicit aspect expressions* that are nouns and noun phrases from a large number of reviews in a given domain. The approach first identifies nouns and noun phrases using a POS tagger and then counts their occurrence frequencies using a data mining algorithm, keeping only the frequent nouns and noun phrases using an experimentally determined frequency threshold. Hu and Liu (2004) used association rule mining for this purpose. This approach works because aspects are usually expressed as nouns and noun phrases and when people comment on different aspects of an entity, the vocabulary that they use usually converges. Thus, frequently occurring nouns and noun phrases are usually genuine and important aspects. Irrelevant contents in reviews tend to be quite different in different reviews. Hence, those infrequent nouns are likely to be nonaspects or less important aspects. This approach is also applicable to entity extraction because in English, an entity name is often written with the first letter of each word in uppercase. Frequent such phrases are usually important named entities in the domain.

The assumptions made by this approach are that the corpus has a reasonable number of reviews and that the reviews are about the same product or at least about the same type of products, for example, phones. The method will not work if the corpus has a mixture of very different products and/or if each product has only one or two reviews, because in those cases, few nouns or noun phrases will be frequent.

Although this method is very simple, it is quite effective. Some commercial companies are using this method with some enhancements, such as combining it with the method in Section 6.2, which was also used in Hu and Liu (2004). Those candidate aspects with the highest frequency counts are almost always the most important aspects of the product.

The precision of this algorithm can be improved by removing noun phrases that may not be aspects of entities. Popescu and Etzioni (2005) evaluated each discovered noun phrase by computing a PMI score between the phrase and some *meronymy discriminators* associated with the entity class. For example, the meronymy discriminators for the camera class are, "*of camera*," "*camera has*," "*camera comes with*," and so on, which were used to find camera components by web search. The idea is that those discovered phrases (candidate aspects) that often co-occur with these *part-of* relation indicators are likely to be correct aspects. The PMI measure is a simplified version of Equation (3.5) in Section 3.2:

$$PMI(a, d) = \frac{hits(a \wedge d)}{hits(a)hits(d)}, \tag{6.1}$$

where *a* is a candidate aspect identified using the frequency approach and *d* is a discriminator. Web search can be used to find the number of hits of individual terms (or expressions) and also their co-occurrences. If the PMI value of a candidate aspect is too low, it may not be a component of the product because *a* and *d* do not co-occur frequently. The algorithm also distinguishes components/parts from attributes using WordNet's *is-a* hierarchy (which enumerates different kinds of properties) and morphological cues (e.g., "-*iness*," "-*ity*" suffixes).

A refinement of the frequent noun and noun phrase approach is to consider mainly those noun phrases that are in sentiment-bearing sentences or in some syntactic patterns that indicate sentiments (Blair-Goldensohn et al., 2008). In their work, Blair-Goldensohn et al. also applied several filters to remove unlikely aspects, such as dropping aspects that do not have sufficient mentions alongside known sentiment words. They also collapsed aspects at the word stem level and ranked the discovered aspects by a manually tuned weighted sum of their frequency in sentiment-bearing sentences and the type of sentiment phrases/patterns, with appearances in phrases carrying a greater weight. Using sentiment sentences is related to the approach in Section 6.2.

Other frequency-based approaches include that in Ku et al. (2006), which made use of a TFIDF scheme and considered terms (or expressions) at both the document level and the paragraph level. Moghaddam and Ester (2010) augmented the frequency-based approach with an additional pattern-based filter to remove some nonaspect expressions; they additionally predicted aspect ratings. Scaffidi et al. (2007) proposed a method that compares the frequency of the extracted frequent nouns and noun phrases in a review corpus with their occurrence rates in a generic English corpus to identify true aspects.

Zhu et al. (2009) proposed a method based on the Cvalue measure from Frantzi et al. (2000) for extracting multiword aspects. The Cvalue method is also based on frequency, but it considers the frequency of multiword expression *t*, the length of *t*, and also other expressions that contain *t*. After Cvalue finds a set of candidates, the set is refined using a bootstrapping technique with a set of given seed aspects. The idea of refinement is based on each candidate's co-occurrence with the seeds.

Long et al. (2010) extracted aspects (nouns) based on frequency and information distance. Their method first finds the core aspect words using the frequency-based method. It then uses the information distance in Cilibrasi and Vitanyi (2007) to find other related words to an aspect. For example, for aspect *price*, it may find "*$*" and "*dollars*."

6.2 Exploiting Syntactic Relations

Because opinions have targets, it is no surprise that there are many syntactic relations between sentiment expressions and their sentiment or opinion targets, which can be identified by a syntactic parser. For example, in the sentence "*This camera takes great photos*," the opinion or sentiment expression is *great*, and the opinion target is *photos*. Here the targets can be either entities or aspects of entities. Such relationships can be exploited to extract aspects and entities because sentiment words and phrases are often known and most of them are domain independent. In fact, if some sentiment words are unknown, these relations can be used to extract sentiment expressions too (see Section 7.2). In addition to these relations, the general conjunctions can be exploited as well. The most useful one is *and* because the conjoined expressions are usually of the same type. For example, in the sentence "*Picture quality and battery life are great*," if we know that *battery life* (or *picture quality*) is an aspect, we can infer that *picture quality* (or *battery life*) is an aspect too.

There is yet another type of relation that we can exploit. Because aspects are components and attributes of entities and there are also linguistic constructions that are commonly used to express such semantic relationships, we can use these linguistic constructions for aspect and entity extraction. For example, in the sentence "*The voice quality of the iPhone is not as good as I expected*," if we know that *voice quality* is an aspect, we can extract *iPhone* as an entity, and if we know that *iPhone* is an entity, we can extract *voice quality* as an aspect. In English, a common way to express such relationships is through the use of genitives. Apart from genitives, some other patterns also exist.

This section studies some of these relations and the existing extraction techniques that exploit them. In Section 6.2.1, we study some techniques that make use of the opinion and target relations and conjunctions for aspect extraction. In Section 6.2.2, we study part-of and attribute-of relations and their application to aspect extraction.

6.2.1 Using Opinion and Target Relations

The frequency-based aspect extraction method described in Section 6.1 (Hu and Liu, 2004) also has a technique to extract infrequent aspects based on opinion and target relations. The technique is based on the idea that sentiment words often describe or modify aspects in a sentence. If a sentence does not have a frequent aspect but does have some sentiment words, the nearest noun or noun phrase to a sentiment word is extracted as an aspect. Because no parser was used in Hu and Liu (2004), the "nearest" function approximates the dependency relation between the sentiment word and the noun or noun phrase that the sentiment word modifies, which usually works well. For example, in the following sentence,

"*The software is amazing*."

if we know that *amazing* is a sentiment word, then *software* is extracted as an aspect. This idea turns out to be very useful in practice even when it is applied alone. The sentiment pattern method in Blair-Goldensohn et al. (2008) uses a similar idea.

To make this method more principled, a dependency parser can be used to identify the dependency relations of sentiment (or opinion) words and opinion targets to extract *aspect-sentiment* pairs (Zhuang et al., 2006). After being parsed by a dependency parser (e.g., using MINIPAR; Lin, 2007), words in a sentence are linked by dependency relations. Figure 6.1 shows the dependency graph of the sentence, "*This movie is not a masterpiece*." If *movie* and *masterpiece* are labeled as aspect and sentiment word respectively, a dependency relation can be found as the sequence *"NN – nsubj – VBZ – dobj – NN,"* where NN and VBZ are POS tags, and *nsubj* and *dobj* are dependency relation tags. The algorithm first identifies reliable dependency relation templates from the training data and then uses them to identify valid aspect-sentiment pairs in the test data. Somasundaran and Wiebe (2009) and Kobayashi et al. (2006) employed a similar approach. The dependency idea was further generalized into the double propagation (DP) method for simultaneous extraction of both sentiment words and opinion targets (including both entities and aspects) in Qiu et al. (2009, 2011). We discuss the DP method next.

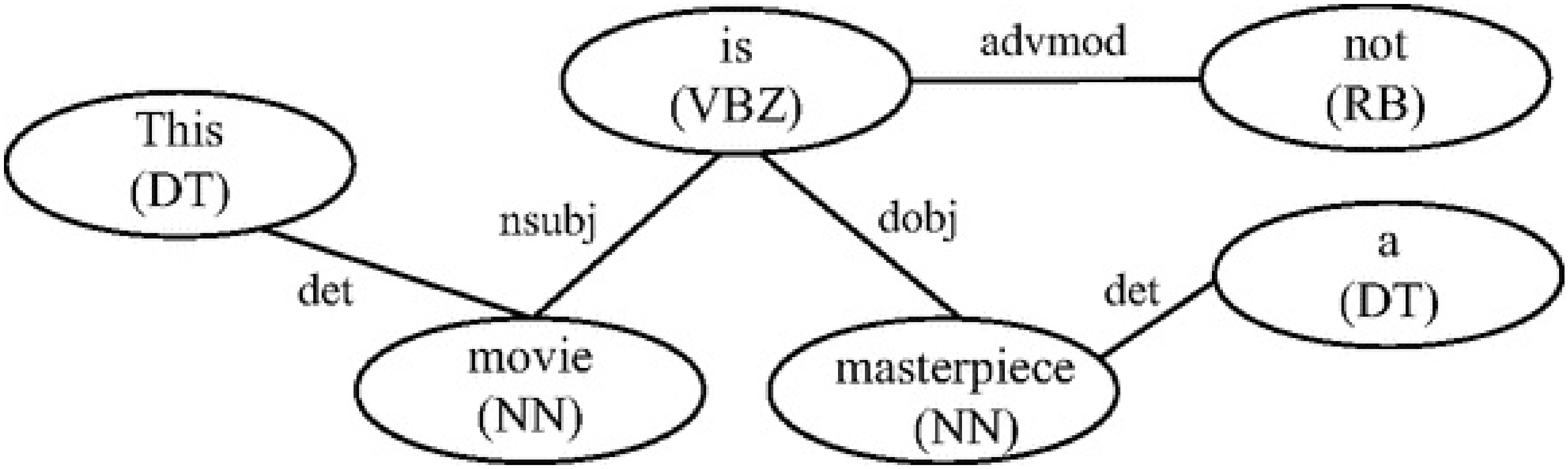


Figure 6.1. A dependency graph.

Double propagation (DP). DP is a bootstrapping method for extracting both sentiment words and aspects at the same time by exploiting certain dependency relations between sentiments and targets (Qiu et al., 2009, 2011). It needs only a small set of seed sentiment words (which are adjectives) as input; no seed aspects are required.

Dependency relations between sentiments/opinions and their targets (or aspects) allow sentiment words to be recognized by identified aspects, and aspects to be identified by known sentiment words. The extracted sentiment words and aspects are used to identify new sentiment words and new aspects, which are used again to extract more sentiment words and aspects. This propagation process ends when no more sentiment words or aspects can be found. As the process involves propagation through both sentiment words and aspects, the method is thus called *DP*. Extraction rules are based on some special dependency relations.

The method also imposes some constraints on the rules. Sentiment words are assumed to be adjectives and aspects nouns or noun phrases. The dependency relations between sentiment words and aspects include *mod*, *pnmod*, *subj*, *s*, *obj*, *obj2*, and *desc*, while the relations for sentiment words and aspects themselves include only the conjunction relation *conj*. OA-Rel denotes the relations between sentiment words and aspects, OO-Rel between sentiment (or opinion) words themselves, and AA-Rel between aspects. Each relation in OA-Rel, OO-Rel, or AA-Rel is a triple $\langle \mathrm{POS}(w_i), R, \mathrm{POS}(w_j) \rangle$, where $\mathrm{POS}(w_i)$ is the POS tag of word w_i and R is one of the preceding dependency relations.

The extraction process uses a rule-based approach. For example, in "*Canon G3 produces great pictures*," the adjective *great* is parsed as depending on the noun *pictures* through *mod*, formulated as an OA-Rel ⟨*JJ*, *mod*, *NNS*⟩. If we know that *great* is a sentiment word and are given the rule that a noun on which a sentiment word directly depends through *mod* is taken as an aspect, we can extract *pictures* as an aspect. Similarly, if we know that *picture* is an aspect, we can extract *great* as an opinion word using a similar rule. The propagation performs four subtasks:

1. extracting aspects using sentiment words

2. extracting aspects using extracted aspects

3. extracting sentiment words using extracted aspects

4. extracting sentiment words using both given and extracted sentiment words

OA-Rels are used for tasks 1 and 3, AA-Rels for task 2, and OO-Rels for task 4. Four types of rules are defined for these four subtasks (shown in Table 6.1). In the table, *o* (or *a*) stands for the output (or extracted) sentiment word (or aspect). {*O*} (or {*A*}) is the set of known sentiment words (or aspects) either given or extracted. *H* means any word. *POS*(*O*(or *A*)) and *O*(or *A*)-*Dep* stand for the POS tag and dependency relation of the word *O* (or *A*) respectively. {*JJ*} and {*NN*} are sets of POS tags of potential sentiment words and aspects respectively. {*JJ*} contains *JJ*, *JJR* and *JJS*; {*NN*} contains *NN* and *NNS*. {*MR*} consists of dependency relations, which is the set {*mod*, *pnmod*, *subj*, *s*, *obj*, *obj2*, and *desc*}. {*CONJ*} contains *conj* only. The arrows mean dependency. For example, *O* → *O-Dep* → *A* means *O* depends on *A* through the relation *O-Dep*. Specifically, $R1_i$ is employed to extract aspects (*a*) using sentiment words (*O*), $R2_i$ to extract opinion words (*o*) using aspects (*A*), $R3_i$ to extract aspects (*a*) using extracted aspects (A_i), and $R4_i$ to extract sentiment words (*o*) using known sentiment words (O_i).

Table 6.1. Rules for aspect and opinion word extraction

Rule ID	Observed relation (line 1) and constraints (lines 2–4)	Output	Examples
$R1_1$ (OA-Rel)	$O \rightarrow O\text{-}Dep \rightarrow A$ s.t. $O \in \{O\}$, $O\text{-}Dep \in \{MR\}$, $POS(A) \in \{NN\}$	$a = A$	*The phone has a good "screen".* *good → mod → screen*
$R1_2$ (OA-Rel)	$O \rightarrow O\text{-}Dep \rightarrow H \leftarrow A\text{-}Dep \leftarrow A$ s.t. $O \in \{O\}$, $O/A\text{-}Dep \in \{MR\}$, $POS(A) \in \{NN\}$	$a = A$	*"iPod" is the best mp3 player.* *best → mod → player ← subj ← iPod*
$R2_1$ (OA-Rel)	$O \rightarrow O\text{-}Dep \rightarrow A$ s.t. $A \in \{A\}$, $O\text{-}Dep \in \{MR\}$,	$o = O$	same as $R1_1$ with *screen* as the known word and *good* as the extracted word

	$POS(O) \in \{JJ\}$		
$R2_2$ (OA-Rel)	$O \rightarrow O\text{-}Dep \rightarrow H \leftarrow A\text{-}Dep \leftarrow A$ s.t. $A \in \{A\}$, $O/A\text{-}Dep \in \{MR\}$, $POS(O) \in \{JJ\}$	$o = O$	same as $R1_2$ with *iPod* is the known word and *best* as the extracted word.
$R3_1$ (AA-Rel)	$A_{i(j)} \rightarrow A_{i(j)}\text{-}Dep \rightarrow A_{j(i)}$ s.t. $A_{j(i)} \in \{A\}$, $A_{i(j)}\text{-}Dep \in \{CONJ\}$, $POS(A_{i(j)}) \in \{NN\}$	$a = A_{i(j)}$	*Does the player play dvd with <u>audio</u> and "video"?* *video → conj → audio*
$R3_2$ (AA-Rel)	$A_i \rightarrow A_i\text{-}Dep \rightarrow H \leftarrow A_j\text{-}Dep \leftarrow A_j$ s.t. $A_i \in \{A\}$, $A_i\text{-}Dep = A_j\text{-}Dep$ OR ($A_i\text{-}Dep = subj$ AND $A_j\text{-}Dep = obj$), $POS(A_j) \in \{NN\}$	$a = A_j$	*Canon "G3" has a great <u>len</u>.* *len → obj → has ← subj ← G3*
$R4_1$ (OO-Rel)	$O_{i(j)} \rightarrow O_{i(j)}\text{-}Dep \rightarrow O_{j(i)}$ s.t. $O_{j(i)} \in \{O\}$, $O_{i(j)}\text{-}Dep \in \{CONJ\}$, $POS(O_{i(j)}) \in \{JJ\}$	$o = O_{i(j)}$	*The camera is <u>amazing</u> and "easy" to use.* *easy → conj → amazing*
$R4_2$ (OO-Rel)	$O_i \rightarrow O_i\text{-}Dep \rightarrow H \leftarrow O_j\text{-}Dep \leftarrow O_j$ s.t. $O_i \in \{O\}$, $O_i\text{-}Dep = O_j\text{-}Dep$ OR ($O_i/O_j\text{-}Dep \in \{pnmod, mod\}$), $POS(O_j) \in \{JJ\}$	$o = O_j$	*If you want to buy a <u>sexy</u>, "cool", accessory-available mp3 player, you can choose iPod.* *sexy → mod → player ← mod ← cool*

Note: Column 1 is the rule ID, column 2 is the observed relation (line 1) and the constraints that it must satisfy (lines 2–4), column 3 is the output, and column 4 is an example. In each example, the underlined word is the known word and the word in double quotation marks is the extracted word. The corresponding instantiated relation is given right below the example.

This DP method was originally designed for English, but it has also been applied successfully to Chinese online discussions (Zhai et al., 2011). This method can also be reduced for finding aspects only using a large sentiment lexicon (without any propagation).

Wang and Wang (2008) proposed a similar method to perform the task. Given a list of seed sentiment words, they also used a bootstrapping algorithm to identify both product aspects and sentiment words in an alternating fashion. Mutual information was employed to measure the association between potential aspects and sentiment words and vice versa. Additionally, linguistic rules were also extracted to identify infrequent aspects and sentiment words. A similar idea was employed in Hai et al. (2012) as well. However, instead of employing a set of sentiment words as seeds, this method starts with a small set of aspects as seeds, on which the algorithm iteratively enlarges by mining aspect-opinion, aspect-aspect, and opinion-opinion dependency relations. Two association models, namely, likelihood ratio tests and latent semantic analysis, were used to compute pairwise associations between expressions (aspects or opinions). The whole algorithm bootstraps the initial seeds to find more aspects.

Xu et al. (2013) proposed a sophisticated algorithm to improve the DP method in three ways: (1) detecting general and frequent opinion targets (or aspects) which are incorrect, for example, *thing* and *people*, (2) discovering more long-tail or infrequent targets, and (3) detecting discovered adjectives that are not sentiment words, for example, *every* and *many*. The algorithm works in two steps. Step 1 first utilizes the opinion and target relations similar to those in the DP method to extract opinion words and targets from the corpus. The extraction results are then used to build a sentiment graph. A graph propagation method based on reinforcement relationships among the items is executed on the graph to rank the candidate opinion targets and opinion words. Those items ranked high are more likely to be correct. In step 2, the algorithm builds a self-learning classifier to refine the candidate opinion targets discovered in the first step. The refined results of opinion targets are also subsequently exploited to refine the discovered candidate opinion words. Li et al. (2012) extended the DP method to cross-domain extraction of opinion words and opinion targets. They proposed a new bootstrapping method for the task. In each iteration, the algorithm uses a cross-domain classifier and opinion and target syntactic patterns to identify some most confident opinion words and opinion targets. The cross-domain classifier is trained on the source domain lexicons and the extracted lexicons in the new domain to predict the labels of the unlabeled data in the new domain.

Wu et al. (2009) employed a phrase dependency parser rather than a normal dependency parser to extract noun phrases and verb phrases, which form the candidate aspects (or targets). The system then uses a language model to filter out those unlikely aspects. Note that a normal dependency parser identifies only the dependency of individual words, but a phrase dependency parser identifies the dependency of phrases, which can be more suitable for aspect or target extraction. Note also that the idea of using dependency relations has been explored by many researchers for many different purposes (Kessler and Nicolov, 2009).

For practical use, the set of relations in Table 6.1 can be significantly expanded by the following:

1. *Adding verb- and noun-based relations*. The DP method uses only adjectives as sentiment words. Verb and noun sentiment words may be used too. For example, using the sentiment verb *hate*, we can extract the entity *iPhone* from the sentence "*I hate the iPhone*" because *iPhone* is the object of *hate* and the target of the opinion expressed by *hate*. Using the sentiment noun *masterpiece*, we can extract *iPhone 5* as the opinion target from the sentence "*The iPhone* 5 *is a masterpiece*." However, we must note that allowing verb and noun as sentiment words to participate in propagation can be quite dangerous because a large number of wrong aspects may be extracted.

2. *Adding comparative- and superlative-based relations*. So far, we only used relations in regular opinion sentences. For comparative sentences, some dependency relations used in regular opinion sentences are still applicable. For example, $R1_1$ in Table 6.1 can be used to extract the aspect *voice quality* from the sentence "*The iPhone* 5 *has better voice quality than Moto X*." For a regular opinion sentence, if opinion targets are entities, then there is usually only one opinion target unless there are conjunctions connecting multiple entities. However, for comparative sentences, there are usually two entities, both of which are opinion targets, for example, "*iPhone 5 is better than Moto X*." We can design comparative dependency relations to extract both *iPhone 5* and *Moto X* as entities because they are both opinion targets.

3. *Adding the composition rules in Section 5.2.1*. For most of those opinion rules, it is fairly easy to identify the dependency relations among the constituents in them and the location of opinion targets. These relations can then be applied for aspect and/or entity extraction. For example, in the sentence "*Enbrel has reduced my joint pain*," it is easy to extract both the entity *Enbrel* and the aspect *joint pain* based on the composition rule: decreasing (reduced) negative (joint pain) is positive. As another example, from "*This car consumes a lot of gas*," we can extract *gas* as a resource) aspect because it satisfies the composition rule of consuming a large quantity of resource. However, simply applying such rules can result in many errors. Zhang and Liu (2011a) proposed a more sophisticated method for more accurate extraction of resource usage aspects.

Identify Resource Usage Aspects. In many applications, resource usage is an important aspect, for example, "*This washer uses a lot of water*." Here *water usage* is an aspect of the *washer*, and this sentence indicates a negative opinion about water usage as consuming too much resource is undesirable. There is no opinion word in this sentence. Discovering resource words or phrases, called *resource expressions*, is an important problem for sentiment analysis. In Section 5.2.1, we presented some opinion rules involving resources. We reproduce two of them here:

PO :: = CONSUME SMALL_LESS RESOURCE
NE :: = CONSUME LARGE_MORE RESOURCE

In our example, *water* should be extracted as a resource word. Zhang and Liu (2011a) formulated the resource word extraction problem based on a bipartite graph and proposed an iterative algorithm to solve it based on the following observation:

Observation: The sentiment or opinion expressed in a sentence about resource usage is determined by the triple,

(usage_verb, quantifier, resource_noun),

where *resource_noun* is a noun or noun phrase representing a resource name.

For example, in "*This washer uses a lot of water*," *uses* is the usage verb, *a lot of* is the quantifier phrase, and *water* is the noun representing a resource. However, simply applying this rule or pattern can be error-prone, for example, "*This filter will cause a lot of trouble for you*," where *trouble* is not a resource. The method in Zhang and Liu (2011a) performs the extraction by exploiting a special reinforcement relationship between *resource usage verbs* (e.g., *consume*) and *resource expressions* (e.g., *water*) based on a bipartite graph. The quantifiers were not used in computation but were employed to identify candidate usage verbs and candidate resource expression. The algorithm assumed that a list of quantifiers was given (see Section 5.2.3). The problem was solved using an iterative algorithm similar to the HITS algorithm in Kleinberg (1999). To start the iterative computation, some global *seed resource expressions* are employed to find and to score some strong resource usage verbs. These scores are then applied as the initialization for the iterative computation for any application domain. When the algorithm converges, a ranked list of candidate resource expressions is identified.

Note that to identify grammar relations for extraction, a full parsing is needed. However, parsing is a very expensive operation in NLP. If one wants to fully parse a large number of opinion documents, it is impractical without a large number of machines because a parser can only parse a small number (typically fewer than twenty) of sentences per second. However, in practice, it is possible to do without full parsing. Shallow parsing or even just POS tagging may be sufficient. Because the dependency relations can be approximated by linear patterns of words and POS tags, a good pattern matching algorithm can do the extraction job.

For informal texts in the social media, parsing errors can be serious and thereby harm the extraction. In Liu et al. (2012), a method is proposed based on word alignment in machine translation (MT) to discover opinion targets. Word alignment is a common MT method that tries to align words in sentences of different languages (parallel corpora). In this work, only monolingual alignment is applied, that is, a sentence is aligned with itself. However, the alignment is constrained in such a way that adjectives in one sentence are aligned with nouns in the other sentence (both are the same sentence). Like that in Qiu et al. (2009, 2011), it assumes that sentiment words are adjectives and opinion targets are nouns and noun phrases. Because the alignment is based on statistical information of the corpus, it does not require parsing and thus will not be affected by parsing errors. In Liu et al. (2013), instead of using a purely unsupervised alignment model, the authors integrated the opinion and target relationship patterns in Qiu et al. (2009, 2011) with the alignment model. The idea is to use some high-precision patterns to identify an initial set of seed alignments (which are incomplete) and use them as constraints to construct the full alignments using the EM algorithm. When the EM algorithm converges, we have the complete alignments, which are a set of opinion expression and opinion target pairs. The method also has a second step that computes the confidence of each opinion target based on the bipartite graph constructed with the discovered candidate opinion expression and opinion target pairs and a random walk algorithm.

> **Greeting.** It is important to discard relations that represent greetings or good wishes such as *good morning*, *good afternoon*, *good night*, *happy birthday*, *happy anniversary*, *happy holidays*, *good luck*, *best of luck*, *warm regards*, and so on. Clearly *morning*, *afternoon*, *night*, *luck*, and so on, in these greeting and good wish contexts are not aspects in any application domain. Every language has a large number of such greetings. They can be either manually compiled or discovered through data mining.

6.2.2 Using Part-of and Attribute-of Relations

In any language, there are probably some lexico-syntactic patterns that are frequently used to express part-of and attribute-of relations, for example, "*the battery of the iPhone*" (part-of) and "*the voice quality of the iPhone*" (attribute-of). Expressions that depict such relations can clearly be exploited for aspect extraction because aspects are often parts or attributes of entities. Zhang et al. (2010) proposed several such lexico-syntactic patterns in addition to the opinion and target relations in Section 6.2.1 for aspect extraction to improve the recall of the DP algorithm. Using lexico-syntactic patterns to recognize part-of relations (Moldovan and Badulescu, 2005; Girju et al., 2006) and attribite-of relations have actually been investigated in different contexts (Almuhareb, 2006; Hartung and Frank, 2010).

It turns out that the patterns used for recognizing part-of and attribute-of relations are quite similar. The most frequently used patterns are related to genitives. In English, there are two kinds of genitives, *s-genitives* and *of-genitives*. For s-genitives, the modifier is morphologically linked to the possessive clitic *'s* and precedes the head noun (i.e., NP_{modif}'s NP_{head}), whereas for of-genitive, the modifier is syntactically marked by the preposition *of* and follows the head noun (i.e., NP_{head} of NP_{modif}) (Moldovan and Badulescu, 2005). However, the semantic meanings of these genitive constructions and the other patterns (see later) can be quite diverse. Although researchers have studied the genitive constructions for a long time, the specific meaning of a genitive in a particular context is still hard to pin down. For example, genitive constructions can encode relations such as *part-of* (iPhone's battery), *possession* (John's iPhone), *attribute-of* (iPhone's price), *kinship* (John's brother), *source-from* (John's birth city), or *make-produce* (Apple's phone) (Girju et al., 2006). In applications, it is very difficult to determine the correct semantic relation in each context, as the system needs to analyze the two noun constituents and use some commonsense knowledge. Slightly good news for sentiment analysis is that for aspect extraction we do not need to recognize whether a relation is part-of, attribute-of, or even make-produce.

For our purpose, we want to restrict NP_{modif} to be a *named entity* or a *class concept phrase* (CP). By class CP, we mean the name of an entity type. For example, if we are analyzing car reviews, the CP is *car* or synonyms of *car*, for example, *vehicle* or *automobile*. It can also be some general terms such as *product* or *unit*, for example, "*the price of this unit*" and "*the price of this product*." For simplicity of presentation, we use CP to represent both class concept and named entity (e.g., iPhone). The following lexico-syntactic patterns were proposed in Zhang et al. (2010) and cover of-genitives but not s-genitives. In all of them, the NP is the aspect (part or attribute).

NP Prep CP. NP and CP are connected by a preposition word (Prep). For example, "*battery of the camera*" is an instance of this pattern where *battery* (NP) is the *part* and *camera* (CP) is the *class concept* noun. Notice that we ignore determiners here. In Zhang et al. (2010), only three prepositions, *of*, *on*, and *in*, were used, for example, "*I did not see the price of the car*," "*There is a valley on the mattress*," and "*I found a hole in my mattress*."

CP with NP. For example, in the phrase, "*mattress with a cover*," *cover* is an aspect for *mattress*.

CP NP. For example, in "*car seat*," *seat* is an aspect of *car*, which is a CP. CP can be a named entity as well, for example, "*iPhone battery*."

CP Verb NP. The verbs (Verb) include *has*, *have*, *include*, *contain*, *consist*, and *comprise*. These verbs usually indicate a *part-of* relation. For example, in a sentence, "*The phone has a big screen*," we can infer that *screen* is an aspect for *phone*, which is a class concept.

To use these patterns, the class CP for a domain corpus needs to be identified, which is fairly easy because the noun phrase with the highest frequency in the corpus is almost always the most used class CP. In an application, the user can provide it without any problem. It is also useful to know the entity names in the corpus. Extraction of named entities will be discussed in Section 6.7.

Because these patterns may not always extract the correct aspects, the resulting aspects extracted using these patterns are just candidates. The algorithm in Zhang et al. (2010), which still use the DP method for extraction, ranks aspect candidates by aspect importance. That is, if an aspect candidate is genuine and important, it should be ranked high. For an unimportant aspect or noise, it should be ranked low. Two major factors were used to determine aspect importance: *aspect relevance* and *aspect frequency*. The former describes how likely an aspect candidate is a genuine aspect, as indicated by three clues. First, if an aspect is modified by multiple sentiment words, it is more likely to be relevant. For example, in the mattress reviews domain, *delivery* is modified by *quick*, *cumbersome* and *timely*. It shows that reviewers put emphasis on the word *delivery*. Thus, *delivery* is likely to be a genuine aspect. Second, if an aspect was extracted by multiple lexico-syntactic patterns, it is more likely to be relevant. For example, in the car reviews domain, if we have the sentences, "*The engine of the car is large*" and "*The car has a big engine,*" we can infer that *engine* is very likely to be an aspect of the car because both sentences contain part-of relations indicating that *engine* is a part of the car. Third, if an aspect is extracted by both a sentiment word modification relation and a lexico-syntactic pattern in the same sentence, then it is more likely to be correct. For example, the sentence "*There is a bad hole in the mattress*" strongly indicates that *hole* is an aspect for the mattress because it is modified by sentiment word *bad* and also satisfies the 'NP Prep CP' pattern.

Zhang et al. (2010) also showed that there are mutual enforcement relations between opinion words, lexico-syntactic patterns, and aspects. That is, an adjective is more likely to be a sentiment word if it modifies many genuine aspects. Likewise, if an aspect candidate can be extracted by many sentiment words and lexico-syntactic patterns, it is also more likely to be a genuine aspect. Thus, the HITS algorithm (Kleinberg, 1999) can be used to measure aspect relevance.

Aspect frequency is another important factor affecting aspect ranking. It is desirable to rank those frequent aspects more highly than infrequent aspects. The final ranking score for a candidate aspect a ($S(a)$) is the score of aspect relevancy ($r(a)$) multiplied by the log of aspect frequency ($f(a)$):

$$S(a) = r(a) \log(f(a)). \tag{6.2}$$

The idea is to push the frequent candidate aspects up by multiplying the log of frequency. Log is taken to reduce the effect of big frequency count numbers.

Finally, we note that many applications share aspects. For example, all products have *price*, and all electronics products have *batteries*. Thus aspects are accumulative, and can be organized as an ontology for different products or product categories semi-automatically or manually. However, automated discovery is still necessary because products and services and their aspects change constantly due to changes or improvements to the products. An old or fixed ontology will not be up-to-date. Furthermore, fixed ontologies may not be able to cover some specific usage experiences of the users.

6.3 Using Supervised Learning

Aspect extraction is a special information extraction problem. Many algorithms based on supervised learning for information extraction (Mooney and Bunescu, 2005; Sarawagi, 2008; Hobbs and Riloff, 2010) are clearly applicable to aspect extraction. The most dominant methods are those based on *sequential learning* (or *sequential labeling*). Like all supervised techniques, they need manually labeled data for training, that is, manually annotated aspects and non-aspects in each sentence of a training corpus. The current state-of-the-art sequential learning methods include *hidden Markov models* (HMM) (Rabiner, 1989) and *conditional random fields* (*CRF*) (Lafferty et al., 2001), which are introduced in the following two subsections.

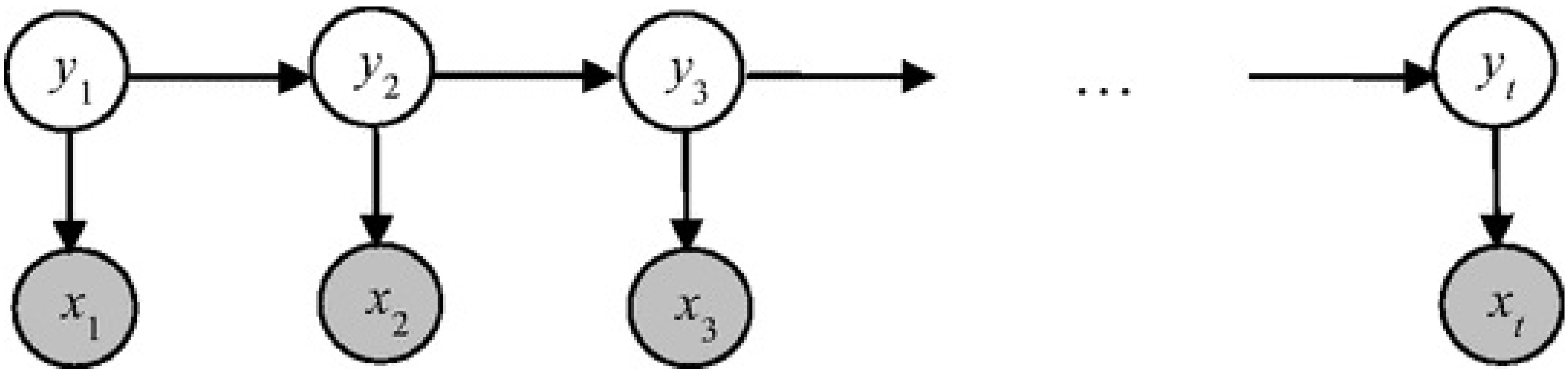


Figure 6.2. Hidden Markov model.

6.3.1 Hidden Markov Models

A HMM is a directed sequence model for a wide range of state series data. It has been successfully applied to many sequence labeling problems such as NER (Named Entity Recognition) and POS tagging in NLP. A generic HMM model is illustrated in Figure 6.2, where

$\mathbf{y} = <y_1, y_2, \ldots, y_t>$: hidden state sequence
$\mathbf{x} = <x_1, x_2, \ldots, x_t>$: observation sequence

A HMM of a sequence of observations **x** assumes that there is a *hidden* sequence of states **y**. Observations are dependent on the hidden states. Each state has a probability distribution over the possible observations. Two independence assumptions are made to model the joint distribution $p(\mathbf{y}, \mathbf{x})$. First, state y_i only depends on its immediate predecessor state y_{i-1}. y_i is independent of all its ancestor y_1, y_2, y_3,…, y_{i-2}. This is called the *Markov* property. Second, the observation x_i only depends on the current state y_i. With these assumptions, we can specify the HMM using three probability distributions: $p(y_1)$ over the initial state, a state transition distribution $p(y_i \mid y_{i-1})$ and an observation distribution $p(x_i \mid y_i)$. The joint probability of a state sequence **y** and an observation sequence **x** factorizes as follows:

$$p(\mathbf{y}, \mathbf{x}) = \prod_{i=1}^{t} p(y_i \mid y_{i-1}) p(x_i \mid y_i) \tag{6.3}$$

where we write the initial state distribution $p(y_1)$ as $p(y_1 \mid y_0)$ (Sutton and McCallum, 2011). y_0 is a dummy state.

Given some observation sequences, we can learn the model parameter of the HMM that maximizes the observation probability. That is, the learning can be done by building a model to best fit the training data. With the learned model, we can find an optimal state sequence for a new observation sequence.

In aspect extraction, we can regard the words or phrases in a review as observations and aspect or opinion expression labels as underlying states. Jin and Ho (2009) utilized a lexicalized HMM to extract product aspects and opinion expressions from reviews, which integrates linguistic features such as POS and lexical patterns into the HMM. For example, an observable state for the lexicalized HMM is represented by a pair ($word_i$, POS($word_i$)), where POS($word_i$) represents the part of speech of $word_i$.

6.3.2 Conditional Random Fields

One limitation of the HMM is that its assumptions may not be adequate for real-life problems, which leads to reduced accuracy. To address the limitation, linear-chain CRF (Lafferty et al., 2001) was proposed as an undirected sequence model, which models the conditional distribution $p(\mathbf{y} \mid \mathbf{x})$ over hidden sequence $\mathbf{y}$ given observation sequence $\mathbf{x}$ (Sutton and McCallum, 2011). That is, the conditional model is trained to label an unknown observation sequence $\mathbf{x}$ by selecting the hidden sequence $\mathbf{y}$ that maximizes $p(\mathbf{y} \mid \mathbf{x})$. The model thereby allows relaxation of HMM's strong assumptions of independence. The linear-chain CRF model is illustrated in Figure 6.3, where

$\mathbf{y} = < y_1, y_2, \ldots, y_t >$: hidden state sequence

$\mathbf{x} = < x_1, x_2, \ldots, x_t >$: observation sequence

The conditional distribution $p(\mathbf{y} \mid \mathbf{x})$ takes the form

$$p(\mathbf{y} \mid \mathbf{x}) = \frac{1}{Z(\mathbf{x})} \prod_{i=1}^{t} \exp\left\{\sum_{k=1}^{K} \lambda_k f_k(y_i, y_{i-1}, \mathbf{x}_i)\right\} \tag{6.4}$$

where $Z(\mathbf{x})$ is a normalization function

$$Z(\mathbf{x}) = \sum_{\mathbf{y}} \prod_{i=1}^{t} \exp\left\{\sum_{k=1}^{k} \lambda_k f_k(y_i, y_{i-1}, \mathbf{x}_i)\right\} \tag{6.5}$$

CRF introduces the concept of *feature functions*. Each feature function has the form $f_k(y_i, y_{i-1}, \mathbf{x}_i)$ and λ_k is its corresponding weight. Figure 6.3 indicates that CRF makes independence assumption among $\mathbf{y}$, but not among $\mathbf{x}$. One argument for the feature function f_k is the vector $\mathbf{x}_i$, which means each feature function can depend on observation $\mathbf{x}$ from any step. That is, all the components of the global observations $\mathbf{x}$ are needed in computing feature function f_k at step i. Thus, CRF can introduce more features than HMM at each step (Sutton and McCallum, 2011).

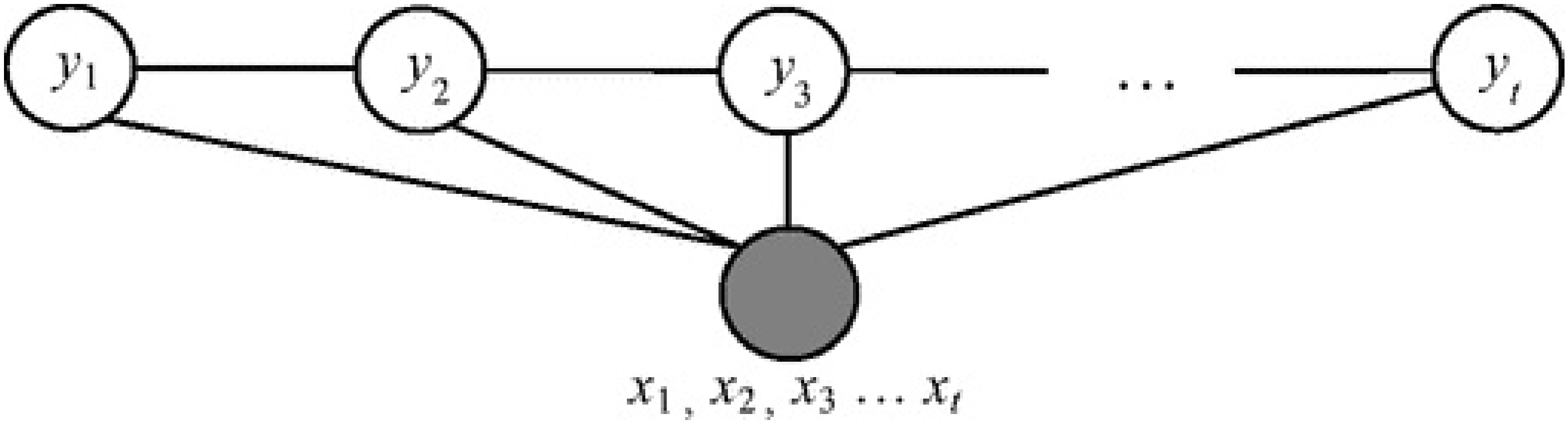


Figure 6.3. Linear chain conditional random fields.

Jakob and Gurevych (2010) utilized CRF to extract opinion targets (or aspects) from sentences which contain an opinion expression. They employed the following features or clues to form feature functions for their CRF-based approach:

Token. The string of the current token.

Part of speech. The POS tag of the current token.

Short dependency path. Because sentiment expressions and their targets are often related syntactically, this feature captures several direct dependencies that link tokens with each sentiment expression in a sentence.

Word distance. Because noun phrases are good candidates for opinion targets in product reviews, this feature captures the closest tokens to each sentiment expression in a sentence.

The possible class labels are represented following the Inside-Outside-Begin (IOB) labeling scheme: *B-Target*, identifying the beginning of an opinion target; *I-Target*, identifying the continuation of a target, and *O* for other (nontarget) tokens.

Similar work has also been done in Li et al. (2010). To model the long distance dependency with conjunctions (e.g., *and*, *or*, *but*) at the sentence level and deep syntactic dependencies for aspects, positive opinions and negative opinions, they integrated two CRF variations, Skip-chain CRF and Tree-CRF, for the extraction of both aspects and opinions. Unlike the original CRF, which can only use word sequences in learning, Skip-chain CRF and Tree-CRF enable CRF to exploit structure features. CRF was also used in Choi and Cardie (2010) and in Qiu et al. (2009, 2011).

Yang and Cardie (2013) proposed a method to jointly extract opinion targets, opinion (or sentiment) expressions, and opinion holders, and also identify the associated opinion linking relations, IS-ABOUT and IS-FROM. The IS-ABOUT relation is the opinion and target relation and the IS-FROM relation is the opinion and its holder relation. The extraction of opinion targets, opinion expressions, and opinion holders uses CRF. The identification of relations uses supervised learning. Each relation is basically represented as a pair. An opinion expression and its target form an IS-ABOUT relation, and an opinion expression and its opinion holder form an IS-FROM relation. The classification identifies the appropriate pairs. Because all these tasks are related to each other, a joint optimization framework was proposed to perform all the tasks together rather than in a pipelined or sequential manner in which the interaction between different extraction tasks cannot be exploited and error propagation cannot be controlled.

Besides HMM and CRF, researchers have also used several other supervised methods. Liu et al. (2005) and Jindal and Liu (2006b) used sequential rules, which are mined based on supervised sequential pattern mining with class labels. Kobayashi et al. (2007) used a tree-structured classification method. Their method first finds candidate aspect and opinion word pairs using a dependency parse tree, and then employs the tree-structured classification method to learn and to classify the candidate pairs as being an aspect and evaluation relation or not. Aspects are extracted from the highest scored pairs. The features used in learning include contextual clues, statistical co-occurrence clues, among others. Yu et al. (2011) used a partially supervised learning method, called one-class SVM (Manevitz and Yousef, 2002), to extract aspects from Pros and Cons of reviews. Ghani et al. (2006) used both traditional supervised learning and semi-supervised learning for aspect extraction. Kovelamudi et al. (2011) used a supervised method but also exploited some relevant information from Wikipedia. Klinger and Cimiano (2013) applied factor graph to extract both target entities and opinion expressions. A similar work was also done in Mitchell et al. (2013) based on CRF. Zhou et al. (2013) proposed an unsupervised label propagation method to extract opinion targets from Chinese microblogs. This method is different from the commonly used label propagation method in Zhu and Ghahramani (2002) which is a semi-supervised algorithm that spreads label distributions throughout the graph from a small set of nodes seeded with some initial label information.

6.4 Mapping Implicit Aspects

In Section 2.1, we called aspect expressions that are expressed as nouns and noun phrases the *explicit aspects*, for example, *picture quality* in "*The picture quality of this camera is great*." All other expressions that indicate aspects are called *implicit aspects* (not including pronouns that need coreference resolution). There are many types of implicit aspect expressions. Adjectives and adverbs are perhaps the most common types because most adjectives describe some specific attributes or properties of entities, for example, *expensive* describes *price*, and *beautiful* describes *appearance*. *Price* and *appearance* are called *attribute nouns* of *expensive* and *beautiful* respectively. Implicit aspects can be verbs too. In general, implicit aspect expressions can be arbitrarily complex, for example, "*This camera will not easily fit in a pocket*." '*fit in a pocket'* indicates the aspect *size*. Researchers have worked on mapping adjectives to noun aspects, but have done little to map verbs or to discover verbs or verb phrases indicating aspects, for example, "*The machine can play DVD's*, *which is its best feature*." I am also not aware of any research that investigates more complex implicit aspect expressions such as '*fix in a pocket*.' In what follows, we discuss some existing approaches to mapping adjectives to noun aspects.

6.4.1 Corpus-Based Approach

Su et al. (2008) proposed a clustering method to map implicit aspect expressions, assumed to be sentiment adjectives, to their corresponding explicit aspects. The method exploits the mutual reinforcement relationship between an explicit aspect and a sentiment word forming a co-occurring pair in a sentence. Such a pair may indicate that the sentiment word describes the aspect, or that the aspect is associated with the sentiment word. The algorithm finds the mapping by iteratively clustering the set of explicit aspects and the set of sentiment words separately. In each iteration, before clustering one set, the clustering results of the other set is used to update the pairwise similarity of the set. The pairwise similarity in a set is determined by a linear combination of intra-set similarity and inter-set similarity. The intra-set similarity of two items is the traditional similarity. The inter-set similarity of two items is computed based on the degree of association between aspects and sentiment words. The association (or mutual reinforcement relationship) is modeled using a bipartite graph. An aspect and an opinion word are linked if they have co-occurred in a sentence. The links are also weighted based on the co-occurrence frequency. After the iterative clustering, the strongest *n* links between aspects and sentiment word groups form the mapping.

In Hai et al. (2011), a two-phase co-occurrence association rule mining approach was proposed to match implicit aspects (assumed to be sentiment words) with explicit aspects. In the first phase, the approach generates association rules involving each sentiment (adjective) word as the condition and an explicit aspect as the consequence, which co-occur frequently in sentences of a corpus. In the second phase, it clusters the rule consequents (explicit aspects) to generate more robust rules for each sentiment word. For application or testing, given a sentiment word with no explicit aspect, it finds the best rule cluster and then assigns the representative word of the cluster as the final identified aspect.

These corpus-based approaches alone have some weaknesses (Fei et al., 2012):

1. It is difficult to discover attributes that do not co-occur with their adjectives due to linguistic conventions. For example, in English, people do not say “*The price of the iPhone is expensive*.” Instead, they say “*iPhone is expensive*” or “*The price of the iPhone is high*.” It is thus hard for a corpus-based approach to find *price* as an attribute of *expensive*. Instead, it may wrongly find *price* as an attribute of *high*.

2. Even if an adjective and one of its attribute nouns do appear in a corpus, if the corpus is limited in size (e.g., the number of reviews for a product can be very small), they may not co-occur in many sentences and thus may not be associated reliably.

6.4.2 Dictionary-Based Approach

In Fei et al. (2012), a dictionary-based approach was proposed to complement the corpus-based approach and address the preceding problems. The first problem is tackled because dictionaries typically define adjectives using their attributes. For example, *expensive* is defined as "*Marked by high prices*" in thefreedictionary.com. The second problem is also addressed because dictionaries are not restricted by any specific corpus (which has limited coverage). Each adjective in the dictionary can be studied individually. Although not all attribute nouns of an adjective may appear in a single dictionary, multiple dictionaries can be employed to improve the coverage. In their experiments, five online dictionaries were used. The goal was to find all attribute nouns for an adjective. It does not identify the specific mapping of an adjective with one or more suitable attribute nouns in a specific sentence due to different senses. However, it provides a more complete set of attributes of an adjective for a corpus-based approach to choose from subsequently using existing methods such as those in Hartung and Frank (2010, 2011).

Instead of using the classic supervised classification, Fei et al. (2012) employed a relational learning method called *collective classification* (Sen et al., 2008), which can take advantage of the rich lexical relationships between words in dictionaries for classification. In traditional supervised learning, each instance is drawn independently of others (Mitchell, 1997). However, in real-life data, instances are often not independent of each other. Such data are often represented as a graph where nodes are instances and links are their relations. The classification of one node can influence the classification of its neighboring nodes. Collective classification performs classification based on the graph in an iterative fashion. Each iteration uses the classification results of the previous iteration as additional or enhanced features to improve the accuracy.

In the context of our task, we have synonym, antonym, hyponym, and hypernym relations among words, which naturally form a graph. Each instance denotes a pair with an adjective A_i and one of its candidate attribute nouns c_{ij}, that is, (A_i, c_{ij}). The candidate attribute nouns of each adjective are nouns found in the dictionary definitions of the adjective, Owing to the relational features (which will be detailed later), we use a graph representation of instances with a set of nodes (pairs), $V = \{(A_i, c_{ij}) \mid c_{ij} \in C_i, A_i \in A\}$, and a neighborhood function N where $N_{ij} \subseteq V - \{(A_i, c_{ij})\}$. Each node (a pair (A_i, c_{ij})) in V is represented with a vector $\mathbf{x}_{ij}$ of features, $f_1, f_2, \ldots, f_n$, and an associated class label y_{ij} in the domain of $\{+1, -1\}$. The $+1$ class means *attribute noun*, and the -1 class means *not attribute noun*. V is further divided into two sets of nodes: L, labeled nodes, and U, unlabeled nodes. Our task is to predict the label for each node $u_{ij} \in U$.

A collective classification algorithm called the *iterative classification algorithm* (ICA) (Sen et al. 2008) was employed to solve this problem. ICA is given in Figure 6.4. Its training process (not in Figure 6.4) trains a classifier h just like traditional supervised learning, using the labeled set L with all features. The classification or testing step is the core of the algorithm.

Algorithm 6.1 ICA - Iterative classification

1. for each node $u_{ij} \in U$ // each node is a pair
2.   compute $\mathbf{x}_{ij}$ using only $L \cap N_{ij}$
3. $y_{ij} \leftarrow h(\mathbf{x}_{ij})$
4. endfor
5. repeat // iterative classification
6.   generate an ordering O over pairs in U
7.   for each node $o_{ij} \in O$ do
8.   compute $\mathbf{x}_{ij}$ using current assignments to N_{ij}
9. $y_{ij} \leftarrow h(\mathbf{x}_{ij})$
10.   endfor
11. until all class labels do not change

Figure 6.4. Iterative classification algorithm (ICA).

In testing, the learned classifier h assigns a class label to each node $u_{ij} \in U$ in the test data (lines 1–4). Line 2 computes the feature vector $\mathbf{x}_{ij}$ for u_{ij}. This (and also line 8) is an important step of this algorithm which makes it different from the conventional supervised learning. It computes all the relational features for u_{ij} using the neighbors of u_{ij}. Note that relational features are not detailed here as they are quite involved. Interested readers should refer to the original paper for details. Line 2 is slightly different from line 8 as in line 2 not all nodes have been assigned class labels, so we compute $\mathbf{x}_{ij}$ based on the intersection of the labeled nodes (L) and u_{ij}'s neighbors. Line 3 uses h to assign a class (y_{ij}) to node u_{ij}. Lines 1–4 are considered as the initialization step.

After initialization, the classifier is run iteratively (lines 5–11) until the class labels of all nodes no longer change. The iterations are needed because some relational features of a node depend on the class labels of its neighbors. Such labels are assigned in each iteration and may change from one iteration to the next. In each iteration (lines 6–10), the algorithm first generates an ordering of nodes to be classified. We order them randomly to reduce bias as random ordering makes the process stochastic. Line 8 does the same job as line 2. Line 9 does the same job as line 3. Classifier *h* does not change in the iterations.

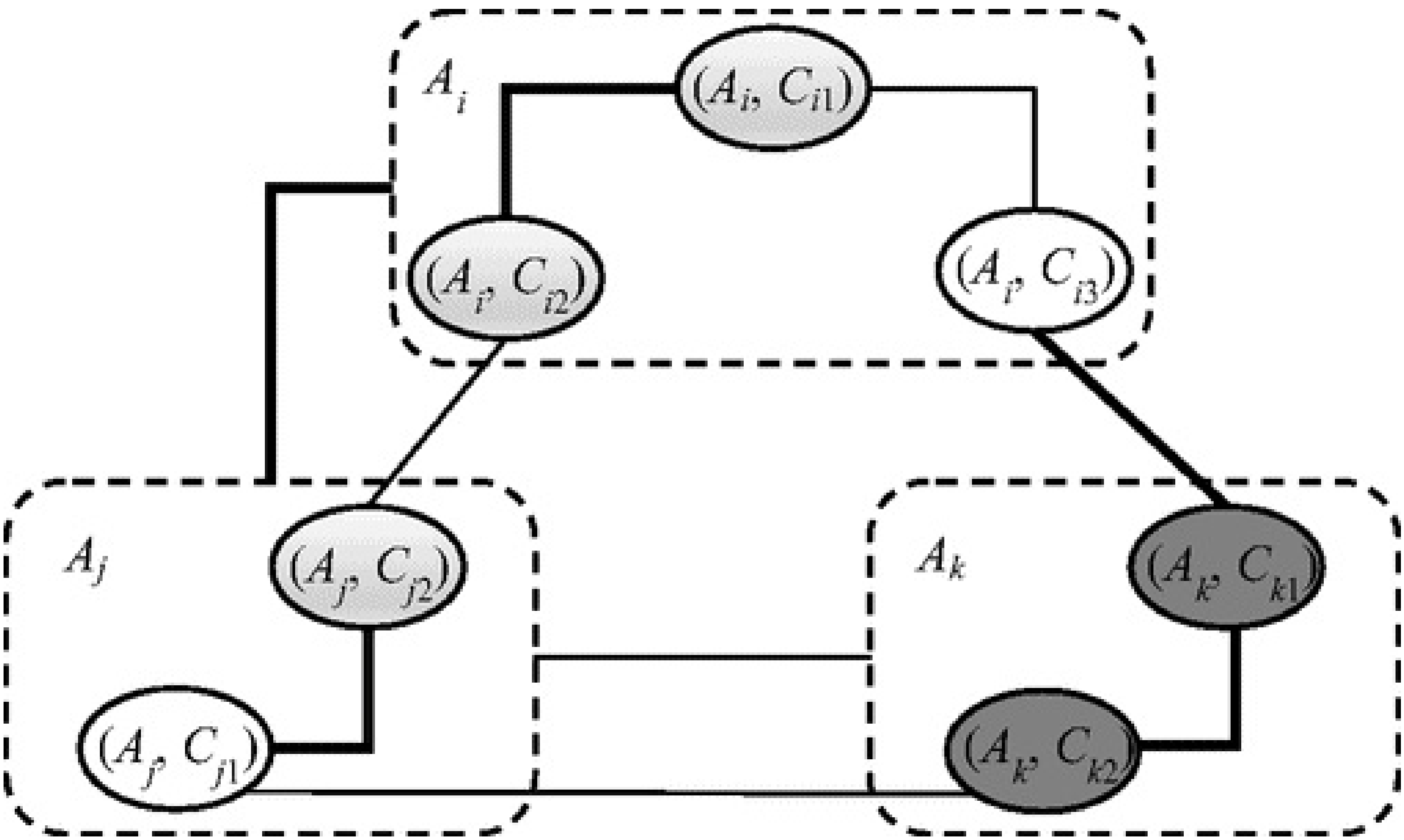


Figure 6.5. An example of a graph of word relations and an ICA iteration.

Figure 6.5 shows a simple example of a graph based on some relationships of words. It can be considered as a snapshot of an iteration of ICA. Each oval node denotes an instance (an adjective and attribute pair). Each dash-lined box encloses all pairs that belong to the same adjective. A link between two oval nodes denotes a relationship between two (candidate) attribute nouns, and a link between two dash-lined boxes denotes a relationship between two adjectives. Thin lines connect synonyms and thick lines connect antonyms. The dark shaded nodes denote those labeled pairs, the lightly shaded nodes denote those candidate attribute nouns whose labels have been predicted (unlabeled at the beginning), and unshaded oval nodes denote those candidate attribute nouns whose labels are yet to be predicted in the iteration. In the figure, adjectives A_k and A_j are synonyms, attribute noun c_{k2} (labeled) and candidate attribute noun c_{j1} are synonyms, and candidate attribute nouns c_{j1} and c_{j2} are antonyms. In the previous iteration, ICA has predicted/labeled c_{j2} as an attribute noun of A_j. Because c_{j2}, c_{j1}, and c_{k2} are related, the label of c_{j1} will be affected by the labels of c_{j2} and c_{k2} in this iteration.

6.5 Grouping Aspects into Categories

Clearly, people use different words or phrases to describe the same aspect (or aspect category). For example, *sound quality* and *voice quality* refer to the same aspect of phones. We call *sound quality* and *voice quality* aspect expressions (see Section 2.1.6). After aspect expressions have been extracted, they need to be grouped or clustered into aspect categories. Each category represents a unique aspect (see Section 2.1.6). Grouping aspect expressions is critical for opinion analysis and summary.

The most obvious approach to solving this problem is to use WordNet or another thesaurus dictionary to find synonymous expressions. However, this approach is far from sufficient because of a few reasons:

- Many synonyms are domain dependent (Liu et al., 2005). For example, *movie* and *picture* are synonyms in movie reviews, but they are not synonyms in camera reviews as picture is more likely to be synonymous to photo while movie to video.
- Many aspect expressions are multiword phrases, which cannot be easily handled with dictionaries.
- Many aspect expressions describing the same aspect are not general or domain-specific synonyms. For example, *expensive* and *cheap* can both indicate the aspect *price* but they are antonyms, not synonyms of each other or of *price* (see Section 6.4).
- In most practical applications, the task of aspect grouping cannot be solved completely in an unsupervised manner because it is often a subjective task, i.e., different applications or even different users may have different categories in mind depending on the application needs. In some cases, this is due to different levels of granularity in analysis. For example, in a real-life application of car reviews, one user wants to group aspect expressions related to *exterior design* and *interior design* into one category and call it *design*, but another user wants them separate, because the two users are in charge of different tasks. If two categories are used, if one says "*The design of the car is great*," we have to assign it to both the interior and exterior design categories. In some other cases, it is not easy to decide which category an aspect expression belongs to. Are these four sentences describing the same aspect or different aspects, "*This car works very well*," "*This car is reliable*," "*The quality of this car is great*," and "*The car broke down the next day*"? Different people may have different answers.

Carenini et al. (2005) proposed the first method to solve this problem. Their method was based on several similarity metrics defined using string similarity, synonyms, and lexical distances measured using WordNet. The method requires a given taxonomy of aspects (more specifically, aspect categories) for a particular domain. Its objective is to merge each discovered aspect expression to an aspect node in the taxonomy based on the similarities. Experiments based on digital camera and DVD reviews showed promising results. In Yu et al. (2011), a more sophisticated method was presented to also use publicly available aspect hierarchies/taxonomies of products and the actual product reviews to produce the final aspect hierarchies. A set of distance measures was also combined using an optimization strategy.

Zhai et al. (2010) proposed a semi-supervised learning method to group aspect expressions into some user-specified aspect categories. To reflect the user needs, they first manually labeled a small number of seed aspect expressions for each category. The system then assigns the rest of the aspect expressions to suitable categories using a semi-supervised learning method working with labeled and unlabeled examples. The method uses the Expectation Maximization (EM) algorithm in Nigam et al. (2000). It also employs two pieces of prior knowledge to provide a better initialization for EM: (1) aspect expressions sharing some common words are likely to belong to the same group, for example, *battery life* and *battery power*, and (2) aspect expressions that are synonyms in a dictionary are likely to belong to the same group, for example, *movie* and *picture*. These two pieces of knowledge help EM produce better classification results. In Zhai et al. (2011), soft constraints were used to help label some initial examples. The constraints are generated based on sharing of words and lexical similarity (Jiang and Conrath, 1997). The learning method also used EM, but it eliminated the need of asking the user to provide seeds.

In Guo et al. (2009), the authors presented a method called multilevel latent semantic association. At the first level, all the words in aspect expressions are grouped into a set of concepts/topics using the topic model Latent Dirichlet Allocation (LDA) (Blei et al., 2003). LDA, which we will discuss in greater detail in Section 6.6, groups words in documents into clusters where each cluster represents a topic. The results from the first level are used to build latent topic structures for aspect expressions. For example, we have four aspect expressions *day photos*, *day photo*, *daytime photos* and *daytime photo*. If LDA groups the individual words *day* and *daytime* into topic10, and *photo* and *photos* into topic12, the system will group all four aspect expressions into one group, call it topic10-topic12, which is called a latent topic structure. At the second level, aspect expressions are grouped by LDA again but according to their latent topic structures produced at level 1 and their context snippets in reviews. Following the preceding example, *day photos*, *day photo*, *daytime photos* and *daytime photo* in topic10-topic12 combined with their surrounding words form a document. LDA runs on such documents to produce the final result. In Guo et al. (2010), a similar idea was used to group aspect expressions from different languages into aspect categories, which can be used to compare opinions along different aspects from different languages (or countries).

In Zhai et al. (2011), a topic model called Constrained-LDA was proposed for grouping or clustering aspect expressions. The algorithm assumes that the aspect expressions have already been discovered by another system. Constrained-LDA incorporates two forms of constraints into LDA, which are *must-links* and *cannot-links*. A must-link constraint means that two aspect expressions should be in the same cluster. A cannot-link constraint means that two aspect expressions should be in different clusters. The constraints are extracted automatically. This method can handle a large number of must-link and cannot-link constraints. The constraints can also be relaxed, that is, they are treated as soft (rather than hard) constraints and may not be satisfied. For aspect categorization, also called aspect resolution, Constrained-LDA uses the following constraints: (1) if two aspect expressions share one or more words, they are assumed to form a must-link, i.e., they should be in the same topic, e.g., "*battery power*" and "*battery life*", and (2) if two aspect expresions occur in the same sentence and they are not connected by "*and*", they form a cannot-link. The reason for the second constraint is that people normally do not repeat the same aspect in the same sentence. We will describe the Constrained-LDA model in detail in Section 6.6.5 for a different but similar purpose.

6.6 Exploiting Topic Models

As discussed in the preceding sections and in Section 2.1.6, aspect extraction has two tasks, aspect expression extraction and grouping. In terms of aspect expression extraction, we need to extract both explicit and implicit expressions. The two tasks are usually performed in two separate steps. However, statistical topic modeling performs both tasks simultaneously in a single step and also handles explicit as well as implicit aspects to some extent, which are highly desirable. In this section, we explore topic models for aspect extraction and aspect-based sentiment analysis.

Topic modeling is a principled approach for discovering topics from a large corpus of text documents. The most common outputs of a topic model are a set of word clusters and a topic distribution for each document. Each word cluster is called a *topic* and is a probability distribution over words (also called *topical terms*) in the corpus. In this section, we use *term* rather than *expression* just to conform to the topic modeling literature. The topic distribution of a document gives the proportion of each topic in the document. There are two basic topic models, *probabilistic Latent Semantic Analysis* (pLSA) (Hofmann, 1999) and *Latent Dirichlet Allocation* (LDA) (Blei et al., 2003). They are both unsupervised methods. Although they are primarily used to model and extract topics from text documents, they can be extended to model many other types of information. For readers who are not familiar with topic models, graphical models, and Bayesian networks, besides reading papers in the topic modeling literature, the book *Pattern Recognition and Machine Learning* by Christopher M. Bishop (2006) is an excellent source of background knowledge.

In the context of sentiment analysis, topics are basically aspects (or more precisely aspect categories). Each topical term or word in a topic is an aspect word (or expression). In most current topic models, a topical term is an individual word or unigram. We discuss topical terms that can be phrases in Section 6.6.5. Theoretically speaking, the key advantage of topic modeling for aspect extraction is that it is able to perform both explicit and implicit aspect expression extraction and, at the same time, group them. For example, it may extract and group *price*, *cost*, *expensive*, and *cheap* together under one aspect or topic. These capabilities are very useful for sentiment analysis. In addition to models for aspect extraction, many joint models have also been proposed by researchers to model both aspects and sentiments based on the idea that sentiments or opinions have targets.

This section first introduces the LDA model because most existing topic models for aspect extraction and sentiment analysis are based on LDA. It then gives an overview of the current models (Section 6.6.2). In Section 6.6.3, we describe some weaknesses of unsupervised models and present several *knowledge-based topic models*, also called *semi-supervised topic models*, to overcome these weaknesses. These models were proposed to exploit prior domain knowledge from the user to guide model inference to produce better results. In Section 6.6.4, we take a major step forward to mine prior domain knowledge from the big data, which makes the knowledge-based topic modeling approach fully automatic. This also introduces the important new concept of *lifelong topic modeling* to machine learning. Finally, we discuss two models that can consider aspect expressions as multiword phrases. Multiword phrases are important in practice because many aspects cannot be expressed with single words. For example, if '*battery life*' is split into two separate words *battery* and *life*, the meaning of '*battery life*' is lost.

6.6.1 Latent Dirichlet Allocation

LDA is an unsupervised learning model that assumes that each document consists of a mixture of topics and each topic is a probability distribution over words. It is a document generative model that specifies a probabilistic procedure by which documents are generated. Like most other topic models, LDA can be depicted graphically and is based on Bayesian networks.

The input to LDA is a corpus consisting of a set of documents *D*. The outputs from LDA are a distribution over topics for each document, called *document-topic* distribution θ,and a distribution over words for each topic, called *topic-word* distribution ϕ. Both θand ϕ are assumed to follow multinomial distributions. To smooth the distributions, it is also assumed that they have Dirichlet priors with hyperparameters, αand β, respectively. Because the Dirichlet distribution is the conjugate prior of the multinomial distribution, using Dirichlet priors simplifies the problem of statistical inference. Note that the Dirichlet distribution has, in fact, a vector of parameters and each parameter can have a different value. In LDA, however, most researchers used the same value for all parameters. Such a Dirichlet distribution is commonly called a symmetric Dirichlet distribution.

Let the number of topics be *T* (usually specified by the user). The topics are indexed by {1,…, *T*}, and the entries in the vocabulary of the corpus are indexed by {1,…, *V*}, where *V*is the number of unique words in the entire document corpus. The corpus has *D* documents. Each document *d*is a sequence of N_d words. *w*is the bag of all observed words with cardinality, $|\boldsymbol{w}| = \sum_d N_d$. $\boldsymbol{z}$ denotes the topic assignments of all words in all documents, and z_i denotes the topic assignment of *i*th word w_i in document *d*. Note that for simplicity of notations we omit the subscript of document *d* for w_i and z_i.

As a generative model, LDA's procedure for generating documents is as follows:

for each topic $t \in \{1,\ldots, T\}$ **do**

draw a word distribution for topic *t*, $\phi_t \sim Dirichlet(\beta)$

for each document $d \in \{1,\ldots, D\}$ **do**

draw a topic distribution for document *d*, $\theta_d \sim Dirichlet(\alpha)$

for each term w_i, $i \in \{1,\ldots, N_d\}$ **do**

draw a topic for the word, $z_i \sim Multinomial(\theta_d)$

draw a word, $w_i \sim Multinomial(\varphi_{z^i})$

The graphical or plate notation of LDA is given in Figure 6.6, where θ, ϕand *z* are latent variables, and word *w* is observed. Dirichlet hyperparameters αand βare regarded as constants and are thus also observed. All the observed value nodes are shaded, and all latent variable nodes are not shaded.

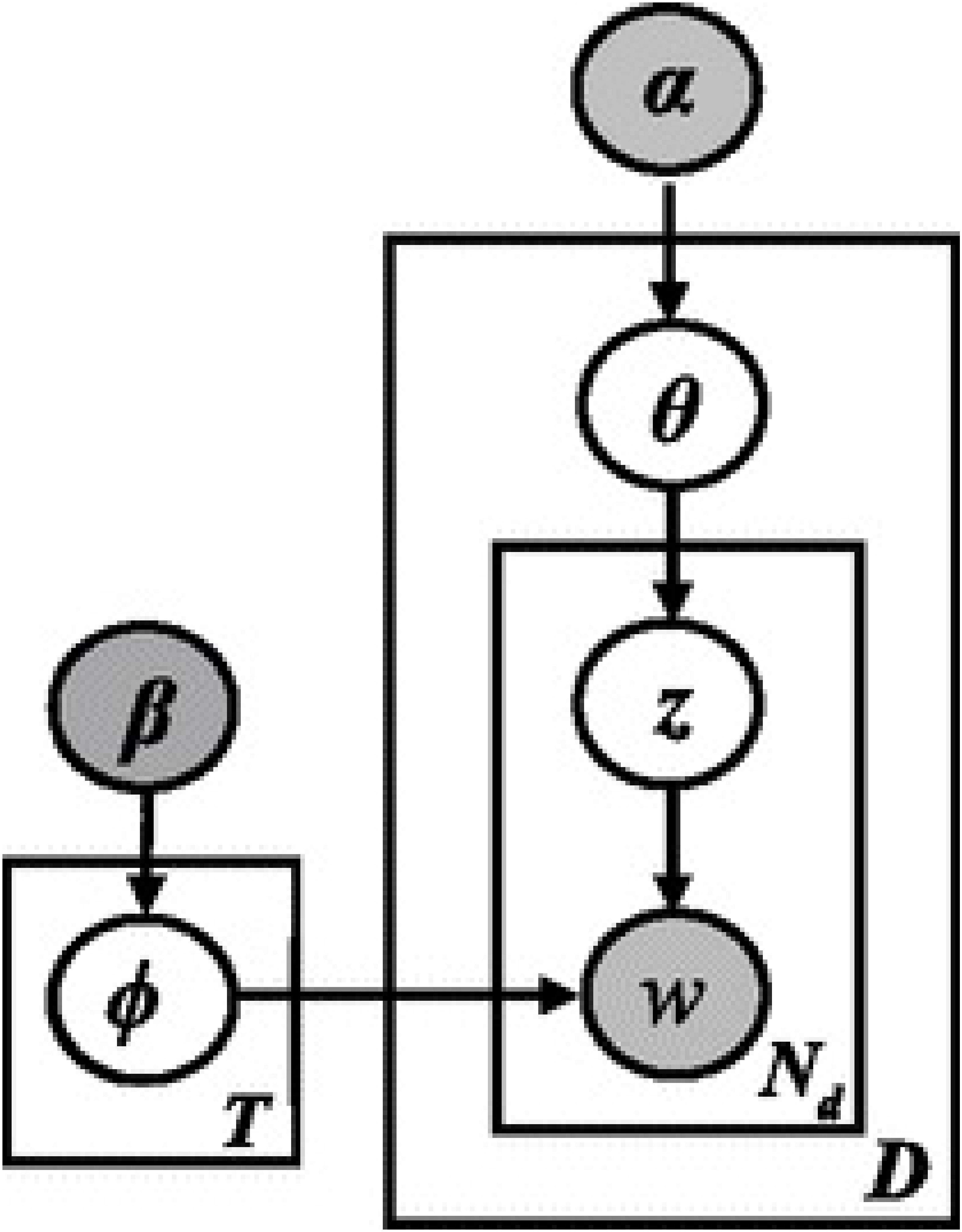


Figure 6.6. The graphical representation of LDA in plate notation.

To obtain the distributions θand ϕ, two main algorithms, variational inference (Blei et al., 2003) and Gibbs sampling (Griffiths and Steyvers, 2004), were proposed. These methods do not directly estimate distributions θ and ϕ. Instead, they estimate the posterior distribution over z (the assignment of topics to words), given the observed words $\boldsymbol{w}$, while marginalizing out θ and ϕ. Each z_i gives an integer value {1…T} for the topic to which each word w_i in a document d is assigned. From the topic assignments z, we can compute distributions θ and ϕ. Because Gibbs sampling, a Markov Chain Monte Carlo (MCMC) algorithm, is more commonly used, we briefly describe it here.

For Gibbs sampling–based LDA, the most important process is the updating of topic for each word w_i in each document d according to the probabilities calculated using Equation (6.6),

$$P(z_i = t \mid z^{-i}, \boldsymbol{w}) \propto \frac{(n_{t,d}^{-i} + \alpha)}{\sum_{t'=1}^{T}(n_{t',d}^{-i} + \alpha)} \frac{n_{w_i,t}^{-i} + \beta}{\sum_{v'=1}^{V}(n_{v',t}^{-i} + \beta)}, \tag{6.6}$$

where $z_i = t$ represents the assignment of topic t to the i^{th} word (w_i) in document d (i.e., z_i indicates the topic assignment for word w_i), and z^{-i} represents the topic assignments for all words in the corpus except the i^{th} word w_i in d. $n_{t,d}^{-i}$ is the number of times that topic $t$has been assigned to words in document d excluding the i^{th} word w_i . $n_{w_i,t}^{-i}$ is the number of times that word $v = w_i$ has been assigned to topic $t$excluding the current instance w_i . In other words, it is the number of times that topic $t$has been assigned to the vocabulary word $v = w_i$ excluding the current instance w_i of v. Here, v is the corresponding vocabulary word for w_i .

Deriving the preceding sampling equation is quite involved (see the Wikipedia entry for LDA; see also Griffiths and Steyvers, 2004; Steyvers and Griffiths, 2007; Carpenter, 2010). But the final equation is quite intuitive. The equation basically consists of two parts. The left part is the probability that topic t is assigned to the words in document d. The right part is the probability that word w_i is assigned to topic t. From the equation, we can see that the probability of a word in a document being assigned to a topic depends on how dominant the topic is in the document, as well as how likely the word is for the topic in the corpus.

In fact, Equation (6.6) can be further simplified to equation (6.7) because $\sum_{t'=1}^{T}(n_{t',d}^{-i}+\alpha)$ is a constant for all topics.

$$P(z_i = t \mid \mathbf{z}^{-i}, \mathbf{w}) \propto (n_{t,d}^{-i}+\alpha)\frac{n_{w_i,t}^{-i}+\beta}{\sum_{v'=1}^{V}(n_{v',t}^{-i}+\beta)} \tag{6.7}$$

To compute the final probability for each topic, we need to perform normalization.

$$P(z_i = t \mid \mathbf{z}^{-i}, \mathbf{w}) = \frac{(n_{t,d}^{-i}+\alpha)\frac{n_{w_i,t}^{-i}+\beta}{\sum_{v'=1}^{V}(n_{v',t}^{-i}+\beta)}}{\sum_{t'}^{T}(n_{t',d}^{-i}+\alpha)\frac{n_{w_i,t'}^{-i}+\beta}{\sum_{v'=1}^{V}(n_{v',t'}^{-i}+\beta)}} \tag{6.8}$$

The algorithm for Gibbs sampling is given in Figure 6.7, which represents one sweep of the documents in the corpus (Mimno et al. 2011). Note that superscript – *i* is not used for counts because the related counts have been decremented in lines 3 and 4.

1. **for** each document $d \in D$ **do**
2.   **for** each word w_i in document d **do**
3. $n_{z_i,d} \leftarrow n_{z_i,d} - 1$
4. $n_{w_i,z_i} \leftarrow n_{w_i,z_i} - 1$
5.   sample z_i from $P(z_i = t \mid \mathbf{z}^{-i}, \mathbf{w}) \propto (n_{t,d}+\alpha)\frac{n_{w_i,t}+\beta}{\sum_{v'=1}^{V}(n_{v',t}+\beta)}$, for $t \in \{1, \ldots, T\}$
6. $n_{z_i,d} \leftarrow n_{z_i,d} + 1$
7. $n_{w_i,z_i} \leftarrow n_{w_i,z_i} + 1$
8.   **endfor**
9. **endfor**

Figure 6.7. One sweep of Gibbs sampling in LDA.

After a large number of iterations of Gibbs sampling for words in all documents, we obtain the estimated topic distribution for each document, called *document-topic* distribution $\hat{\theta}$, and the word distribution in each topic, called *topic-word* distribution $\hat{\phi}$, using Equations (6.9) and (6.10):

$$\hat{\theta}_{t,d} = \frac{(n_{t,d}+\alpha)}{\sum_{t'=1}^{T}(n_{t',d}^{-i}+\alpha)} \tag{6.9}$$

$$\hat{\phi}_{v,t} = \frac{n_{v,t} + \beta}{\sum_{v'=1}^{V}(n_{v',t} + \beta)}. \tag{6.10}$$

The $\hat{\theta}_{t,d}$ value represents the predictive probability or distribution of sampling topic t in document d, and the $\hat{\phi}_{v,t}$ value represents the predictive probability or distribution of sampling a new instance of vocabulary word v from topic t.

In most applications, the user is interested in $\hat{\phi}_{v,t}$ which gives a list of words (the vocabulary) under each topic t ranked according to their probability values in $\hat{\phi}_{v,t}$. The top-ranked words often give a good indication of the topic label. For example, in a set of reviews, LDA finds the following top-ranked words for a topic: *price*, *money*, *expensive*, *cost*, *cheap*, *purchase*, *deal*. We can see that the topic is about product *price*, and then we can label the topic with *price*.

6.6.2 Using Unsupervised Topic Models

Various topic models, which are mostly extensions of LDA, have been proposed for aspect extraction, joint modeling of both aspects and sentiment words, and joint modeling of aspects and sentiment ratings on the aspects. We discuss each of them in turn.

Titov and McDonald (2008a) first applied LDA and pLSA directly to review corpora for aspect extraction. They showed that global topic models such as LDA is not suitable for detecting aspects because they depend on topic distribution differences and word co-occurrences among documents to identify topics and word probability distribution in each topic. However, opinion documents such as reviews about a particular type of product are quite homogenous, meaning that every document or review basically talks about the same set of aspects of the product. This makes global topic models ineffective for discovering aspects but are effective for discovering entities (e.g., different brands or product names). This means that treating each review as a document for topic modeling is ineffective. The authors then proposed a multigrain topic model. The global model discovers entities while the local model discovers aspects treating a few sentences (or a sliding text window) as a document. Each discovered aspect is a topic (also called a unigram language model, a multinomial distribution over words). Different words expressing the same or related facets are automatically grouped together under the same aspect. This technique does not separate aspects and sentiment words.

Branavan et al. (2008) reported a method that makes use of the aspect descriptions in keyphrases in Pros and Cons of reviews to help find aspects in the detailed review text. Their model consists of two parts. The first part clusters the keyphrases in Pros and Cons into aspect categories based on distributional similarity. The second part builds a topic model modeling the topics or aspects in the review text. Their final topic model models these two parts simultaneously. The two parts are integrated based on the idea that the model biases or constrains the assignment of hidden topics in the review text to be similar to the topics represented by the keyphrases in the Pros and Cons of the review, but it also permits some words in the document to be drawn from other topics not represented by the keyphrases. This flexibility in the coupling allows the model to learn effectively in the presence of incomplete keyphrases, while still encouraging the keyphrase clustering to cohere with the topics supported by the review text. Clearly this approach also does not separate aspects and sentiments. Several other papers on aspect extraction also do not distinguish aspect and sentiment words (Chen et al., 2013a, 2013b). This approach is reasonable because most adjective sentiment words actually describe or modify some aspects of entities (see Section 6.4.2). For example, when we say "*This car is expensive*," we refer to the *price* aspect of the car, and when we say "*This car is beautiful*," we refer to the *appearance* aspect.

Most existing topic models for sentiment analysis are actually joint models that model both aspects and sentiments, although they may not separate the two types of words. Mei et al. (2007) built the first aspect-sentiment mixture model based on an aspect model, a positive sentiment model, and a negative sentiment model learned with the help of some external training data. Their model was based on pLSA. Here we describe two representative joint models in some detail to give a flavor of them. The first model is the aspect and sentiment unification model (ASUM) of Jo and Oh (2011), and the second model is the MaxEnt-LDA model of Zhao et al. (2010). Both these models are extensions of LDA. The main difference between them is that ASUM does not separate aspect words and sentiment words, whereas MaxEnt-LDA does.

The ASUM model produces a set of sentiment-aspect topics. Each topic consists of a mixture of sentiment words of a particular polarity or orientation (positive or negative) and aspect words of a particular aspect for the sentiment polarity. In other words, it is a multinomial distribution over both aspect and sentiment words. ASUM achieved this by constraining the words in a sentence to come from one topic. Aspect words and sentiment words are not explicitly separated under each topic. We will see this in the graphical model and the generative process of ASUM.

Let the number of aspects be T. The aspects or topics are indexed by $\{1, \ldots, T\}$. Let the number of documents in the corpus be D. Each document $d$consists of S sentences. Each sentence s in d consists of N words. Let the number of sentiment or opinion orientations be O (positive and negative). The model has five latent variables, θ, φ, π, z, and o. Their meanings will be explained in the generative process. There are also the usual hyperparameters, α, β, and γ. The graphical representation of ASUM in plate notation is given in Figure 6.8.

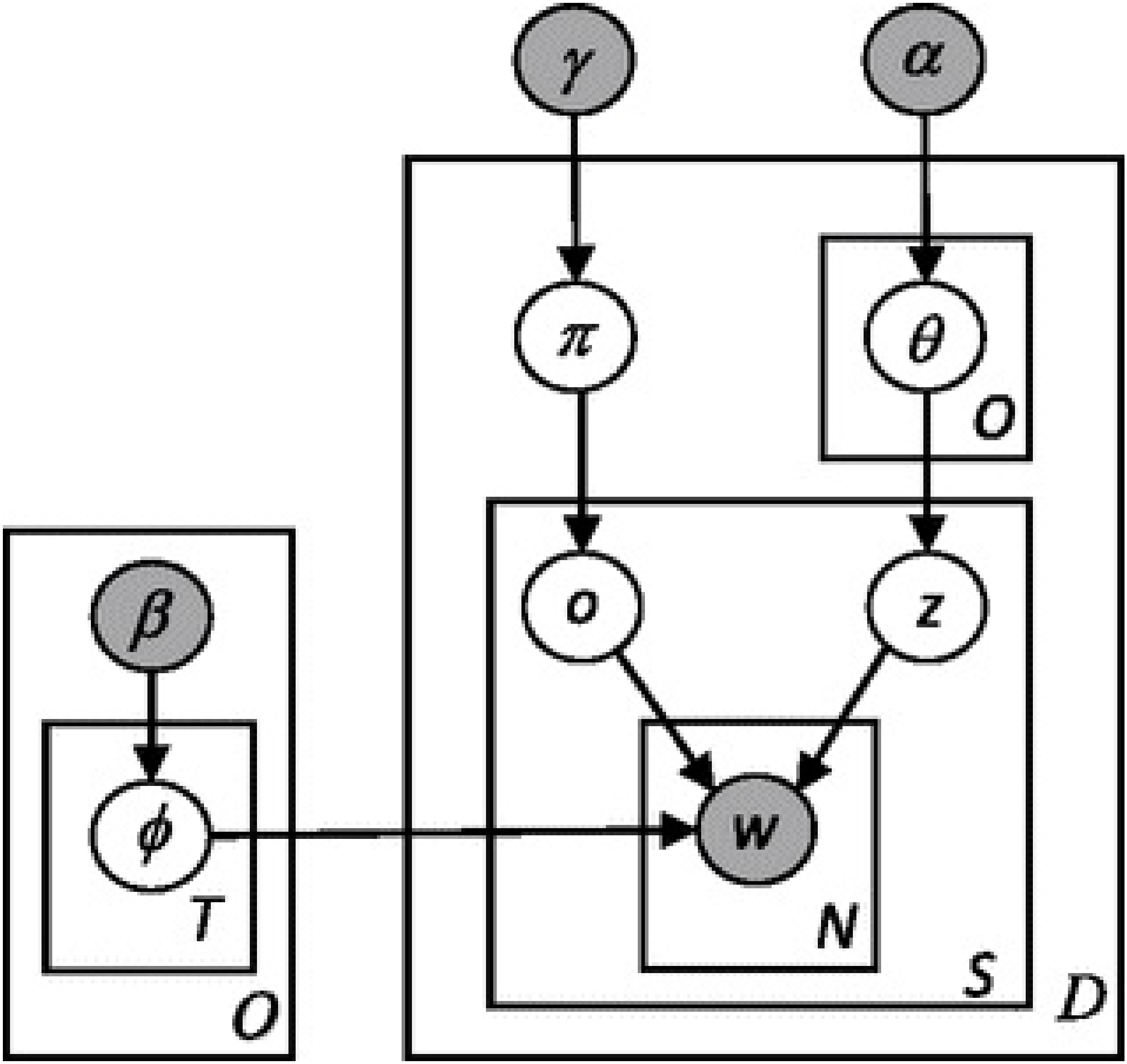


Figure 6.8. The plate notation of ASUM.

The generative process of ASUM is as follows:

for every pair of sentiment $o \in \{1,\ldots, O\}$ and aspect $z \in \{1,\ldots, T\}$ **do**

Draw a word distribution $\varphi_{o,z} \sim Dirichlet(\beta_o)$

for each document $d \in \{1,\ldots, D\}$ **do**

Draw the document d 's sentiment distribution $\pi_d \sim Dirichlet(\gamma)$

for each sentiment o **do**

Draw an aspect distribution $\theta_{d,o} \sim Dirichlet(\alpha)$

for each sentence $s \in \{1,\ldots, S\}$ **do**

Choose a sentiment $j \sim Multinomial(\pi_d)$

Given sentiment j, choose an aspect $t \sim Multinomial(\theta_{d,j})$

for each w_i, $i \in \{1,\ldots, N\}$ **do**

Generate word $w_i \sim Multinomial(\varphi_{j,t})$

To separate positive and negative sentiment polarities, ASUM exploits some prior sentiment words and uses an asymmetric β. For example, we expect that the words *good* and *great* are not likely to be in negative expressions, and similarly the words *bad* and *annoying* are not likely to be in positive expressions. A set of given general seed postive and negative words is used to set β. In detail, the seed words are encoded into β for each sentiment such that the elements of β corresponding to the general positive sentiment words have small values for negative senti-aspects, and the general negative sentiment words have small values for positive senti-aspects. The seed sentiment words are not aspect specific. Such aspect specific sentiment words should be discovered. In inference, the asymmetric setting of β leads the words that co-occur with the general sentiment words to be more probable in the corresponding senti-aspects. Symmetric β, which is commonly used in most other models, does not utilize this prior knowledge. The Gibbs sampling equation can be found in the original paper.

We now turn to the MaxEnt-LDA model, which is a hybrid of maximum entropy (MaxEnt) and LDA (Zhao et al., 2010). It jointly discovers both aspect words and aspect-specific opinion words leveraging word context features to help separate aspect words and opinion (or sentiment) words. Again, the key difference between MaxEnt-LDA and ASUM is that MaxEnt-LDA explicitly separates aspect words and opinion words, while ASUM does not do. However, MaxEnt-LDA does not separate positive and negative sentiment orientations or polarities, as ASUM does. Aspect and opinion word separation in MaxEnt-LDA is achieved through an *indicator variable* (also called a *switch variable*) drawn from a multinomial distribution governed by a set of parameters. This indicator variable determines whether a word in a sentence is an aspect word, an opinion word, or a background word. It uses MaxEnt on some labeled training data to learn the parameters of the distribution from which the indicator variable's value is drawn. A second indicator variable is also used to determine general and specific types of aspect or opinion. Thus MaxEnt-LDA represents a rather fine-grained model. For example, in a restaurant review, each word in a sentence s of the review can be one of the few types. The word may be a specific aspect word (e.g., *waiter* for the *staff* aspect), a general aspect word (e.g., *restaurant*), an opinion word specific to the aspect (e.g., *friendly*), a generic opinion word (e.g., *great*), or a commonly used background word (e.g., *know*).

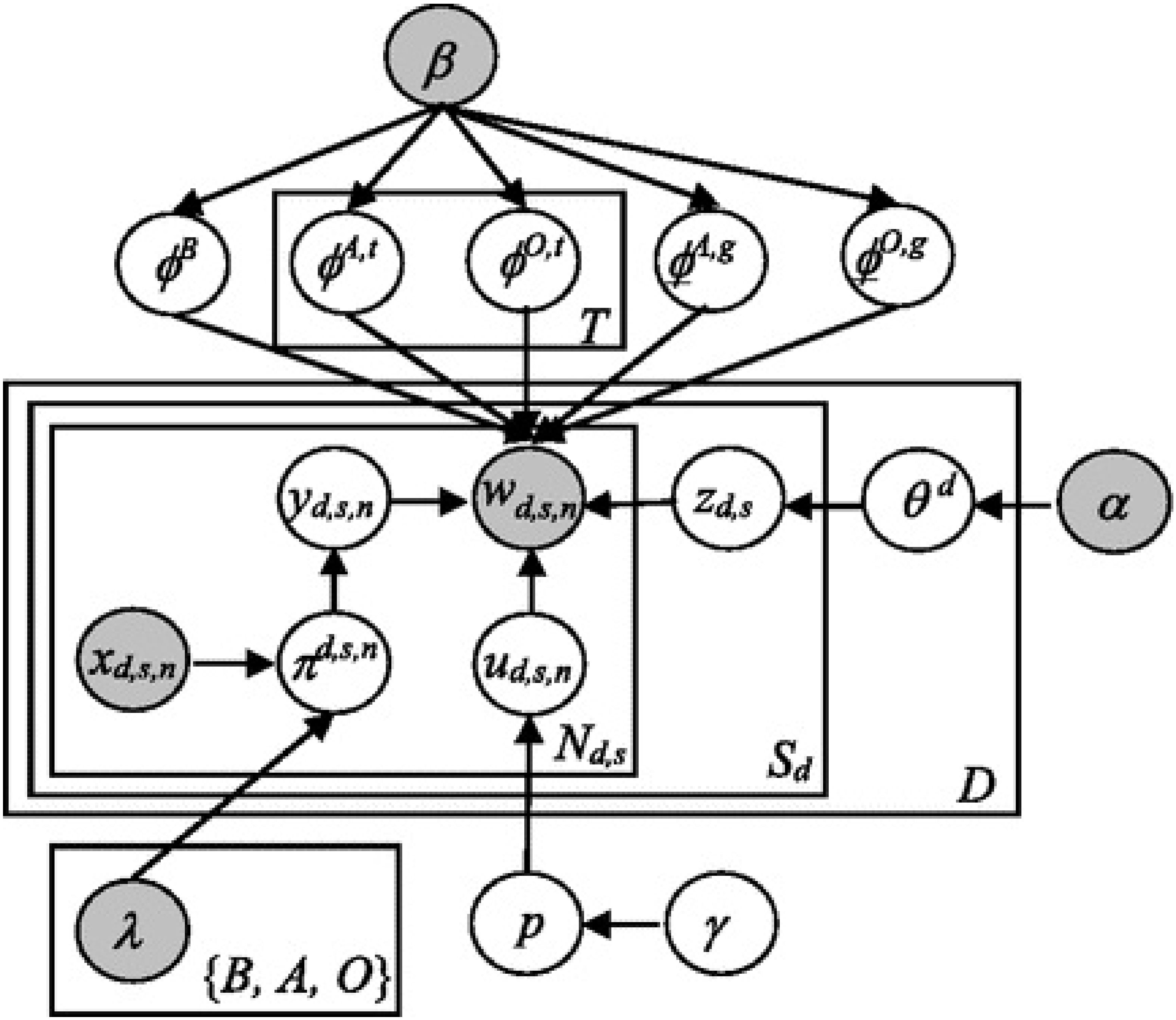


Figure 6.9. The plate notation of MaxEnt-LDA.

The graphical representation of MaxEnt-LDA in plate notation is given in Figure 6.9. Subscripts and superscripts are used here in the plates to explicitly indicate the nested structure and different kinds of distributions. The generative process of MaxEnt-LDA is as follows:

Draw a background word distribution $\phi^B \sim Dirichlet(\beta)$

Draw a general aspect word distribution $\phi^{A,g} \sim Dirichlet(\beta)$

Draw a general opinion word distribution $\phi^{O,g} \sim Dirichlet(\beta)$

Draw a specific (0) and generic (1) type distribution $p \sim Beta(\gamma)$

for each aspect $t \in \{1,\ldots, T\}$ **do**

Draw an aspect word distribution for aspect t, $\phi^{A,t} \sim Dirichlet(\beta)$

Draw an aspect-specific opinion word distribution for aspect t, $\phi^{O,t} \sim Dirichlet(\beta)$

for each document $d \in \{1,\ldots, D\}$ **do**

Draw an aspect distribution for document d, $\theta^d \sim Dirichlet(\alpha)$

for each sentence $s \in \{1,\ldots, S_d\}$ **do**

Draw an aspect assignment $z_{d,s} \sim Multinomial(\theta^d)$

for each word $w_{d,s,n}$ in sentence s, $n \in \{1,\ldots, N_{d,s}\}$ **do**

Set background (0), aspect (1) and opinion (2) type distribution $\pi_{d,s,n}$

$\leftarrow$ MaxEnt($x_{d,s,n}$, λ)

Draw an assignment for indicator $y_{d,s,n} \sim Multinomial(\pi_{d,s,n})$

Draw an assignment for indicator $u_{d,s,n} \sim Bernoulli(p)$

$$\text{Draw } w_{d,s,n} \sim \begin{cases} Multinomial(\phi^{B}) & if\ y_{d,s,n} = 0 \\ Multinomial(\phi^{A,z_{d,s}}) & if\ y_{d,s,n} = 1,\ u_{d,s,n} = 0 \\ Multinomial(\phi^{A,g}) & if\ y_{d,s,n} = 1,\ u_{d,s,n} = 1 \\ Multinomial(\phi^{O,z_{d,s}}) & if\ y_{d,s,n} = 2,\ u_{d,s,n} = 0 \\ Multinomial(\phi^{O,g}) & if\ y_{d,s,n} = 2,\ u_{d,s,n} = 1 \end{cases}$$

The distribution $\pi_{a,s,n}$ needs additional explanation. It is produced by a MaxEnt classifier. The training data consist of a set of sentences with labeled background words, opinion words, and aspect words in the sentences. The classifier is built based on the observation that aspect words and opinion words usually play different syntactic roles in a sentence. Aspect words tend to be nouns, whereas opinion words tend to be adjectives, although words of other parts of speech can serve as sentiment words as well, for example, *hate* and *dislike*. The feature vector, represented by $x_{d,s,n}$, can be any arbitrary clues extracted from the sentence contexts of these words. Zhao et al. (2010) used two types of features: (1) lexical features, which include the previous, the current, and the next words $\{w_{d,s,n-1}, w_{d,s,n}, w_{d,s,n+1}\}$, and (2) POS tag features, which include the previous, the current, and the next POS tags $\{POS_{d,s,n-1}, POS_{d,s,n}, POS_{d,s,n+1}\}$. λ_l are the model weights for l = 0, 1, 2, which represent background, aspect, and sentiment classes, respectively. The detailed Gibbs sampling equations for inference can be found in Zhao et al. (2010).

Apart from ASUM and MaxEnt-LDA, there are many other aspect-sentiment joint models. For example, a joint aspect-sentiment model similar to that of ASUM was proposed in Lin and He (2009). It also does not separate aspect words and sentiment words. Brody and Elhadad (2010) identified aspects by using topic models and then identified aspect-specific sentiment words by considering only adjectives. Li et al. (2010) proposed Sentiment-LDA and Dependency-Sentiment-LDA models to find aspects with positive and negative sentiments. It does not find aspects independently and also does not separate aspect words and sentiment words. Lazaridou et al. (2013) improved the model in Lin and He (2009) by considering four discourse relations, which enables the model to handle sentiment or aspect changes in the same sentence due to contrast indicated by *but*. Sauper et al. (2011) worked on short snippets extracted from reviews, for example, "*battery life is the best I've found.*" It combines topic modeling with a HMM, where the HMM models the sequence of words with types (aspect word, sentiment word, or background word). Their model is related to HMM-LDA proposed in Griffiths et al. (2005), which models the word sequence as well. Variations of the joint topic modeling approach were also taken in Liu et al. (2007) and Lu and Zhai (2008).

Another line of work that uses topic modeling for sentiment analysis aims to associate aspects with opinion/sentiment ratings, that is, to predict aspect ratings based on joint modeling of aspects and ratings. Titov and McDonald (2008) proposed a model that discovers aspects from reviews and also extracts textual evidence supporting each aspect rating. Lu et al. (2009) defined the problem of rated aspect summarization of short comments from eBay.com. Their aspect extraction is based on a topic model called structured pLSA, which can model the dependency structure of phrases in short comments. To predict the rating for each aspect in a comment, it combines the overall rating of the comment and the classification result of a learned classifier for the aspect based on all the comments. Wang et al. (2010) reported a probabilistic rating regression model to assign ratings to aspects. Their method first uses some given seed aspects to find more aspect words using a heuristic bootstrapping technique. It then predicts aspect ratings using the proposed probabilistic rating regression model, which is also a graphical model. The model makes use of review ratings and assumes that the overall rating of a review is a linear combination of its aspect ratings. The model parameters are estimated using the maximum likelihood estimator and an EM style algorithm.

A series of joint models were also proposed in Lakkaraju et al. (2011) based on the composite topic model of HMM-LDA in Griffiths et al. (2005), which considers both word sequence and word-bag. The models thus can capture both syntactic structures and semantic dependencies similar to that in Sauper et al. (2011). They are able to discover latent aspects and their corresponding sentiment ratings. Moghaddam and Ester (2011) reported a joint topic model for finding and group aspects and deriving their ratings as well.

6.6.3 Using Prior Domain Knowledge in Modeling

Although topic modeling is a principled approach based on probabilistic inferencing and can be extended to model many types of information using joint models, it does have some weaknesses that limit its practical use in sentiment analysis applications. One main issue is that it needs a large volume of data and a significant amount of tuning to achieve reasonable results. Owing to this large data requirement, one often has to collect opinion documents for many entities of the same category. For example, one may be interested in opinions about a particular hotel, but that hotel may not have thousands of reviews needed for effective topic modeling. One has to supplement it with reviews from a large number of other hotels. With the large data, it is not hard for topic modeling to find very general and frequent topics or aspects. However, it becomes very difficult to find locally frequent but globally infrequent aspects, for example, those specific aspects of the hotel that the user is really interested in, because every hotel is different. Such locally frequent aspects are often most useful because they tell the user specific pros and cons of the particular hotel. General and frequent aspects can also be easily found by the non-topic modeling based methods discussed in earlier sections, and those methods may also find less frequent aspects without the need of a large amount of data. In short, the results from the current topic models are usually not granular or specific enough for most practical sentiment analysis applications. They are more useful for users to get some high-level ideas about what a document collection is about.

That being said, topic modeling is still a powerful and flexible tool with a great potential if it is improved. Continued research will make it more useful in practice. One promising research direction is *knowledge-based topic modeling* (*KBTM*), also known as *semi-supervised topic modeling*, KBTM can incorporate existing natural language and prior domain knowledge in modeling to guide the model inference to generate better topics without the need of large volumes of data. Some initial work has been done in this direction (Andrzejewski and Zhu, 2009; Andrzejewski et al., 2009; Zhai et al., 2011; Mukherjee and Liu, 2012; Chen et al., 2013a, 2013b). DF-LDA (Andrzejewski et al., 2009), which is not specific to aspect extraction, is perhaps the first model that can incorporate prior domain knowledge in modeling. The knowledge is in the form of *must-links* and *cannot-links*. A must-link states that two words should belong to the same topic whereas a cannot-link indicates that two words should not be in the same topic. In Andrzejewski et al. (2011), more general knowledge in the form of first-order logic was used. Seeded models were proposed in Lu et al. (2011), Burns et al. (2012), Jagarlamudi et al. (2012), and Mukherjee and Liu (2012), which allow the user to specify some prior seed terms for some topics. Petterson et al. (2010) also used word similarity as priors. However, these knowledge-based models have three major shortcomings:

Inability to handle multiple senses. A word typically has multiple meanings or senses. For example, *light* can mean “of little weight” or “something that makes things visible.” DF-LDA (Andrzejewski et al., 2009) cannot handle multiple senses because its definition of must-link is transitive. That is, if A and B form a must-link, and B and C form a must-link, it implies a must-link between A and C, indicating A, B, and C should be in the same topic. For example, the word *light* can have two must-links indicating two distinct senses: {light, heavy} and {light, bright}. Transitivity will force words *heavy* and *bright* to belong to the same topic, which is wrong. This case also applies to the models in Petterson et al. (2010), Andrzejewski et al. (2011), and Mukherjee and Liu (2012). Although the model in Jagarlamudi et al. (2012) allows multiple senses, it requires that each topic has at most one seed set, which is restrictive as the amount of knowledge should not be limited.

Sensitivity to the adverse effect of knowledge. When using must-links or seed sets, these models basically try to ensure that the words in a must-link or a seed set to have similar probabilities under a topic. This causes a serious problem. If a must-link comprises of a frequent word and an infrequent word, the probability of the frequent word under a topic will decrease while the probability of the infrequent word will increase due to the redistribution of the probability mass. This harms the final topics/aspects because the attenuation of the frequent (often domain important) words may result in some irrelevant words being ranked higher (with higher probabilities) (Chen et al. 2013d).

Inability to create additional topics when needed. This issue is caused by cannot-links. There are two types of cannot-links: consistent or inconsistent with the corpus domain. For example, in the reviews of domain “Computer,” a topic model may generate two topics *Battery* and *Screen* that represent two different aspects. A cannot-link {battery, screen} is thus consistent with the corpus. However, the words *Amazon* and *Price* may appear in the same topic due to their high co-occurrences in the review corpus. To separate them, a cannot-link {amazon, price} can be added, which, however, is inconsistent with the corpus. In this case, the number of topics needs to be *increased* by 1 because the mixed topic needs to be split into two individual topics *Amazon* and *Price*. In almost all existing KBTM models, the number of topics is specified by the user and cannot be changed in the modeling process.

To address these shortcomings, Chen et al. (2013b) first defined *m-set* (*must-set*) as a set of words that should belong to the same topic and *c-set* (*cannot-set*) as a set of words that should not be in the same topic. They are similar to must-link and cannot-link, respectively, but m-sets do not enforce transitivity (which causes the first shortcoming). M-sets and c-sets are also more expressive in providing knowledge in the context of a set rather than just a link pair. They then proposed the topic model *MC-LDA* (LDA with M-set and C-set). MC-LDA adds a new latent variable *s* in LDA to distinguish multiple senses. Then, deviating from the standard topic modeling approaches (which is based on a simple Pólya urn sampling scheme), the *generalized Pólya urn* (GPU) model (Mahmoud, 2008) was used to address the second shortcoming of adverse effect of knowledge. However, these extensions are unable to deal with c-sets, for which an *Extended GPU* (E-GPU) model was proposed. E-GPU extends the GPU model to enable multi-urn interactions, which is necessary for handling c-sets and for adjusting the number of topics.

Requiring prior domain knowledge from the user can be quite demanding because the user has to know the domain very well. Even if she knows the domain well, she may not be able to provide knowledge suitable for topic models. Chen et al. (2013a) thus proposed to exploit domain-independent general knowledge from dictionaries. Specifically, they used one form of general knowledge, the lexical semantic relations of words such as synonym, antonym, and adjective-attribute relations, to help produce more coherent topics. Using such general knowledge, however, causes a difficulty for topic models. That is, a word can have multiple meanings/senses, each with a different set of synonyms and antonyms. However, not every meaning or sense is suitable or correct for a particular domain. Wrong knowledge can result in poor quality resulting topics. To deal with the problem, a new model, called GK-LDA, was proposed to try to identify wrong knowledge during modeling (Chen et al., 2013a).

6.6.4 Lifelong Topic Models: Learn as Humans Do

Although knowledge-based topic modeling (KBTM) can achieve better results, acquiring user knowledge is not always easy because the user may not know the domain well or may be unwilling to provide any knowledge because he wants the system to discover knowledge for him. General knowledge such as lexical semantic relations in dictionaries can help to some extent, but it often has too many errors owing to multiple word senses and not being application specific. Lifelong topic modeling, proposed in Chen and Liu. (2014a), aims to mine prior knowledge automatically from the results of past modeling without the need for the user to input any prior domain knowledge. This approach works like human learning. Here we use the term *learning* as topic modeling is an unsupervised learning method. We humans always retain the results learned in the past and use them to help future learning. In machine learning, this paradigm is called *lifelong learning*. In our case, we also call it *lifelong topic modeling* because we use topic models. The approach represents an important step forward because it closes the modeling loop in the sense that the whole KBTM process is made fully automatic.

Lifelong learning for topic modeling assumes that the system performs topic modeling continuously in different task domains. After each modeling task is completed, it stores all the resulting topics in a *topic base*. In performing the next or new modeling task in a particular domain, the system finds some prior knowledge from the topic base to help the new modeling. The reason that we can find useful prior knowledge from the topic base is because although every task domain is different, there is a decent amount of concept or aspect overlapping across domains (Chen et al., 2014). For example, every product review domain has the aspect or topic *price*, reviews of most electronic products also share the aspect of *battery* and reviews of some products share the aspect of *screen*. Aspects produced from a single domain can be erroneous (i.e., an aspect or topic may contain some irrelevant words in its top-ranked positions), but if we can find a set of shared words among some aspects or topics generated from multiple domains, these shared words are more likely to be correct or coherent for a particular aspect or topic. They can serve as a piece of prior knowledge to be used to improve topic modeling in the new domain, which is also called the *target domain*.

For example, we have product reviews from three domains. We run LDA to generate a set of topics from each domain. Every domain has a topic about *price*, which is listed as follows with its top four words (words are ranked based on their probabilities under each topic):

Domain 1: price, color, cost, life

Domain 2: cost, picture, price, expensive

Domain 3: price, money, customer, expensive

These topics are clearly not perfect due to the incoherent words, *color*, *life*, *picture*, and *customer*. However, if we want those topical words that appear together at least in two topics from two different domains, we can find the following two sets:

{*price*, *cost*} and {*price*, *expensive*}.

The words in each set are likely to belong to the same topic. Then, {*price*, *cost*} and {*price*, *expensive*} can serve as *prior knowledge* or *must-links* for a knowledge-based topic model to help improve the output topics for each of the three domains or a new domain. For example, after running a knowledge-based model on the reviews of Domain 1, we may find the new topic: {*price*, *cost*, *expensive*, *color*}, which has three coherent words in the top four positions rather than only two words as in the original topic. This represents a good topic improvement (although there is still an incoherent word *color* in it, it may be pushed down if there is more discovered prior knowledge). Note that here, Domain 1 also serves as the target domain, but the target domain can also be a completely new domain.

The preceding discussion indicates that lifelong topic modeling needs document collections from a large number of domains to mine topics from each of them and put them into a *topic base*. We then use the topics in the topic base to discover reliable must-links and cannot-links to be used to help improve topic modeling in the current new or test domain. The resulting topics are added to the topic base for future use. The lifelong topic modeling methods in Chen and Liu (2014a, 2014b) took a two-phase approach:

> **Phase 1 (*Initialization*).** Given *n* prior document collections $D = \{D_1, \ldots, D_n\}$, we first run a topic model (e.g., LDA) on each collection $D_i \in D$ to produce a set of topics S_i. Let $S = \bigcup S_i$, which we call the *topic base* with all *prior topics* (or *p-topics* for short). This phase is only needed for initialization. In subsequent modeling, it will not be used.

> **Phase 2 (*Lifelong topic modeling*).** Given in a new document collection D^t, we first mine some prior knowledge *K* from all p-topics in topic base *S*. We then run a knowledge-based topic

> model (KBTM) guided by the prior knowledge *K* to generate a set of topics A^t for the new collection D^t. To enable lifelong modeling or learning, the resulting topics A^t are also incorporated or added into *S*. Thus, *S*becomes bigger and bigger.

Phase 1 is very simple as it just runs a topic model on each domain corpus $D_i \in D$. We will not discuss it further. Here we elaborate on the two substeps of phrase 2.

Step 1: Mining quality knowledge from all p-topics ***S*****.** Without quality knowledge to guide the modeling process, we will not obtain quality aspects. As stated earlier, knowledge from only a single domain can be erroneous. However, if the knowledge is shared by multiple domains, it is more likely to be of high quality. In Chen et al. (2014), the authors proposed to use a clustering method to cluster p-topics (topics in the topic base) and then use the topics in each cluster to find sets of shared topical words. Each set of words, which is a must-set, serves as a piece of prior knowledge to be used to guide the modeling to extract aspects in the target domain. In their experiments, they used reviews from thirty-six types of products or domains and showed promising results. In Chen and Liu (2014a), a more effective method was proposed, which embeds Step 1 in Step 2 to mine more targeted knowledge. We discuss this method in Step 2. In this case, the authors used reviews from fifty domains in their experiments and showed that the new method produced superior results.

Step 2: Modeling guided by mined knowledge. For reliable aspect extraction or modeling using the mined prior knowledge, possible errors in the knowledge need to be dealt with. In particular, a piece of automatically mined knowledge may be wrong or domain specific (i.e., the words in a piece of knowledge, e.g., a must-link, are semantically coherent in some domains but not in others). In leveraging such knowledge in a new aspect extraction process, the system must detect those inappropriate pieces of knowledge; otherwise, the discovered aspects will be incoherent. Chen et al. (2014) proposed a new topic model, called AKL (Automated Knowledge LDA), which can exploit the automatically learned prior knowledge and also deal with the issue of incorrect knowledge to produce superior topics/aspects.

In Chen and Liu (2014a), a more effective model called lifelong topic modeling (LTM) was proposed without the need of clustering in Step 1 because setting the right number of clusters is very difficult. As mentioned earlier, LTM embeds Step 1 inside Step 2 to find more targeted knowledge. Specifically, the algorithm first runs a KBTM on the test document collection D^t without any knowledge (which is equivalent to LDA) until its topics (A^t) stabilize. To distinguish these topics from p-topics (topics in the topic base), these topics are called the *current topics* (or *c-topics* for short). For each c-topic $a_j \in A^t$, the algorithm finds a set of matching or similar p-topics M_j^t of a_j in *S*(topic base, the set of all p-topics). It then mines M_j^t to generate a set of prior knowledge sets K_j^t or must-links, for c-topic a_j specificially. After that, it continues the execution of the KBTM on D^t, which is now guided by the must-links in K^t (which is the union of all K_j^t), to generate better c-topics (Chen and Liu, 2014a). The intuition of this method is as follows: After running a model on D^t with no knowledge, we obtain its initial topics A^t. To improve each topic $a_j \in A^t$, we find only those p-topics M_j^t in all p-topics *S*that are similar to a_j. We then mine must-links from M_j^t for topic a_j. These must-links are thus targeted and should be of high quality for topic a_j. In Chen and Liu (2014b), a technique is also proposed to mine cannot-links, which enable a KBTM to produce even better results, especially when the test document collection is small. These two techniques are quite involved. Interested readers should refer to the corresponding papers, which include mechanisms for handling wrong knowledge and multiple senses of words.

Lifelong learning or modeling is quite suitable for aspect extraction because there is a great deal of aspect sharing among different entities and such sharing can be exploited to produce better aspects from a review corpus. To end this subsection, I would like to make a few remarks about lifelong learning.

1. The key to lifelong modeling is to find quality knowledge from past modeling results and to recognize possible wrong knowledge. Without these capabilities, a lifelong topic model will not produce good results.

2. Although related, lifelong learning here is different from traditional transfer learning or domain adaptation because in transfer learning, knowledge from a single source domain is used to help learning in a target domain. This has at least two shortcomings. First, it is very hard to obtain high-quality knowledge from only a single source domain as we have seen from some example topics. Second, a single source domain may not have many shared concepts or topics with the target domain. Usually, it is the user who has to find a very similar source domain for the target domain to enable effective transfer learning. These weaknesses make transfer learning hard to apply to real-life applications. In contrast, the lifelong learning approaches in Chen and Liu (2014a, 2014b) exploit a large number of source domains to deal with the two problems. They can find high-quality prior knowledge from any source domain that is relevant or useful to the target/new domain.

3. In general, NLP tasks seem to be ideal for lifelong learning or modeling because a word appearing in different domains or contexts often has the same meaning and represents the same concept. Without such shared concepts, lifelong learning or modeling will not be possible. Lifelong topic modeling techniques basically transfer concepts across domains. Although a word can have multiple senses, such senses can be recognized (Chen and Liu, 2014a, 2014b).

6.6.5 Using Phrases as Topical Terms

Most current topic models are based on individual words, but many aspect expressions in real-life applications are multiword phrases, for example, *hotel staff*. If *hotel* and *staff* are treated as two separate words, *staff* is still fine, but *hotel* and '*hotel staff*' have very different meanings and should belong to different aspects. If *hotel* and *staff* are put in the same topic, it is not appropriate. But if *hotel* and *staff* are put in two separate topics, it is a problem too because when the system sees '*hotel staff*,' the system may treat them as two separate aspects.

One way to consider phrases in topic models is to use n-grams. However, using n-grams makes the space highly sparse, which can result in poor clustering or topic formation. By sparse we mean two things. First, because a phrase can consist of any number of words, we may need 1–4 – grams, which give a huge number of terms. Second, each 2-, 3-, or 4-gram is much less frequent than each individual word, which makes it difficult to connect terms and find their semantic relations in topic modeling. In other words, due to the sparsity the higher-level co-occurrences, which is what topic models are based on (Heinrich, 2009), are adversely affected, which in turn can produce poor topics. Higher-order co-occurrences of terms mean how often they co-occur in different contexts. For example, w_1 co-occurring with w_2 which in turn co-occurs with w_3 denotes a second-order co-occurrence between w_1 and w_3. Although there are topic models which model bigram orders (Wallach, 2006), such models are hard to scale to arbitrary n-grams because all possible ordering sequences of n-grams need to be sampled in inferencing. There are also approaches that use statistical correlation of unigram topics to form multiword phrases (Blei and Lafferty, 2009; Andrzejewski and Buttler, 2011; Zhao et al., 2011). Statistical correlation, however, does not necessarily guarantee to generate semantically coherent phrases.

Here we describe two approaches which find phrases first and then run two special topic models, respectively. The first model is the Constrained-LDA model in Zhai et al. (2011), and the second model is the LDA(p_GPU) model based on the *generalized Pólya urn* (*GPU*) model (Fei et al., 2014). To find phrases in the first step, we can use a chunking or shallow parsing tool, or we can even use an existing aspect extraction method, for example, CRF (Jakob and Gurevych, 2010), which is a supervised method, or DP (Qiu et al., 2011), which is an unsupervised method. They all can find phrases as aspect expressions, but they do not perform aspect grouping or clustering as we discussed earlier. However, the resulting phrases are usually too sparse for effective modeling.

To deal with the sparsity problem, Constrained-LDA introduces a bias to guide the inference process (e.g., using an approximate Gibbs distribution) so that a term's topic assignment is focused on topics with similar terms to this term. Here a *term* means a word and phrase. The intuition is that similar terms should be assigned to similar topics. The sparsity problem is solved with similarity because similarity in effect increases the co-occurrence space or frequency of similar terms.

Many similarity functions can be used in this context. For example, one function is the sharing of words, that is, two expressions are similar if they share some words, for example, *picture* and *picture quality*. More generally, if two terms have synonymous words, they are more likely to be similar, for example, *picture* and *photo quality*. In the topic updating process of the Gibbs sampling, we can consider similarity relationships and assign similar terms to similar topics based on their similarity value. There are multiple ways to do this. One way is to intervene the Gibbs sampler so that when it updates the topic assignment for each term in a document, the system alters the conditional probability so that it focuses the term on some specific or similar topics. The original Gibbs sampler for LDA is

$$P(z_i = t \mid z^{-i}, w) \propto \left(n_{t,d}^{-i} + \alpha\right) \frac{n_{w_i,t}^{-i} + \beta}{\sum_{v'=1}^{V}(n_{v',t}^{-i} + \beta)}, \tag{6.11}$$

where $z_i = t$ represents the assignment of topic $t \in \{1,\ldots, T\}$ to the ith word (w_i) in document d (i.e., z_i indicates the topic assignment for word w_i), and z^{-i} represents topic assignments for all words in the corpus except the ith word w_i in d. $w$is the bag of all observed words in the corpus; $n_{t,d}^{-i}$ is the number of times that topic $t$has been assigned to words in document $d$excluding the ith word w_i. $n_{w_i,t}^{-i}$ is the number of times that vocabulary word $v = w_i$ has been assigned to topic $t$excluding the current instance w_i of v. Here v is the corresponding vocabulary word for w_i. T is the number of topics (which is an input parameter specified by the user), and V is the vocabulary size of the corpus. Variables $\alpha$and $\beta$are the hyperparameters for the document-topic and topic-word Dirichlet distributions, respectively.

To guide topic assignment in LDA by allowing similarity functions to be encoded, we augment Equation (6.11) with a bias function. That is, if a term w_i is assigned to a particular topic t, then another term that is similar to w_i should be given a high probability of belonging to the topic t. To achieve this in topic updating, a bias function $f(z_i = t)$ is multiplied to the probability calculated by the original Gibbs sampler (Equation (6.11)) to produce the final probability for topic updating. This gives Equation (6.12):

$$P(z_i = t \mid \mathbf{z}^{-i}, \mathbf{w}) \propto f(z_i = t)\left(n_{t,d}^{-i} + \alpha\right) \frac{n_{w_i,t}^{-i} + \beta}{\sum_{v'=1}^{V}\left(n_{v',t}^{-i} + \beta\right)}; \tag{6.12}$$

$f(z_i = t)$ can be seen as encoding some pre-existing knowledge or constraints in the model. The computation of this bias function depends on the types of similarities. This augmented topic model is called *Constrained-LDA* (Zhai et al., 2011), which models similarity with must-links and cannot-links. Recall that a must-link constraint means that two terms should belong to the same topic, while a cannot-link constraint means that two terms cannot belong to the same topic. $f(z_i = t)$ is computed as follows: For a term w_i, if w_i is not constrained by any must-links or cannot-links, $f(z_i = t) = 1$; otherwise, $f(z_i = t)$ is calculated in four (4) steps:

> **Step 1.** Computing must-topics' and cannot-topics' weights for w_i. Here must-topics mean the topics to which the term w_i should be assigned, while cannot-topics mean the topics to which the term w_i should not be assigned. For a given term w_i, its *must-linked terms* and *cannot-linked terms* are first found by querying must-links and cannot-links stores, which are the sets of other terms in the must-links and cannot-links that contain w_i respectively. Second, the topics of these terms are obtained from the current topic models. Then, w_i's must-topics and cannot-topics weights are calculated.
>
> For example, w_i's must-linked (and respectively cannot-linked) *terms* that the sampler has assigned to topic t thus far are M_1 and M_2 (and C_1, C_2, and C_3). So, for topic t, w_i's must-topics' and cannot-topics' weights are $m\_weight_t(w_i) = |\{M_1, M_2\}| = 2$ and $c\_weight_t(w_i) = |\{C_1, C_2, C_3\}| = 3$ respectively. Here, $m\_weight_t(w_i)$ or $c\_weight_t(w_i)$ is interpreted as the weight that w_i should or should not be assigned to topic t.

> **Step 2.** Adjust the relative influences between the must-link category and the cannot-link category. In extracting the two types of constraints (see later), the qualities of must-links and cannot-links may be different from each other. A damping factor λ is used to adjust the relative influences based on the constraint qualities. Specifically, all the must-topics' weights are multiplied by λ, while the cannot-topics' weights are multiplied by $(1- \lambda)$. Following the example in step 1, $m\_weight_t(w_i)$ is adjusted to 2λ while $c\_weight_t(w_i)$ is adjusted to $3(1-\lambda)$. In (Zhai et al., 2011), the default value for λ was empirically set to 0.3.
>
> On the basis of the results of these two steps, Steps 3 and 4 convert the *weights* of must-topics and cannot-topics to biases $f(z_i = t)$, $t = 1, \ldots, T$.

Step 3. Aggregate the weights for each candidate topic. For the given term w_i, its candidate topics can fall into one of the three types, must-topics, unconstrained topics and cannot-topics. Must-topics are the topics that w_i should be assigned to, while cannot-topics are the topics that w_i should not be assigned to. Thus, if t is in must-topics, we add $m\_weight_k(w_i)$ to $f(z_i = k)$ to increase the probability that w_i is assigned to topic t. If t is in cannot-topics, $c\_weight_k(w_i)$ is subtracted from $f(z_i = t)$ to decrease the probability that w_i will be assigned to topic t. In the preceding example, for the candidate topic t, the value for $f(z_i = t)$ is: $c\_weight_t(w_i) - m\_weight_t(w_i) = 2\lambda - 3(1-\lambda) = 5\lambda - 3$.

Step 4. Normalize and relax the weight of each candidate topic. Because the constraints are not guaranteed to be correct especially when the constraints are extracted automatically (see later), there should be a parameter to adjust the constraint's strength according to the quality of the constraints. If the constraints are completely correct, the model should treat these constraints as hard-constraints. If the constraints are all wrong, the model should discard them. To achieve this aim, $\{f(z_i = t) \mid t = 1,\ldots, T\}$ are adjusted by the relaxation factor ηusing the following procedure:

First, before being relaxed, $\{f(z_i = t) \mid t = 1,\ldots, T\}$ are normalized to [0, 1] using Equation (6.13). In Equation (6.13), max and min represent the maximum and minimum values of $\{f(z_i = t) \mid t = 1,\ldots, T\}$, respectively:

$$f(z_i = t) = \frac{f(z_i = t) - \min}{\max - \min}. \tag{6.13}$$

Then, $\{f(z_i = t) \mid t = 1,\ldots, T\}$ are relaxed by the relaxation factor ηbased on Equation (6.14). The default value of ηis set to 0.9 in (Zhai et al., 2011):

$$f(z_i = t) = f(z_i = t) \times \eta + (1 - \eta). \tag{6.14}$$

Extracting constraints. In Zhai et al. (2011), must-link and cannot-link constraints are automatically extracted based on two observations.

Observation 1: Two noun phrases (or terms) w_i and w_j that share one or more words are likely to belong to the same topic, for example, *battery life* and *battery power*. That is, w_i and w_j form a must-link constraint. It is possible to extend this observation of word sharing to synonyms, but it could result in more errors because many dictionary synonyms are not synonyms in a particular domain.

Observation 2: A sentence may comment on several product aspects, for example, "*I like the picture quality, the battery life, and zoom of this camera*" and "*The picture quality is great, the battery life is also long, but the zoom is not good.*" From either of the sentences, we can infer that *picture quality*, *battery life* and *zoom* are unlikely to be synonyms or belong to the same topic simply because people normally will not repeat the same aspect in the same sentence. This observation allows us to form many cannot-link constraints automatically. Specifically, if two terms w_i and w_j occur in the same sentence, the two terms form a cannot-link, that is, they should be in different topics.

Clearly the must-links and cannot-links generated from the two observations are not perfect, Constrained-LDA allows constraints to be relaxed. Incidentially, *adjectives* and their *attribute nouns* can also form must-link constraints. As we discussed in Section 6.4.2, most adjectives describe some specific attributes of objects. For example, *expensive* and *cheap* usually describe the *price* attribute of an object, and *beautiful* describes the *appearance* or *look* of an object, which allow us to generate two must-link (in fact, must-set) constraints, {*expensive*, *cheap*, *price*} and {*beautiful*, *appearance*, *look*}.

In Fei et al. (2014), another modeling approach was proposed. Its model inference is based on the GPU (*generalized Pólya urn*) model (Mahmoud, 2008). The algorithm treats phrases as individual terms and allows their component words to have some connections or co-occurrences with them. The intuition is that when the algorithm sees a phrase, it assumes to also see a small fraction of its component words; and when it sees each individual word, it assumes to also see a small fraction of its related phrases. Furthermore, not all words in a phrase are equally important. For example, in '*hotel staff*', *staff* is more important as it is the head noun, which represents the semantic category of the phrase. The GPU model can realize this idea easily in the topic model context.

To conclude the discussion of aspect extraction, we note that besides the methods discussed in this section and those in Sections 6.1, 6.2, and 6.3, there are still other works on aspect extraction. For example, Yi et al. (2003) used a mixture language model and likelihood ratio to extract product aspects. Fang and Huang (2012) performed aspect-based analysis using latent structural models. Ma and Wan (2010) used the centering theory and supervised learning. Meng and Wang (2009) extracted aspects from product specifications, which are structured data. Kim and Hovy (2006) used semantic role labeling. Stoyanov and Cardie (2008) exploited coreference resolution. Toprak et al. (2010) designed a comprehensive annotation scheme for aspect-based opinion annotation. Earlier annotations were partial and mainly for the special needs of individual papers. Carvalho et al. (2011) annotated a collection of political debates with aspects and other information.

6.7 Entity Extraction and Resolution

Entity extraction in the sentiment analysis context is similar to the classic problem of *named entity recognition* (NER). In fact, the opinion target extraction methods are also able to extract many entities as entities may be opinion targets in some cases, for example, “*iPhone is great*,” where *iPhone* is the target of sentiment word *great*. In this section, we focus on entity extraction only.

NER has been studied extensively in several fields, for example, information retrieval, text mining, data mining, machine learning, and NLP under the name of information extraction (Mooney and Bunescu, 2005; Sarawagi, 2008; Hobbs and Riloff, 2010). There are two main approaches to information extraction: rule-based and statistical. Early extraction systems were mainly based on rules (e.g., Riloff, 1993). More recent approaches primarily use statistical machine learning. The most popular learning models used in these approaches are hidden Markov models (HMMs) (Rabiner, 1989) and conditional random fields (CRFs) (Lafferty et al., 2001). Both HMM and CRF are supervised sequence learning methods, which we briefly introduced in Section 6.3. A comprehensive survey of the general information extraction tasks and algorithms can be found in Sarawagi (2008). Owing to the prior work on the topic, specific work in the context of sentiment analysis is not extensive. This section focuses on the problems in the context of sentiment analysis and also surveys the general approaches from other research areas.

6.7.1 Problem of Entity Extraction and Resolution

The most general entity extraction problem in sentiment analysis can be stated as follows:

> **Problem statement 6.1**: Given a corpus C, we want to solve the following two subproblems:

1. Identify all entity expressions or mentions M in corpus C.

2. Cluster all entity expressions in M into synonymous groups. Each group represents a unique real-world object or entity.

The first subproblem is the traditional *NER* problem, while the second subproblem is the traditional *entity resolution* (ER) problem.

However, few real-life sentiment analysis applications actually need to solve this general problem. In a typical application, the user wants to find opinions about a set of entities of interest. For example, a smart phone producer may want to find consumer opinions about a set of smart phones, which may be a subset of their own phones, a subset of their competitors' phones, or a combination of both. A political candidate may want to find public sentiments about herself and her political rivals. Thus, most sentiment analysis applications need to solve the following problem:

> **Problem Statement 6.2.** Given a corpus C and a set of desired entities $E = \{e_1, e_2, \ldots, e_n\}$, identify all manifestations or mentions, denoted by M_i, of each entity e_i in E from C.

Each mention m_{ij} ($\in M_i$) is an entity expression that refers to entity e_i. For example, the brand *Motorola* is an entity, which is the official name of the Motorola brand, but it may be written as Motorola, Moto, or Mot in different social media posts and/or even different sentences in the same post.

This problem is similar to but also different from traditional NER and ER problems. In traditional NER, the objective is to recognize or extract all named entities of certain types in a corpus, for example, names of people, names of organizations, and so on. However, in our case, the interest is only the manifestations or mentions of the set of desired entity E, which is a subset of all entities that exist in corpus C. For example, the user may only be interested in some particular car brands rather than all cars in the market. The problem thus requires *entity linking*, a special case of ER. The problem (Problem 6.2) is solved in two steps:

1. *Entity extraction.* Identify all entities, more specifically, entity mentions M, in C. This is a full named entity extraction (NER) step.

2. *Entity linking*. For each *entity mention* (also called *entity expression*) *m* ($\in M$) with its associated context document where the entity expression occurs and a set of desired entities *E*, the system identifies the entry in *E* to which *m* belongs; or *nil* if there is no corresponding entry in *E*. This task is the same as the traditional entity linking (also known as *entity disambiguation*) (McNamee and Dang, 2009).

For example, in the following review:

I brought a Moto phone two months ago. I had been very satisfied with the phone until today. It stopped working in the morning. I called the Mot service center. The service rep said I can get a replacement right away if I send the phone to the Motorola collection center in Illinois. My old Nokia phone never had any problem.

Step 1 should find *Moto*, *Mot*, *Motorola* and *Nokia* as entity mentions (or *entity expressions*). If the desired set of entities *E* is only {Motorola}, step 2 should link Moto, Mot, and Motorola with Motorola in *E*. For Nokia, the algorithm should return nil because it does not refer to any entity in *E*.

Because the entity extraction task is fairly clear, in what follows, we give some additional discussions about the entity linking task. Entity linking basically resolves two name ambiguity problems (Dredze et al., 2010; Gottipati and Jiang, 2011):

1. *Polysemy*. This refers to the case where more than one entity shares the same name. For example, *Apple* may refer to *Apple Inc*. (the maker of iPhone and iPad), *Apple Daily* a Hong Kong newspaper, or anything else that uses *Apple* in its name.

2. *Synonymy*. This refers to the case where there are multiple name variations (or orthographically different mentions) for an entity like the Motorola example. These include abbreviations (Chicago Symphony Orchestra vs. CSO), shortened forms (Volkswagen vs. Vwagen), aliases or alternative names (New York vs. the Big Apple) and alternate spellings (Osama vs. Ussamah vs. Oussama).

When the task is performed with a set of entity mentions without the set *E* of desired entities, it is called *entity resolution* (*ER*). ER clusters entity mentions, where each cluster corresponds to a single real-world entity. In the next two subsections, we describe some existing research in solving these two problems.

Before proceeding, it is useful to understand the types and the nature of the data or corpora that are often used in sentiment analysis, which have an impact on whether we need to perform both the entity extraction and entity linking tasks. There are three main types of corpora:

1. *Entity-focused corpora*. Online reviews of products and services are this type of corpus. Because reviews are usually listed under their respective products or services in web pages, we know which entity that a set of reviews evaluates based on the meta-data scraped from the review page. In this case, entity extraction may not be needed because we know the entity that each review evaluates. Some other entities may be mentioned in the review text, but they are rare. Of course, if we want more accurate analysis, entity extraction and entity linking should be carried out for each review to identify mentions of other entities (often used for comparison purposes) and even mentions of the reviewed entity because it can have name variations.

2. *Domain-focused corpora.* Such a corpus mainly includes forum discussions. A forum site normally focuses on discussions of a particular type of products or topics. For example, HowardForums.com hosts discussions about mobile phones. Entity extraction is needed in this case because unlike reviews, there is no meta-data to show the entities that are discussed in each post except in its text content. Clearly entity linking is needed too.

3. *Open domain corpora.* In this case, the corpus can contain documents of any entity or topic. Twitter is such a corpus. People can post tweets about anything they want. Again there is little meta-data to tell what each post talks about except hashtags that may be used in a small number of tweets to indicate topics. In this case, both entity extraction and entity linking are required.

For different types of corpora, entity extraction and linking may be performed differently. The size of the corpus also plays an important role. For reviews, entity extraction may not be necessary (although we still can do both extraction and linking for improved sentiment analysis accuracy). For domain-focused corpora, we will need both extraction and linking. However, for a huge corpus, we may not be able to do extraction or linking from the whole corpus due to computational and other difficulties. In such cases, *keyword search* is often applied as the first step, where the keywords (often compiled manually) are usually name variations of the desired entities in E. The entity keywords are used to search the corpus to retrieve relevant posts. As it is often the case that in the same domain different entities usually have different names (i.e., entity names are unambiguous), entity linking may not be necessary because the entity names are manually compiled.

For open domain corpora, the situation is similar to domain-focused corpora. In this case, the corpus is often very large, which renders it almost impossible to perform entity extraction on the whole corpus. Twitter and Weibo, for example, have hundreds of millions of posts per day and are examples of such corpora. Even if you have the computational power to perform NER, the data owner (e.g., twitter.com or weibo.com) may not give you the whole corpus unless you pay them an exorbitant amount of money. However, they do allow one to search their data using keywords either for free or with a small fee. Because it is hard to perform NER on the whole corpus, a comprehensive list of name variations for each desired entity is needed as keywords to perform search on such a corpus to extract relevant posts.

In this case, the keywords representing entities of interest are likely to be ambiguous due to diverse topics of the corpus. Then, a classification step is needed to identify those posts containing the desired entities. For example, searching for all posts related to Google using the keyword "google" is probably unambiguous as there is no other entity called Google apart from the Google search engine company, but searching for Apple Inc. (the consumer electronics company) using "apple" as the keyword may retrieve many irrelevant posts. Classification can be used to separate those relevant and irrelevant posts. Entity linking may be used to solve this problem too, which we discuss later.

For the last two types of corpora, it is still advisable to perform an entity extraction in the reduced corpus because the posts in the corpus may also contain unrelated entities. Some opinions in a post may be directed at them rather than the desired entities although the desired entities are mentioned in the post. Recognizing such undesired entities helps identify the target of each opinion. Furthermore, as discussed earlier, many entity names contain sentiment words, for example, *Best Buy* (the name of a store in the United States), and *Pretty Woman* (a movie title) because many companies and organizations use auspicious names to project a positive image for their brands, products or services. Such sentiment words (e.g., *best* and *pretty* in the preceding examples) in entity names can cause real problems for sentiment classification if they are not identified.

6.7.2 Entity Extraction

Although the most effective approaches for entity extraction are HMM (Rabiner, 1989) and CRF (Lafferty et al., 2001), these supervised methods require labeling of training data to learn a model to perform the extraction task on the test data, which is not always possible. Here we focus on two semi-supervised approaches which have been applied to extract entities from opinion documents and are based on the machine learning models of *learning from positive and unlabeled examples* (also called *PU learning*) and *Bayesian Sets*.

For both these models, the user does not have to label any training data. Instead, she only needs to provide some unambiguous seed entity names, meaning that the appearances of these names in the given corpus represent the same entity of interest. The objective of these models is to identify all named entities of the same type as the seeds from a given corpus.

PU learning is a two-class classification model. It is stated as follows (Liu et al., 2002): given a set P of positive examples of a particular class and a set U of unlabeled examples (containing hidden positive and negative cases), build a classifier using P and U for classifying the data in U or future test cases. The results can be either binary decisions (whether each test case belongs to the positive class or not), or a ranking based on how likely each test case belongs to the positive class represented by P.

The entities in E or an extended E can serve as the seeds. In most applications, the entities in E are of the same type such as phones or cars. Li et al. (2010) used this approach. Their algorithm first identifies candidate entities D from the corpus, which are single words or phrases with the following POS tags: NNP (proper noun), NNPS (plural proper noun), and CD (cardinal number). A phrase with a sequence of NNP, NNPS and CD tags is regarded as one candidate entity (CD cannot be the first word unless it starts with a letter), for example, "Windows/NNP 7/CD" and "Nokia/NNP N97/CD" are regarded as two candidates "Windows 7" and "Nokia N97."

For each seed $e_i \in E$, every mention or occurrence of e_i in the corpus forms a vector representing a positive example in P. The vector is made of surrounding words context of the seed mention. Similarly, for each candidate entity $d \in D$, every occurrence also forms a vector as an unlabeled example in U. Thus, each unique seed or candidate entity may produce multiple feature vectors, depending on the number of times that it appears in the corpus. The components in the feature vectors are term frequencies. Using the P and U sets, the PU learning algorithm S-EM given in Liu et al. (2002) was applied to learn a model to label the unlabeled examples in U. Those positively labeled examples in U are entities of interest. The algorithm can also rank the discovered entities based on how likely they belong to the seed set S using the classification results. Note that S-EM is based on the

EM algorithm with naïve Bayes classification as its base classifier. Clearly many other PU learning algorithms can be used as well (Liu, 2006, 2011).

In Zhang and Liu (2011c), Bayesian sets (Ghahramani and Heller, 2006) is employed. However, two heuristic changes were made to the original Bayesian Sets algorithm by identifying high-quality features and by raising weights of some features. The algorithm produces a final ranking of candidate entities. The classic method of distributional similarity (Lee, 1999; Pantel et al., 2009) from NLP can be adapted to solve the problem as well by comparing the similarity of the surround words of each candidate entity with those of the seed entities and then ranking the candidate entities based on the similarity values. In Li et al. (2010) and Zhang and Liu (2011c), it was shown that PU learning and Bayesian sets markedly outperform distributional similarity.

In summary, the advantage of using semi-supervised learning is that the user does not need to label any training data, which is labor-intensive and time-consuming and has to be done for each application domain. To provide a set of seed entities is fairly easy if the user knows the domain to some extent.

6.7.3 Entity Linking

Once entity mentions are found, entity linking is performed. Owing to polysemy, even in cases where the entity names are manually compiled for keyword search, entity linking may still be needed on the returned posts to ensure that each keyword in the context of the post actually refers to a desired entity.

There is a fairly long history of study on entity linking in the NLP community. Most investigations in recent years are due to the evaluation task of the Text Analysis Conference (TAC). The entity linking task of TAC is defined as follows (Ji et al., 2010):

> Given a query Q that consists of a name string N_q (which we call an entity expression) and a background document B_q in which the name appears and a knowledge base KB of known entities, the system is required to identify the KB entry to which the query name string N_q refers; or nil if there is no corresponding KB entry. Each entry of the knowledge base KB consists of a name string N_e (which may be regarded as the official name of an entity e), an entry type T_e which can be PER (person), ORG (organization), GRE (geopolitical entity), or UKN (unknown), and some disambiguating text D_e (e.g., text from the Wikipedia page of the entity).

This is the same as the entity linking problem that we are interested in. However, depending on applications, the user desired entities for sentiment analysis may or may not be names of persons, organizations, or geopolitical entities, but products, services and brands. In our case, if we attach each desired entity with a disambiguating text and type, our desired entity becomes an entry in the KB.

Many approaches have been proposed in recent years to solve the entity linking problem. For example, a learning to rank approach is proposed in Dredze et al. (2010) and Zheng et al. (2010). Both algorithms consist of three main steps: candidate generation, candidate ranking, and determining NIL. The candidate generation step selects a set of likely KB entries for each query based on a set of heuristic rules. Candidate ranking uses the supervised learning to rank approach. The step treats each pair of the query and a candidate entity (a KB entry) for the query as an example and represents the pair as a feature vector. Each feature is a relationship between the two, for example, similarity of context texts, similarity of entity name strings, or whether they have the same entity type. The learned ranker is applied to rank the test set, which are also pairs for each query. In Zheng et al. (2010), the top-ranked candidate entity is the predicted KB entry for the query. To deal with NIL (when there is no KB entry for a query), a separate binary classifier is learned to determine whether the top-ranked candidate entity is the corresponding entity for the query or not. Dredze et al. (2010) took a different approach to handling NIL by actually including NIL as a KB entry for ranking. An additional set of features indicating NIL is included.

Instead of treating entity linking as a ranking problem, Zhang et al. (2010) treated it as a classification problem. They also used the pair (query, entity) as an example like the preceding approaches. For the class label, if the entity is the corresponding KB entry for the query, it is positive; otherwise it is negative. Then a two class classifier is trained to directly predict the KB entry entity for a query. If no pair for a query is predict positive, then the query has no corresponding entry in KB, that is, NIL. A similar approach was also given in Milne and Witten (2008).

To use supervised learning, one needs to carefully engineer a large number of features and also label many training examples. The work in Gottipati and Jiang (2011) proposed an unsupervised approach based on statistical language model-based information retrieval, specifically, KL-divergence based retrieval model. The approach also performs query expansion. The top-ranked KB entry with the same entity type as the query and with a score value greater than a threshold is assigned to the query as its corresponding entity in the KB. If no such KB entry is found, NIL is returned to indicate that there is no corresponding entity in the KB for the query. More recent research used graph propagation (Hoffart et al., 2011; Liu et al., 2012) and topic modeling to solve the problem (Han and Sun, 2012; Yogatama et al., 2012).

In sentiment analysis applications involving consumer products, there is usually another level of complexity because products typically have brands and models, which form a hierarchical relationship. For example, if a user wants to find consumer opinions about Apple Inc., opinions about its products of iPad and iPhone may also be relevant. Then we may need to identify the brands and the product models under each brand. However, separating brands and models and discovering what models are under what brands are usually not difficult. Some heuristic rules should be able to do the job.

6.7.4 Entity Search and Linking

As discussed earlier, if the corpus is very large and contains a large and diverse set of entities or topics, we need to use keyword search to find relevant posts for sentiment analysis. In such cases, we only need to deal with the polysemy problem but do not need to deal with the synonym problem because the set of alternative names for an entity has been compiled as keywords and used in search. Then the entity linking problem becomes the following (Davis et al., 2012):

> Given a large corpus C, and a set of alternative names n_1, n_2,…, n_m of an desired entity e. These names (treated as keywords) are used to search in C. Each returned document containing n_i needs to be classified as relevant or not relevant to e. In other words, we need to determine whether the mention of n_i in the returned document actually refers to e or not.

This problem clearly can be solved using the standard supervised classification approach. That is, after searching C using $n_1, n_2, \ldots, n_m$, some returned documents can be manually labeled. Documents referring to the desired entity e are labeled positive and others are labeled negative. A supervised learning algorithm such as SVM can be applied to the training data to build a classifier to classify each future or test document containing n_i.

In Davis et al. (2012), the problem is instead formulated as a PU learning problem. The authors argued that supervised learning needs a large number of manually labeled posts or tweets and manual labeling is time-consuming and labor-intensive. However, in many cases, acquiring some positive examples is relatively easy or inexpensive. For instance, if the corpus C is a stream of Twitter posts (tweets), it is possible to use hashtags of the entity to search for relevant tweets. Using this set of possibly noisy positive examples and other retrieved tweets as the set of unlabeled examples, PU learning can be performed to identify additional positive examples in the unlabeled set. In the paper, the authors uses the EM algorithm with an association rule-based classifier (Velosoa et al., 2006), which consists of a set of class association rules (Liu et al., 1998).

6.8 Opinion Holder and Time Extraction

Like entity extraction, opinion holder and time extraction is also a classic named entity recognition (NER) task because person names and times are named entities. These can be dealt with using current NER techniques. However, in most applications that use social media, we do not need to extract opinion holders and posting times from the text content as opinion holders are usually the authors of the reviews, blogs, or discussion posts and their login ids are usually known. The date and time when a post is submitted are also known as they are often displayed on the web page where the post appears. They can be scraped fairly easily from the page using structured data extraction techniques (Liu, 2006, 2011). It is only when opinion holders and times appear in the actual text, for example, news articles, that they need to be extracted using NER techniques. We give a survey of existing work on news article corpora here.

Kim and Hovy (2004) considered person and organization as the only possible opinion holders and used a named entity recognizer to identify them. Choi et al. (2006) used CRF for their extraction. To train CRF, they used features such as surrounding words, POS of surrounding words, grammatical roles, and sentiment words. Kim and Hovy (2006) proposed a method that first generates all possible holder candidates in a sentence, that is, all noun phrases, including common noun phrases, named entities, and pronouns, and then parses the sentence and extracts a set of features from the parse tree. A learned maximum entropy (ME) model then scores all holder candidates using the features. On the basis of the ME scores, all holder candidates are ranked. The one with the highest score is selected as the holder of the opinion in the sentence. Several other related works also exist. For example, Johansson and Moschitti (2010) dealt with the problem using SVM, Wiegand and Klakow (2010) applied convolution kernels, and Lu (2010) employed a dependency parser. In Ruppenhofer et al. (2008), the authors discussed the issue of using automatic semantic role labeling (ASRL) for identifying opinion holders. They argued that ASRL is insufficient and that other linguistic phenomena such as discourse structures may need to be considered. Kim and Hovy (2006) actually used semantic role labeling for the purpose. In Yang and Cardie (2013), a method was proposed to jointly extract opinion holders, opinion expressions, and opinion targets, and their associated linking relations using CRF and an optimization framework (see Section 6.3.2).

6.9 Summary

Aspect and entity extraction and their resolution are important sentiment analysis tasks as they represent opinion targets or what people talk about in opinion documents. Without their discovery, positive or negative opinions are of limited use. Although these tasks can be regarded as general information extraction problems, most existing methods exploit specific natures of the opinion domain (e.g., opinions having targets) for extraction and resolution.

Despite substantial research, these problems remain to be highly challenging. In many domains, the accuracy of existing algorithms is still low. Additionally, the current approaches mainly focus on extracting aspects that are nouns and noun phrases. In domains where many aspects are verb expressions or their aspects cannot be stated with simple nouns or noun phrases, for example, political and social domains, these extraction algorithms are not very effective.

In the past few years, many unsupervised and semi-supervised topic models have been devised and applied to aspect extraction and joint modeling of sentiments and aspects. However, the current models are still not accurate enough for practical use. Most of the models are based on unigrams, but a large number of aspects in real-life data are multiword phrases. Despite the current shortcomings, I do expect future research on learning models (not necessarily topic models) to be able to exploit a large number of data sets to make major breakthroughs. That is, in the big data age, we can exploit large volumes of data to discover commonsense and domain-specific knowledge, which are crucial for aspect and entity extraction and for their resolution.

Along with aspect and entity extraction, this chapter also reviewed the current opinion holder and time extraction research. Although there is a large body of literature on these extraction tasks, some closely related tasks have received little research attention. For example, limited work has been done on discovering reasons or qualifications for opinions and causes for emotions, except the work of Zhang et al. (2013) and Lee et al. (2013). Zhang et al. (2013) made an attempt to discover opinion reasons using Markov logic networks, whereas Lee et al. (2013) proposed a rule-based method to extract emotion causes. Clearly much further research is still needed to explore these important areas.

7

Sentiment Lexicon Generation

◈

By now, it should be quite clear that words and phrases that convey positive or negative sentiment are instrumental for sentiment analysis. This chapter discusses how to compile such word lists. In the research literature, *sentiment words* are also called *opinion words*, *polar words*, or *opinion-bearing words*. Positive sentiment words such as *beautiful*, *wonderful*, and *amazing* are used to express some desired states or qualities while negative sentiment words such as *bad*, *awful*, and *poor* are used to express some undesired states or qualities. In addition to individual words, there are also sentiment phrases and idioms, for example, *cost an arm and a leg*. Collectively, they are called the *sentiment lexicon* (or *opinion lexicon*). From now on, when we say sentiment words, we mean both individual words and phrases.

Sentiment words can be divided into two types, *base type* and *comparative type*. All the preceding example words are of the base type. Sentiment words of the comparative type (which include the superlative type) are used to express comparative and superlative opinions. Examples of such words include *better*, *worse*, *best*, *worst*, and so on, which are comparative and superlative forms of the base adjectives or adverbs such as *good* and *bad*. We discuss comparative and superlative sentiment words further in Chapter 8. This chapter focuses on sentiment words of the base type.

There are three main existing approaches to compiling sentiment words: *manual approach*, *dictionary-based approach* (discussed in Section 7.1), and *corpus-based approach* (discussed in Section 7.2). The manual approach is labor-intensive and time-consuming, and is thus usually used as a check on automated approaches because automated approaches make mistakes. In Section 7.3, we will also discuss the issue of factual statements implying opinions, which has largely been overlooked by the research community.

This chapter is written in a survey style because past research has constructed numerous sentiment lexicons in many languages. Most of them are publicly available (see Section 7.4 for a list of them in English). Even if a particular language does not have a lexicon, compiling one is not hard. The real problems for sentiment analysis with regard to sentiment words are two: (1) how to identify and to deal with words and phrases that have domain- or context-dependent sentiment orientations, and (2) how to spot factual words and phrases that imply sentiment in a domain context. For the first problem, there are almost always some sentiment words or phrases in a domain that express different orientations in some contexts than their default orientations in a general-purpose lexicon. If these words and their contexts are not identified and dealt with in an application, they can cause major drops in sentiment analysis accuracy. The second problem is even harder to solve because there are too many possibilities and it often needs commonsense and prior domain knowledge to comprehend (see Section 7.3). These two problems are some of the key obstacles to accurate and domain-independent sentiment analysis. Unfortunately, not much research has been done to solve these outstanding problems.

7.1 Dictionary-Based Approach

Using a dictionary to compile sentiment words is an obvious approach because most dictionaries (e.g., WordNet; Miller et al., 1990) list synonyms and antonyms for each word. Thus, a simple technique is to use a few seed sentiment words to bootstrap based on the synonym and antonym structure of a dictionary. Specifically, this method works as follows: A small set of sentiment words (seeds) with known positive or negative orientations (or polarities) is first collected manually, which is very easy. The algorithm then grows this set by searching in the WordNet or another online dictionary for their synonyms and antonyms. The newly found words are added to the seed list, and the next iteration begins. The iterative process ends when no more new words can be found (Hu and Liu, 2004; Valitutti et al., 2004). After the process completes, a manual inspection step is used to clean up the list (remove errors). The list can also be cleaned up by assigning a sentiment strength to each word using a probabilistic method (Kim and Hovy, 2004). Mohammad et al. (2009) additionally exploited many antonym-generating affix patterns like *X* and dis*X* (e.g., honest – dishonest) to increase the coverage.

Kamps et al. (2004) proposed a more sophisticated approach that uses a WordNet distance-based method to determine the sentiment orientation of a given adjective. The distance $d(t_1, t_2)$ between words t_1 and t_2 is the length of the shortest path that connects t_1 and t_2 in WordNet. The orientation of an adjective word t is determined by its relative distance from two reference (or seed) words *good* and *bad*, that is, $SO(t) = (d(t, \text{bad}) - d(t, \text{good}))/d(\text{good}, \text{bad})$. t is positive iff $SO(t) > 0$, and is negative otherwise. The absolute value of $SO(t)$ gives the strength of the sentiment. Along similar lines, Williams and Anand (2009) studied the problem of assigning sentiment strength to each word.

In Blair-Goldensohn et al. (2008), the authors presented a different bootstrapping method that uses a positive seed set, a negative seed set, and also a neutral seed set. The approach works based on a directed, weighted semantic graph where neighboring nodes are synonyms or antonyms of words in WordNet and are not part of the seed neutral set. The neutral set is used to stop the propagation of sentiment through neutral words. The edge weights are preassigned based on a scaling parameter for different types of edges, that is, synonym or antonym edges. Each word is then scored (giving a sentiment value) using a modified version of the label propagation algorithm in Zhu and Ghahramani (2002). At the beginning, each positive seed word is given the score of +1, each negative seed is given the score of −1, and all other words are given the score of 0. The scores are then revised during the propagation process. When the propagation stops after a number of iterations, the final scores after logarithmic scaling are assigned to words as their degrees of being positive or negative.

In Rao and Ravichandran (2009), three graph-based semi-supervised learning methods were tried to separate positive and negative words given a positive seed set, a negative seed set, and a synonym graph extracted from the WordNet. The three algorithms were mincut (Blum and Chawla, 2001), randomized mincut (Blum et al., 2004), and label propagation (Zhu and Ghahramani, 2002). It was shown that mincut and randomized mincut produced better F scores, but label propagation gave significantly higher precisions with low recalls.

Hassan and Radev (2010) presented a Markov random walk model over a word relatedness graph to produce a sentiment estimate for a given word. It first uses WordNet synonyms and hypernyms to build a word relatedness graph. It then defines a measure, called the *mean hitting time* $h(i|S)$, and uses the measure to gauge the distance from a node i to a set of nodes (words) S, which is the average number of steps that a random walker, starting in state $i \notin S$, will take to enter a state $k \in S$ for the first time. Given a set of positive seed words S^+ and a set of negative seed words S^-, to estimate the sentiment orientation of a given word w, it computes the hitting times $h(w|S^+)$ and $h(w|S^-)$. If $h(w|S^+)$ is greater than $h(w|S^-)$, the word is classified as negative. All other outcomes are classified positive. In Hassan et al. (2011), the same method was applied to find the sentiment orientations of foreign words. For this purpose, a multilingual word graph was created with both English words and foreign words. Words in different languages are connected based on their meanings in dictionaries. Other methods based on graphs include those in Takamura et al. (2005, 2006, 2007).

In Turney and Littman (2003), the same PMI-based method as in Turney (2002) was used to compute the sentiment orientation of a given word. Specifically, it computes the orientation of the word from the strength of its association with a set of positive words (*good*, *nice*, *excellent*, *positive*, *fortunate*, *correct*, and *superior*), minus the strength of its association with a set of negative words (*bad*, *nasty*, *poor*, *negative*, *unfortunate*, *wrong*, and *inferior*). The association strength is measured using PMI.

Esuli and Sebastiani (2005) used supervised learning to classify words into positive and negative classes. Given a set P of positive seed words and a set N of negative seed words, the two seed sets are first expanded using synonym and antonym relations in an online dictionary (e.g., WordNet) to generate the expanded sets P' and N', which form the training set. The algorithm then uses all the glosses in the dictionary for each word in $P' \cup N'$ to generate a feature vector. A binary classifier is built using different learning algorithms. The process can also be run iteratively. That is, after the newly identified positive and negative words and their synonyms and antonyms are added to the training set, an updated classifier can be constructed and so on. In Esuli and Sebastiani (2006a), the authors also included the category *objective* (no sentiment). To expand the objective seed set, hyponyms were used in addition to synonyms and antonyms. They then tried different strategies to do the three-class classification. In Esuli and Sebastiani (2006b), a committee of classifiers based on the preceding method was utilized to build the SentiWordNet, a lexical resource in which each synset of WordNet is associated with three numerical scores Obj(*s*), Pos(*s*) and Neg(*s*), describing the degrees to which each word contained in the synset are Objective, Positive, and Negative. Kim and Hovy's (2006) method also starts with three seed sets of positive, negative, and neutral words, which are used to find synonyms in WordNet. The expanded sets, however, have many errors. The method then uses a Bayesian formula to compute the closeness of each word to each category (positive, negative, and neutral) to determine the most probable class for the word. Guerini et al. (2013) proposed a classification method that assigns a sentiment orientation to each word based on the positive and negative scores of each sense of the word in SentiWordNet and various aggregations of the scores as features. Gatti and Guerini (2012) went further to predict the sentiment strength of each word.

Andreevskaia and Bergler (2006) proposed a more sophisticated bootstrapping method with several techniques to expand the initial positive and negative seed sets and to clean up the expanded sets (removing nonadjectives and words in both positive and negative sets). In addition, their algorithm also performs multiple runs of the bootstrapping process using some nonoverlapping seed subsets. Each run typically finds a slightly different set of sentiment words. A net overlapping score for each word is then computed based on how many times the word is discovered in the runs as a positive word and as a negative word. The score is then normalized to [0, 1] based on the fuzzy set theory.

In Kaji and Kitsuregawa (2006, 2007), many heuristics were used to build a sentiment lexicon from HTML documents based on web page layout structures. For example, a table in a web page may have a column clearly indicate positive or negative orientations (e.g., Pros and Cons) of the surround text. These clues can be exploited to extract a large number of candidate positive and negative opinion sentences from a large set of web pages. Adjective phrases are then extracted from these sentences and assigned sentiment orientations based on different statistics of their occurrences in the positive and negative sentence sets respectively.

Velikovich et al. (2010) also proposed a method to construct a sentient lexicon using web pages. It was based on a graph propagation algorithm over a phrase similarity graph. It again assumed as input a set of positive seed phrases and a set of negative seed phrases. The nodes in the phrase graph were the candidate phrases selected from all n-grams up to length ten extracted from 4 billion web pages. Only 20 million candidate phrases were selected using several heuristics, for example, frequency and mutual information of word boundaries. A context vector for each candidate phrase was then constructed based on a word window of size six aggregated over all mentions of the phrase in the 4 billion documents. The edge set was constructed through cosine similarity computation of the context vectors of the candidate phrases. All edges (v_i, v_j) were discarded if they were not one of the twenty-five highest weighted edges adjacent to either node v_i or v_j. The edge weight was set to the corresponding cosine similarity value. A graph propagation method was used to calculate the sentiment of each phrase as the aggregate of all the best paths to the seed words.

In Dragut et al. (2010), yet another but very different bootstrapping method was proposed using WordNet. Given a set of seed words, instead of simply following the dictionary, the authors proposed a set of sophisticated inference rules to determine other words' sentiment orientations through a deductive process. That is, the algorithm takes words with known sentiment orientations (the seeds) as input and produces synsets (sets of synonyms) with orientations. The synsets with the deduced orientations can then be used to further deduce the polarities of other words.

Peng and Park (2011) presented a sentiment lexicon generation method using constrained symmetric nonnegative matrix factorization (CSNMF). The method first uses bootstrapping to find a set of candidate sentiment words in a dictionary and then uses a large corpus to assign polarity scores to each word. This method thus uses both dictionary and corpus. Xu et al. (2010) presented several integrated methods as well using dictionaries and corpora to find emotion words. Their method is based on label propagation in a similarity graph (Zhu and Ghahramani, 2002).

Although there are many existing approaches, I am not aware of any existing study that evaluated these methods independently. Thus, it is hard to tell which one is the best. In general, we note that the advantage of using a dictionary-based approach is that one can easily and quickly find a large number of sentiment words with their orientations. Although the resulting list may have many errors, manual checking can be performed to clean it up. The manual cleanup is time-consuming but is just a one-time effort that requires only a few days for a native speaker. The main disadvantage of the dictionary-based approach is that the sentiment orientations of words collected this way are general or domain and context independent. Many sentiment words actually have context-dependent orientations. For example, if a speaker phone is quiet, it usually indicates a negative sentiment. However, if a car is quiet, it is positive. The sentiment orientation of *quiet* is domain or context dependent. The corpus-based approach can help deal with this problem.

7.2 Corpus-Based Approach

The corpus-based approach has been applied to two main scenarios: (1) given a seed list of known (often general-purpose) sentiment words, discover other sentiment words and their orientations from a domain corpus, and (2) adapt a general-purpose sentiment lexicon to a new one using a domain corpus for sentiment analysis applications in the domain. In practice, the issue can be more complicated than just building a domain-specific sentiment lexicon because in the same domain, the same word can be positive in one context but negative in another. In what follows, we discuss some of the existing work that deals with these problems. Although the corpus-based approach may also be used to build a general-purpose sentiment lexicon, if a very large and very diverse corpus is available, the dictionary-based approach is usually more effective because a dictionary contains all words.

7.2.1 Identifying Sentiment Words from a Corpus

There are two main ideas that have been applied to identify sentiment words in a given corpus. The first idea is to exploit some linguistic rules or conventions on connectives to simultaneously identify sentiment words and determine their orientations in a given corpus. The second idea is to use syntactic relations of opinions and targets to extract sentiment words.

The first idea is proposed in Hatzivassiloglou and McKeown (1997). It uses a set of seed adjectives with known orientations and a corpus to find additional sentiment adjectives in the corpus. One of the rules is about the conjunction AND, which says that conjoined adjectives usually have the same orientation. For example, in the sentence, "*This car is beautiful and spacious*," if *beautiful* is known to be positive, it can be inferred that *spacious* is also positive. This is so because people usually express the same sentiment on both sides of a conjunction. The following sentence is not very likely, "*This car is beautiful and difficult to drive*." It is more acceptable if it is changed to "*This car is beautiful but difficult to drive*." Rules were also designed for other connectives, namely, OR, BUT, EITHER – OR, and NEITHER – NOR. This idea is called *sentiment consistency*. In practice, it is not always consistent. Thus, Hatzivassiloglou and McKeown also applied a machine learning step to determine if two conjoined adjectives have the same or different orientations. First, a graph was formed with same- and different-orientation links between adjectives. Clustering was then performed on the graph to produce two sets of words: positive and negative.

Kanayama and Nasukawa (2006) extended the approach by introducing the concepts of intra-sentential (within a sentence) and inter-sentential (between neighboring sentences) sentiment consistency, which they called *coherency*. The intrasentential consistency is similar to the idea described in the previous paragraph. Intersentential consistency applies this idea to neighboring sentences. That is, the same sentiment orientation is usually expressed in consecutive sentences. Sentiment changes are indicated by adversative expressions such as *but* and *however*. Some criteria were also proposed to determine whether to add a word to the positive or negative lexicon. This study was based on Japanese text and was used to find domain dependent sentiment words and their orientations. Other related work includes those in Kaji and Kitsuregawa (2006, 2007).

The second idea of using syntactic relations of opinions and targets for extraction is originally proposed for extracting aspects or opinion targets (Hu and Liu, 2004; Zhuang et al., 2006). It was later adapted to extract both sentiment words and their opinion targets (aspects) in Wang and Wang (2008) and Qiu et al. (2009, 2011). In fact, both ideas have been employed in Qiu et al. (2009, 2011). Because we have described this approach in detail in Section 6.2.1, we will not discuss it further here. In Volkova et al. (2013), another corpus-based bootstrapping method was proposed to generate sentiment lexicon from tweets. The algorithm employs a set of polarity labeled tweets, and it is thus a semi-supervised method. However, this method does not use opinion and target relations.

7.2.2 Dealing with Context-Dependent Sentiment Words

Although finding domain-specific sentiment words and their orientations are useful, it is insufficient in practice. Ding et al. (2008) showed that many words in the same domain can indicate different orientations in different contexts. For example, in the camera domain, the word "long" clearly expresses opposite opinions in the following two sentences:

"*The battery life is long*" (positive)

"*It takes a long time to focus*" (negative).

Such situations often occur with quantity adjectives, for example, *long*, *short*, *large*, *small*, and so on, and sometimes with other adjectives too. For example, in a car review, the sentence "*This car is very quiet*" is positive, but the sentence "*The audio system in the car is very quiet*" is negative. Thus, finding domain-dependent sentiment words and their orientations is insufficient. The example sentences tell us that both the aspect and the sentiment expressing words or phrases are important. Ding et al. (2008) proposed to use the pair

(*context_sentiment_word*, *aspect*)

to represent an *opinion context*, for example, (*long*, *battery life*). Their method determines context sentiment words and their orientations together with the aspects that they modify. In determining whether a pair is positive or negative, the preceding intra-sentential and inter-sentential sentiment consistency rules about connectives are still applied. The work in Ganapathibhotla and Liu (2008) adopted the same context definition but used it for analyzing comparative sentences. Lu et al. (2011) also used the same context definition and performed the task using a review corpus. Like that in Ding et al. (2008), they assumed that the set of aspects was given. They formulated the problem of assigning each pair the positive or negative sentiment as an optimization problem with a number of constraints. The objective function and constraints were designed based on clues such as a general-purpose sentiment lexicon, the overall sentiment rating of each review, synonyms and antonyms, as well as conjunction "and" rules, "but" rules, and "negation" rules. Wu and Wen (2010) dealt with a similar problem in Chinese. They focused on pairs in which adjectives are quantifiers such as *big*, *small*, *low* and *high*. Their method is based on syntactic patterns as in Turney (2002) (see Section 3.2.1), and uses the web search hit counts to solve the problem.

Zhao et al. (2012) used the web search for the task as well. However, they performed query expansion to include more relevant queries. For example, for the context pair (*long*, *battery life*), they search using four queries "*long battery life*," "*battery life is long*," "*The battery life is very long*" and "*The battery life is not long*." Instead of using the Google general search, they employed Google's advanced search to focus on forum sites that discuss some specific products. They then collected the top one hundred snippets and performed sentiment analysis on them using the lexicon-based method in Hu and Liu (2004). If there are more snippets that are positive, the pair (e.g., (*long*, *battery life*)) is assigned positive; otherwise negative.

Not surprisingly, the methods in Turney (2002) and Takamura et al. (2007) can be considered as methods for finding context-specific opinions too, but they do not explicitly use the sentiment consistency idea. Instead, they used web search to find sentiment orientations (see Section 3.2.1). We should note that all these context definitions are still not sufficient for all cases as the basic rules of sentiment composition discussed in Section 5.2 show. Many contexts can be more complex, for example, consuming a small or large quantity of resources (Zhang and Liu, 2011a), which uses a triple as the opinion context:

(*usage_verb*, *quantifier*, *resource_noun*),

where *resource_noun* is a noun or a noun phrase representing a resource, and *usage_verb* is a verb expressing the concept of consuming or using. This context indicates a sentiment and an aspect. For example, in "*This washer uses a lot of water*," *uses* is the *usage_verb*, *a lot of* is a quantifier phrase, and *water* is the resource. This context represents a negative sentiment and a *water resource usage* aspect. Another example is "*This car eats a lot of gas*." Unfortunately, there is still no systematic study to identify all such sentiment contexts.

A similar problem is to identify contextual subjectivities and sentiments at the phrase or expression level. Contextual sentiment means that although a word or phrase in a lexicon is marked positive or negative, in the context of the sentence expression it may have no sentiment or have the opposite sentiment. Wilson et al. (2005) studied this problem. Their algorithm first labels the subjective expressions in the corpus that contain subjective words or phrases in a given subjectivity lexicon. A subjectivity lexicon is slightly different from a sentiment lexicon because it may contain words that indicate only subjectivity but no sentiment, for example, *feel*, and *think*. The paper took a supervised learning approach with two steps. The first step determines whether the expression is subjective or objective. The second step determines whether the subjective expression is positive, negative, both, or neutral. *Both* means there are both positive and negative sentiments. Neutral is still included because the first step can make mistakes and leave some neutral expressions unidentified. For subjectivity classification, a large and rich set of features was used, which included *word features*, *modification features* (dependency features), *structure features* (dependency tree-based patterns), *sentence features*, and *document features*. For the second step of sentiment classification, the paper used features such as *word tokens*, *word prior sentiments*, *negations*, *modified by polarity*, *conj* *polarity*, and so on. For both steps, the machine learning algorithm BoosTexter AdaBoost.HM (Schapire and Singer, 2000) was employed to build classifiers.

A related problem is expression-level sentiment classification, which determines the sentiment orientation of expressions. Choi and Cardie (2008) classified the expressions annotated in MPQA corpus (Wiebe et al., 2005). Both lexicon-based classification and supervised learning were experimented.

Along similar lines, Kessler and Schütze (2012) used supervised classification to determine sentiment words that have different orientations in specific sentence contexts. Breck et al. (2007) studied the problem of extracting sentiment expressions with any number of words using CRF (Lafferty et al., 2001). In Yang and Cardie (2012), semi-Markov conditional random fields (semi-CRF) (Sarawagi and Cohen, 2004) was used to extract opinion expressions. Semi-CRF is more powerful than CRF for the extraction task because semi-CRF allows one to construct features to capture characteristics of the subsequences of a sentence.

7.2.3 Lexicon Adaptation

Several researchers have studied how to adapt a general sentiment lexicon to a particular domain. Choi and Cardie (2009) investigated the adaptation of a general lexicon to a new one for domain-specific expression-level sentiment classification. Their technique adapts the word-level polarities of a general-purpose sentiment lexicon for a particular domain by utilizing the expression-level polarities in the domain. In return, the adapted word-level polarities are used to improve the expression-level polarities. The word-level and the expression-level polarity relationships are modeled as a set of constraints and the problem is solved using integer linear programming. This work assumes that there is a given general-purpose polarity lexicon L, and a polarity classification algorithm $f(e_l, L)$ that can determine the polarity of the opinion expression e_l based on the words in e_l and L. Jijkoun et al. (2010) also proposed a related method to adapt a general sentiment lexicon to a topic specific one.

Du et al. (2010) studied the problem of adapting the sentiment lexicon of one domain (not a general-purpose lexicon) to another domain. As input, the algorithm assumes the availability of a set of in-domain sentiment-labeled documents, a set of sentiment words from these in-domain documents, and a set of out-of-domain documents. The task is to adapt the in-domain sentiment lexicon for the out-of-domain documents. Two ideas were used. First, a document should be positive (or negative) if it contains many positive (or negative) words, and a word should be positive (or negative) if it appears in many positive (or negative) documents. These are mutually reinforcing relationships. Second, even though the two domains may be under different distributions, it is possible to identify a common part between them (e.g. the same word has the same orientation). The sentiment lexicon adaption was solved using the information bottleneck framework. The same problem was also dealt with in Du and Tan (2009).

7.2.4 Some Other Related Work

Word sense and subjectivity. Wiebe and Mihalcea (2006) investigated the possibility of assigning subjectivity labels to word senses based on a corpus. They first investigated the agreement between annotators who manually assigned labels *subjective*, *objective*, or *both* to WordNet senses. They then evaluated a method based on distributional similarity (Lin, 1998) to automatically assign subjectivity labels/scores to word senses. Their work showed that subjectivity is a property that can be associated with word senses, and word sense disambiguation (WSD) can directly benefit from subjectivity annotations. A subsequent work was reported in Akkaya et al. (2009). Su and Markert (2008) also studied the problem and performed a case study for subjectivity recognition. In Su and Markert (2010), they further investigated this problem and applied it in a cross-lingual environment.

Connotation lexicon. Feng et al. (2011) studied the problem of producing a connotation lexicon, words with positive or negative connotations. A connotation lexicon differs from a sentiment lexicon in that the latter concerns words that express sentiment either explicitly or implicitly, while the former concerns words that are often associated with a specific polarity of sentiment, for example, *award* and *promotion* have positive connotation and *cancer* and *war* have negative connotation. Many are even objective words such as *intelligence*, *human*, and *cheesecake*. The authors proposed a graph-based method exploiting mutual reinforcement to solve the problem. Feng et al. (2013) improved the work by using linear programming and integer linear programming encoding a diverse set of linguistic insights (semantic prosody, distributional similarity, and semantic parallelism of coordination) and prior knowledge drawn from lexical resources as constraints, to construct a broad-coverage connotation lexicon. The work also experimented and compared these algorithms with themselves and with some popular graph-based methods such as HITS, PageRank and label propagation. The results show that linear programming gives the best results.

Brody and Diakopoulos (2011) studied the lengthening of words (e.g., *slooooow*) in microblogs. They showed that lengthening is strongly associated with subjectivity and sentiment, and presented an automatic way to leverage this association to detect domain sentiment and emotion words. Mohtarami et al. (2013) proposed a method to infer sentiment similarity between a pair of words, that is, whether they have the same orientation and intensity. Meng et al. (2012) and Lai et al. (2012) studied how to translate sentiment words from one language to another.

7.3 Desirable and Undesirable Facts

Sentiment words and expressions that we have discussed so far are mainly subjective words and expressions that indicate positive or negative sentiment. However, many objective words and expressions can imply sentiment too because they can represent desirable or undesirable facts in some specific domains or contexts. To understand whether a fact is desirable or not desirable, we often need prior domain knowledge, which means we need pragmatics analysis. Because pragmatics analysis is extremely difficult due to the need of commonsense knowledge, we have to resort to other signs or clues to achieve our objective.

Zhang and Liu (2011b) proposed a technique to identify nouns and noun phrases that indicate aspects and also imply positive or negative sentiment in a particular domain context. These noun phrases (including individual nouns) alone exhibit no sentiment, but in the domain context they may represent desirable or undesirable facts. For example, the words *valley* and *mountain* themselves do not have any sentiment connotation in general, that is, they are objective. However, in the domain of mattress reviews, they often imply negative sentiment as in "*Within a month, a valley has formed in the middle of the mattress*." Here, *valley*, used as a *metaphor*, implies a negative sentiment about the mattress quality. Identifying sentiment orientations of such noun phrases is very challenging but critical for effective sentiment analysis in many domains.

The algorithm in Zhang and Liu (2011b) is based on the following idea: Although many sentences involving such noun phrases read like objective sentences with no explicit sentiment, in some cases the authors may also express explicit sentiment, for example, "*Within a month, a valley has formed in the middle of the mattress, which is terrible*." The context of this sentence indicates that *valley* may not be desirable. These sentiment contexts can be exploited to determine what sentiment a noun phrase may imply. However, the problem with this approach is that noun phrases with no implied sentiment appear frequently in positive or negative sentiment contexts, for example, *voice quality* in "*The voice quality is poor*." To distinguish these two cases, the following observation was used.

Observation. For normal noun phrases which imply no positive or negative sentiment, people can express both positive and negative opinions about them. For example, for the noun phrase "*voice quality*," some people may say "*good voice quality*" and some may say "*bad voice quality*." However, a noun phrase representing a desirable or undesirable fact is often associated with only a single sentiment orientation, either positive or negative, but not both. For example, it is unlikely that both these sentences appear: "*A bad valley has formed*" and "*a good valley has formed*."

With this observation in mind, the approach works in two steps:

1. *Candidate identification*. It first identifies all noun phrases in the corpus and determines the surrounding sentiment context for each of the noun phrases. If a noun phrase occurs in negative (respectively positive) sentiment contexts significantly more frequently than in positive (or negative) sentiment contexts in a large domain corpus, it infers that the noun phrase's sentiment polarity or orientation is likely to be negative (or positive). The significance was assessed using a statistical test. This step produces a list of candidate noun phrases with positive sentiment and a list of candidate noun phrases with negative sentiment.

2. *Pruning*. It prunes the two lists based on the preceding observation. If a noun phrase has been directly modified by both positive and negative sentiment words in the corpus, it is unlikely to imply any sentiment and should be pruned. Two types of dependency relations were used to detect such direct modifications.

Type 1: O → O-Dep → N

It means *O* depends on *N* through relation *O-Dep*, for example, "*This TV has good picture quality*."

Type 2: O → O-Dep → H ← N-Dep ← N

It means both *O* and *N* depend on *H* through relations *O-Dep and N-Dep* respectively, for example, "*The springs of the mattress are bad*."

where *O* is a sentiment or opinion word, *O-Dep* and *N-Dep* are dependency relations. *N* is a noun phrase. *H* means any word. For the first example sentence, given the noun phrase *picture quality*, we can identify its modification sentiment word *good*. For the second example, given the noun *springs*, we can obtain its modification sentiment word *bad*.

This work was just the first attempt to tackle the problem. Its accuracy is not high. Much further research is needed.

7.4 Summary

Owing to the contributions of many researchers, several general-purpose subjectivity, sentiment, and emotion lexicons have been constructed. Some of them are also publically available, for example,

- General Inquirer lexicon (Stone, 1968): (http://www.wjh.harvard.edu/~inquirer/spreadsheet_guide.htm)
- Sentiment lexicon (Hu and Liu, 2004): (http://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html)
- MPQA subjectivity lexicon (Wilson et al., 2005): (http://www.cs.pitt.edu/mpqa/subj _lexicon .html)
- SentiWordNet (Esuli and Sebastiani, 2006): (http://sentiwordnet.isti.cnr.it/)
- Emotion lexicon (Mohammad and Turney, 2010): (http://www.purl.org/net/emolex)

With many lexicons, inconsistency and errors are inevitable. Dragut et al. (2012) studied the problem of polarity or orientation consistency checking among sentiment lexicons or dictionaries and showed that there are considerable inconsistencies in the lexicons that they have studied. They then proposed a fast SAT solver-based method to detect inconsistency.

Despite a significant amount of research, the challenging problems remain. First, there is still not an effective method for discovering and determining domain- and context-dependent sentiments. For example, *suck* is in general negative but for vacuum cleaners, it is often positive. Furthermore, in different sentence contexts, the same word may exhibit different sentiments as we discussed earlier. Besides the techniques discussed in Section 7.2, recent works have also tried to use word vectors and matrix to capture the contextual information of sentiment words (Maas et al., 2011; Yessenalina and Cardie, 2011). However, the existing techniques are still not accurate enough for practical use. Second, in almost every domain, there are some objective words or phrases that describe some desirable and/or undesirable states or qualities and thus imply positive or negative sentiment (see Section 7.3). We still do not have a good method to identify such objective words and phrases. Third, having a sentiment lexicon (even with domain-specific orientations) does not mean that every word in the lexicon always expresses an opinion/sentiment in a sentence. For example, in “*I am looking for a good car to buy*,” *good* does not express either a positive or negative sentiment on any particular car because the sentence actually expresses a desire or intention.

8

Analysis of Comparative Opinions

Apart from directly expressing positive or negative opinions about an entity and/or its aspects, one can also express opinions by comparing similar entities. Such opinions are called *comparative opinions* (Jindal and Liu, 2006a, 2006b). Comparative opinions have different semantic meanings than regular opinions and also different syntactic forms. For example, a typical regular opinion sentence is "*The voice quality of this phone is amazing*," and a typical comparative opinion sentence is "*The voice quality of Moto X is better than that of iPhone 5*." This comparative sentence does not say that any phone's voice quality is good or bad, but simply states a relative ordering in terms of voice quality of the two smart phones. Like regular sentences, comparative sentences can be opinionated or not-opinionated. The above comparative sentence is clearly opinionated because it explicitly expresses a comparative sentiment, while the sentence "*Samsung Galaxy 4* is larger than *iPhone 5*" expresses no sentiment, at least not explicitly. In this chapter, we first define the problem of comparative opinion mining and then present some existing methods for solving the problem. We will study *superlative opinions* as well because their semantic meanings and handling methods are similar.

8.1 Problem Definition

A comparative sentence usually expresses a relation based on the similarities or differences of more than one entity. Linguists have studied comparatives in the English language for a long time. Lerner and Pinkal (1992) defined comparatives as universal quantifiers over degrees. For example, in the sentence "*John is taller than he was*," the degree *d* is John's height and John is tall to degree *d*. In other words, comparatives are used to express explicit orderings between objects with respect to the degree or amount to which they possess some gradable property (Kennedy, 2005). Two broad types of comparatives are as follows:[3]

1. *Metalinguistic comparatives*. Compare the extent to which an entity has one property to a greater or lesser extent than another property, for example, "*Ronaldo is angrier than upset*."

2. *Propositional comparatives*. Make a comparison between two propositions. This category has three subcategories:

a. *Nominal comparatives*. Compare the cardinality of two sets of objects denoted by nominal phrases, for example, "*Paul ate more grapes than bananas*."

b. *Adjectival comparatives*. Usually use words that end with – *er*, *more*, *less*, and so on (occurring with the conjugate *than*) and equative *as* (e.g., *as good as*), for example, "*Ford is cheaper than Volvo*."

c. *Adverbial comparatives*. Similar to nominal and adjectival ones except that they generally occur after a verb phrase, for example, "*Tom ate more quickly than Jane*."

Then there are superlatives, which are a form of adjectives or adverbs that expresses the highest or a very high degree of quality of what is being described. They have two categories:

1. *Adjectival superlatives*. Express that an entity has the most of a particular quality within a group or of its kind, for example, "*John is the tallest person.*"

2. *Adverbial superlatives*. Express that an entity does something to the greatest degree within a group or of its kind, for example, "*Jill did her homework most frequently*"

We can also look at comparisons from the gradability point of view, from which we can group comparisons into two categories: *gradable comparison* and *nongradable comparison* (Kennedy, 2005; Jindal and Liu, 2006a).

> **Gradable comparison.** Expresses an ordering relationship of entities being compared. It has three subtypes:
>
> **1.** *Nonequal gradable comparison*. Expresses a relation of the type *greater* or *less than*, which ranks a set of entities over another set of entities based on some of their shared aspects, for example, "*Coke tastes better than Pepsi*." This type also includes preference, for example, "*I prefer Coke to Pepsi*."
>
> **2.** *Equative comparison*. Expresses a relation of the type *equal to*, which states that two or more entities are equal based on some of their shared aspects, for example, "*Coke and Pepsi taste the same*."
>
> **3.** *Superlative comparison*. Expresses a relation of the type greater or less than all others, which ranks one entity over all others, for example, "*Coke tastes the best among all soft drinks*."

Nongradable comparison. Expresses a relation between two or more entities but does not grade them. There are three main subtypes:

1. Entity *A* is similar to or different from entity *B* based on some of their shared aspects, for example, "*Coke tastes differently from Pepsi*."

2. Entity *A* has aspect a_1, and entity *B* has aspect a_2 (a_1 and a_2 are usually substitutable), for example, "*Desktop PCs use external speakers but laptops use internal speakers*."

3. Entity *A* has aspect *a*, but entity *B* does not have, for example, "*Nokia phones come with earpieces, but iPhones do not*."

This chapter only focuses on gradable comparisons. Nongradable comparisons may also express opinions but they are often more subtle and difficult to determine.

In English, comparisons are typically expressed using *comparative words* (also called *comparatives*) and *superlative words* (also called *superlatives*). Comparatives are formed by adding the suffix -*er* and superlatives are formed by adding the suffix -*est* to their *base adjectives* and *base adverbs*. For example, in "*The battery life of Huawei phones is longer than that of Samsung phones*," *longer* is the comparative form of the adjective *long*. *Longer* (with *than*) here also indicates that this is a comparative sentence. In "*The battery life of Nokia phones is the longest*," *longest* is the superlative form of the adjective *long*, and it indicates that this is a superlative sentence. We call this type of comparatives and superlatives *Type 1 comparatives and superlatives* respectively. For simplicity, we often use *comparative* to mean both *comparative* and *superlative* if superlative is not explicitly stated.

However, adjectives and adverbs with two syllables or more and not ending in *y* do not form comparatives or superlatives by adding *-er* or *-est*. Instead, *more*, *most*, *less*, and *least* are used before such words, for example, *more beautiful*. We call this type of comparatives and superlatives *Type 2 comparatives* and *superlatives*. Both Type 1 and Type 2 are called *regular comparatives* and *superlatives*.

English also has *irregular comparatives* and *superlatives*, that is, *more*, *most*, *less*, *least*, *better*, *best*, *worse*, *worst*, *further/farther* and *furthest/farthest*, which do not follow the preceding rules. However, they behave similarly to Type 1 comparatives and are thus grouped under Type 1.

These standard comparatives and superlatives are only some of the words that indicate comparison. In fact, there are many other words and phrases that can be used to express comparisons, for example, *prefer* and *superior*. For example, the sentence "*The iPhone's voice quality is superior to that of the Blackberry*" says that the iPhone has a better voice quality and is preferred. Jindal and Liu (2006a) compiled a list of such words and phrases (still incomplete). Because these words and phrases usually behave similarly to Type 1 comparatives, they are also grouped under Type 1. All these words and phrases plus the preceding standard comparatives (-*er* words) and superlatives (-*est* words) are collectively called *comparative keywords*.

Comparative keywords used in nonequal gradable comparisons can be further divided into two groups. This grouping is very useful in sentiment analysis.

- *Increasing comparative*. Expresses an increased quantity of some property, for example, *more* and *longer*.
- *Decreasing comparative*. Expresses a decreased quantity, for example, *less* and *fewer*.

Objective of mining comparative opinions (Jindal and Liu, 2006b; Liu, 2010). Given an opinion document *d*, discover in *d* all comparative opinion sextuples of the form

(E_1, E_2, A, PE, h, t),

where E_1 and E_2 are the entity sets being compared based on their shared aspects A (entities in E_1 appear before entities in E_2 in the sentence), PE ($\in \{E_1, E_2\}$) is the preferred entity set of the opinion holder h, and t is the time when the comparative opinion is expressed. In other words, the representation says that the aspects A of entity sets E_1 and E_2 are compared and the opinion holder h's opinion at time t is that the entity set PE's ($PE \in \{E_1, E_2\}$) aspects A are superior. For a superlative comparison, we can use a special universal set U to denote an implicit entity set

> that is not given in the text. For an equative comparison, we can use the special symbol EQUAL as the value for *PE*.

For example, consider the comparative sentence "*Canon's picture quality is better than those of LG and Sony*," written by Jim on 9–25–2011. The extracted comparative opinion is

({Canon}, {LG, Sony}, {picture_quality}, {Canon}, Jim, 9–25–2011)

The preceding representation may not be easily put into a database due to the use of sets, but it can be easily converted to multiple tuples with no sets. The sets based sextuple can be expanded into two tuples without sets:

(Canon, LG, picture_quality, Canon, Jim, Dec-25–2010)

(Canon, Sony, picture_quality, Canon, Jim, Dec-25–2010)

Like mining regular opinions, to mine comparative opinions we need to extract entities, aspects, opinion holders, and times. The techniques used are similar too. In fact, these tasks are often easier for comparative sentences because entities are usually on the two sides of the comparative keyword, and aspects are also nearby. However, for sentiment analysis to identify the preferred entity set, a different method, which we will discuss in Section 8.3, is needed. We also need to identify comparative sentences themselves because not all sentences containing comparative keywords express comparisons and many comparative keywords and phrases are hard to identify (Jindal and Liu, 2006b). In what follows, we focus on studying two comparative opinion specific problems: identifying comparative sentences and determining the preferred entity set.

8.2 Identify Comparative Sentences

Although most comparative sentences contain comparative and superlative keywords, for example, *better*, *superior*, and *best*, many sentences that contain such words are not comparative sentences, for example, "*I cannot agree with you more*." It was shown by Jindal and Liu (2006a) that almost every comparative sentence has a keyword (a word or phrase) indicating comparison. Using a set of keywords, they were able to identify 98% of the comparative sentences (recall = 98%) in their corpus with a precision of 32%. The keywords are as follows:

1. Comparative adjectives (JJR) and comparative adverbs (RBR), for example, *more*, *less*, *better*, and words ending with -*er*. These are counted as only two keywords.

2. Superlative adjectives (JJS) and superlative adverbs (RBS), for example, *most*, *least*, *best*, and words ending with -*est*. These are also counted as only two keywords.

3. Other non-standard indicative words and phrases such as *favor*, *beat*, *win*, *exceed*, *outperform*, *prefer*, *ahead*, *than*, *superior*, *inferior*, *number one*, *up against*, and so on. These are counted individually in the number of keywords.

Because keywords alone are able to achieve a high recall, they can be used to filter out those sentences that are unlikely to be comparative sentences. We just need to improve the precision on the remaining sentences.

Jindal and Liu (2006a) observed that comparative sentences have strong patterns involving comparative keywords, which is not surprising. These patterns can be used as features in learning. To discover these patterns, class sequential rule (CSR) mining was employed in Jindal and Liu (2006a). CSR mining is a special kind of sequential pattern mining (Liu, 2006, 2011). Each training example is a pair (s_i, y_i), where s_i is a sequence and y_i is a class label, that is, $y_i \in$ {comparison, noncomparison}. The sequence is generated from a sentence. Using the training data, CSR can be generated. For classification model building, the left-hand side sequence patterns of the CSR rules with high conditional probabilities were used as features. Naïve Bayes was employed for model building. In Yang and Ko (2011), the authors studied the same problem but in the context of Korean language using a transformation-based learning algorithm, which also produces rules.

> **Classifying comparative sentences into four types.** After comparative sentences are identified, the algorithm also classifies them into four types, *nonequal gradable*, *equative*, *superlative*, and *nongradable*. For this task, Jindal and Liu (2006a) showed that keywords and keyphrases as features were already sufficient. SVM gave the best results.

Over the years, several other researchers have also studied this and related classification problems. For example, Li et al. (2010) studied the problem of identifying comparative questions and the entities (which they call comparators) that are compared but they did not decide the types of comparison. For comparative sentences identification, they also used sequential patterns/rules. However, their patterns are different in that they not only decide whether a question is a comparative question but also find the entities being compared at the same time. For example, the question sentence "*Which city is better, New York or Chicago*?" satisfies the sequential pattern <which NN is better, $C or $C ?>, where $C is an entity. They used the weakly supervised learning method in Ravichandran and Hovy (2002) to learn such patterns. The algorithm is based on bootstrapping, which starts with a user-given pattern. From this pattern, it extracts a set of initial seed entity (comparators) pairs. For each entity pair, all questions containing the pair are retrieved from the question collection and regarded as comparative questions. From the comparative questions and entity pairs, all possible sequential patterns are learned and evaluated. The learning process is the traditional generalization and specialization process. Any words or phrases that match $C in a sentence are extracted as entities. Both Jindal and Liu (2006b) and Yang and Ko (2011) also extracted compared entities, which we discuss in Section 8.5.

8.3 Identifying the Preferred Entity Set

Unlike regular opinions, it does not make much sense to perform sentiment classification on a comparative opinion sentence as a whole because such a sentence does not express a direct positive or negative opinion. Instead, it compares the shared aspects of multiple entities by ranking them to give a *comparative opinion*. That is, it expresses a preference order of the entities based on their aspect comparison. Because most comparative sentences compare two sets of entities, the analysis of an opinionated comparative sentence means to identify the preferred entity set. For application purposes, one may assign positive opinions to the aspects of the entities in the preferred set, and negative opinions to the aspects of the entities in the not preferred set. In what follows, we describe a method for identifying the preferred entity set based on the methods proposed in Ding et al. (2009) and Ganapathibhotla and Liu (2008).

Their methods extend the lexicon-based approach to aspect-based sentiment classification of regular opinions to that of comparative opinions. They thus need a sentiment lexicon for comparative opinions. Similar to opinion (or sentiment) words of the base type, we can divide comparative opinion words into two broad categories:

1. *General-purpose comparative sentiment words*. For Type 1 comparatives, this category includes words like *better*, *worse*, and so on, which often have domain-independent positive or negative sentiments. In sentences involving such words, it is often easy to determine which entity set is preferred. In the case of Type 2 comparatives (formed by adding *more*, *less*, *most*, or *least* before adjectives/adverbs), the preferred entity sets are determined by both words. The following rules apply:

Comparative Negative	:: =	Increasing_Comparative N
	|	Decreasing_Comparative P
Comparative Positive	:: =	Increasing_Comparative P
	|	Decreasing_Comparative N

Here, P (respectively N) denotes a positive (negative) sentiment word or phrase of the base type. The first rule says that the combination of an increasing comparative (e.g., *more*) and a negative sentiment word (e.g., *awful*) implies a *comparative negative opinion* (on the left), which means that the entities on the left of the comparative keyword is not preferred. The other rules have similar meanings. Note that the four rules have already been discussed as composition rules of opinions in Section 5.2, where we used MORE for Increasing_Comparative, and LESS for Decreasing_Comparative.

2. *Context-dependent comparative sentiment words*. In the case of Type 1 comparatives, such words include *higher*, *lower*, and so on. For example, "*Nokia phones have longer battery life than Motorola phones*" carries a comparative positive sentiment about *Nokia phones* and a comparative negative sentiment about *Motorola phones*, that is, *Nokia phones* are preferred with respect to the *battery life* aspect. However, without domain knowledge it is hard to know whether *longer* is positive or negative for *battery life*. This issue is the same as for regular opinions, and this case has also been included in the composition rules of opinions in Section 5.2. Here, *battery life* is considered as a *PPI*.

In the case of Type 2 comparatives, the situation is similar. However, in this case the comparative word (*more*, *most*, *less* or *least*), the adjective/adverb, and the aspect are all important in determining the preference. If we know whether the comparative word is an increasing or decreasing comparative (which is easy because there are only four of them), then the opinion can be determined by applying the four rules in point 1.

To deal with *context-dependent comparative sentiment words*, we refer to Section 7.2, where we used the pair (*context_sentiment_word*, *aspect*) as an opinion context. To determine whether a pair is positive or negative, the algorithm in Ganapathibhotla and Liu (2008) uses a large external corpus of Pros and Cons from product reviews to determine whether the *aspect* and *context_sentiment_word* are more associated with each other in Pros or in Cons. If they are more associated in Pros, *context_sentiment_word* is most likely to be positive. Otherwise, it is likely to be negative. However, because Pros and Cons seldom use comparative opinions, context-dependent comparative sentiment words in a comparative sentence have to be converted to their base forms (e.g., from *longer* to *long*) before being analyzed using the Pros and Cons corpus. The conversion can be done using WordNet with the help of English comparative formation rules. This conversion is meaningful because of the following observation.

> **Observation.** If a base adjective or adverb is positive (or negative), its comparative or superlative form is also positive (or negative), for example, *good*, *better*, and *best*.

After the comparative sentiment words and their orientations are identified, determining which entity set in a sentence is preferred is fairly simple. Without negation, if the comparative is positive (or negative), then the entities before (or after) *than* are preferred. Otherwise, the entities after (or before) *than* are preferred. For superlative sentences, the situation is similar except that the second entity set E_2 may not be explicitly given in the sentence, for example, "*Dell laptops are the worst*." In that case, we use the universal set U to indicate E_2.

8.4 Special Types of Comparison

In dealing with comparative opinions, one of the biggest problems is how to identify whether a sentence expresses a comparative opinion and where the separation of the two sides of the comparison is. Here we focus on gradable comparisons, as they are most useful in practice. For those sentences using standard comparative (–*er*) and superlative (–*est*) adjectives and adverbs, it is relatively easy to determine whether a sentence expresses a comparison or not and to identify the separation point, which is usually the *than* word. However, there are many special comparisons that need special handling.

8.4.1 Nonstandard Comparison

Although most comparative sentences in English use *–er* and *–est* words (plus *more*, *most*, *less*, and *least*), there are still a large number of comparisons that do not use such words. These comparisons typically express user preferences, superiorities, winning or losing in contests, and so on. They may also look syntactically different from standard comparisons, but they have the same or similar meanings. Many such sentences actually give objective (rather than subjective) information that also express some desirable or undesirable states for the entities involved. Thus, they represent fact-implied positive or negative comparative opinions (see Section 2.4.2). In what follows, we first list some phrases and then individual words that are often used to express explicit or implicit comparisons. For each phrase, we provide an example sentence to show its usage context.

ahead of

“*In terms of processor speed, Intel is way ahead of AMD.*”

blow away

“*AMD blows Intel away*”

blow out of water

“*Intel blows AMD out of water.*”

(buy | choose | grab | pick | purchase | select | stick to) over

“*I would select Intel over AMD.*”

“*I would stick to Intel over AMD.*”

X can do something positive Y cannot

“*This earphone can filter high-frequency noise that Sony earphones cannot.*”

cannot race against

“*Touchpad cannot race against iPad.*”

cannot compete with

“*Motorola cannot compete with Nokia.*”

(drop | dump) something for

“*I dumped my Touchpad for a Coolpad.*”

(edge | lead | take) past

“*AMD edged past Intel.*”

edge out

“*Apple edged out Blackberry*.”

get rid of something for

“*I got rid of my Blackberry for an iPhone*.”

gain from

“*Blackberry gained some market shares from iPhone*.”

(inferior | superior) to

“*In terms of quality, Blackberry is superior to iPhone*.”

“*In terms of quality, Blackberry is inferior to iPhone*.”

lag behind

“*iPhones lags behind Samsung phones*”

lead against

“*Team-A leads 3–2 against Team-B*.”

lead by

“*Team-A leads Team-B by 3–2*.”

lose to | against

“*Team-A lost the race to Team-B*.”

on [a] par with

“*Touchpad is on par with iPad*.”

(not | nothing) like

“*My iPhone is not like my ugly old Droid phone*.”

“*My iPhone is nothing like my ugly old Droid phone*.”

prefer to | over

“*I prefer Blackberry to iPhone*.”

Subpar with

“*iPhone is subpar with Blackberry*.”

suck against

“*iPhone sucks against Blackberry*.”

take over

“*iPhone takes over Blackberry*.”

vulnerable to

"*Blackberry is vulnerable to iPhone's attack*."

win against

"*Apple wins the game against Samsung*."

Apart from these phrases, many individual words can also be used to express similar meanings. We list some of the words here: *beat*, *defeat*, *destroy*, *kill*, *lead*, *rival*, *trump*, *outclass*, *outdo*, *outperform*, *outplay*, *overtake*, *top*, *smack*, *subdue*, *surpass*, *win*, and so on.

"*Honda beats Volkswagen in quality*."

"*BMW is killing Nisan*."

"*Blackberry cannot rival iPhone*."

Sentences involving such words must be analyzed with care because many of them do not express comparisons in some contexts due to different senses, idioms, and some specific usages. For example, the word *beat* used in the context of comparison has the sense of *defeat*, *subdue*, *superior to* or *better than*, but *beat* can also mean music beat. The word appears in several idioms too, for example, "*beat me*," "*beat a dead house*," and "*beat around/about the bush*."

To determine whether a sentence using such a word expresses a comparison or not can be a challenge. One of the strong clues is whether more than one entity set is mentioned in the sentence. If there is not an entity on each side of the word, the sentence is not likely to be a comparative sentence. This check is itself not simple because it requires the system to have the entity recognition capability and in many cases the coreference resolution capability as well because an entity might have appeared in a previous sentence.

There are still other nonstandard comparisons that are hard to recognize. For example, the sentence "*With the iPhone, I no longer need my iPad*" is a kind of comparison, but there does not seem to be any strong clue that can be used to recognize this comparison in practice except that there are two entities in the sentence.

8.4.2 Cross-Type Comparison

Comparative, equative, or superlative words and phrases are usually used to express their corresponding comparisons of comparative, equative, or superlative meanings. However, that is not always the case. One type of comparisons may be expressed using another type of comparative constructs.

> **Superlatives expressed using comparatives.** Use comparative words to express superlative meanings in two main ways,

1. by explicitly or implicitly comparing with every other entity, for example,

"*This phone is **better than** every other phone*"

This sentence actually say "*This phone is the best*." In analyzing such sentences, the system should realize that the second entity set in the comparison is the universal set *U* as *every other phone* appeared after the comparative word *better*.

2. by combining negation and comparison involving a phrase expressing the meaning of "*everything else*," for example,

"*You **cannot** find anything **better than** iPhone*."

"*It does **not** get any **better than** iPhone*."

"***No** phone works **better than** iPhone*."

Like 1, these sentences express superlative meanings. However, in this case, the first entity set is the universal set *U*. Such sentences often use *find* and *get* as their main verbs although not always (e.g., the third sentence). In sentences like these, the preferred entity sets often appear after the comparative words, for example, *better*.

Comparatives expressed with negated equatives. Combine an negation word and an equative expression to express a nonequal gradable comparison, for example,

"*The iPhone is not as good as this phone*."

Regular opinions expressed with negated superlatives. When a negation word negates a superlative word in an opinion sentence, the sentence usually expresses a regular opinion rather than a comparative or superlative opinion, for example,

"*Moto X is not the best phone in the world*."

Without any context, this sentence can be treated as negative about *Moto X*. But such sentences are really ambiguous. In some cases, the author may add a clause or even a separate sentence to clarify his real sentiment, for example,

"*Moto X is not the best phone in the world, but it is quite good*."

In sentiment analysis, we can ignore the sentiment expressed in the first part of the sentence.

8.4.3 Single-Entity Comparison

In Section 8.1, we defined comparisons based on two entity sets and some of their shared aspects. However, there are also some types of comparisons that involve only one entity set. In dealing with such comparisons, if they express opinions, we can treat them as regular opinions rather than comparative opinions. It is not known how many types of such comparisons exist. We list a few of them. Our classification is not based on semantic meanings for human understanding but on how they can be recognized syntactically and dealt with in a sentiment analysis system, for example, based on POS tags and some specific words.

1. More or less than normal, usual, sufficient, enough, and so on:

“*This camera’s build-in memory is **more than sufficient**.*”

“*iPhone provides **more than usual** amount of memory.*”

“*After taking the drug, my blood pressure went much **higher than normal**.*”

2. More or less than a particular quality grade:

“*This car is **more than** just **beautiful**.*”

“*Lenovo’s service agents are **more than happy** to help.*”

3. More or less than a particular quantity:

“*I have used this machine for **more than 5** years.*”

“*This car cost **more than $150,000.***”

4. Comparing with some expectations or anticipations:

“*This car is more **beautiful than** I **expected**.*”

5. Comparing with the same entity or aspect in the past:

“*This phone works **better than in the past**.*”

6. Comparing with the feeling in the past:

“I love this car **more than before** (or **ever**).”

7. Comparing different aspects:

“*This car is **more beautiful than lasting**.*”

This type of comparisons needs special handling because it does not compare different entities but two or more aspects of the same entity. For example, the author of the preceding example sentence is more positive about the appearance (or beauty) of the car than about its durability. This case is not covered by our definition in Section 8.1. Of course, it is possible to propose a new definition to cover this case, but it may not be necessary as such comparisons do not appear frequently. In practice, we can simply treat this as two regular opinions, positive about *appearance* and negative about *durability*.

8. Comparative or superlative words appeared in idioms:

“*It is easier said than done*.”

There are also many phrases and idioms that contain the ‘*than*’ word, but does not indicate any gradable comparison, for example, “*other than*,” “*rather than*,” “*different than*,” “*look no further than*,” and so on.

8.4.4 Sentences Involving *Compare* or *Comparison*

It is no surprise that words "*compare*" and "*comparison*" are also commonly used to express comparisons. However, sentences that use these words have very different syntactic forms than standard comparisons. They may or may not use any comparative or superlative words. I single out this type of sentences because of this reason, and also because they need a different method to analyze them. In fact, they are harder to deal with. In what follows, we list four kinds of phrases involving *compare* or *comparison*, classified mainly based on their syntactic differences. These differences help a system to recognize them and deal with them individually. Their semantic meanings are similar except the last one.

(Compared | comparing) (with | to | and): used as participle phrases, that is, *compared* or *comparing* is not used as the main verb of the sentence.

"*Compared Camry with Audi, Audi is more fun to drive*."

"*Compared to everything else in its class, BMW sets the standard*."

"*Compared to Camry BMW is wonderful*."

"*After comparing Camry with Prius we settled on the Prius*."

Only the first sentence uses a comparative word (i.e., *more*) while all other sentences do not use any comparative or superlative word. The first two sentences are easier to handle but the third and fourth sentences are difficult to deal with because there is no comma separating the two clauses in each sentence. Without the comma, the parser often makes mistakes, which causes errors in determining which entity set is preferred.

In these sentences, past participle (in the first three sentences) and present participle phrases (in the fourth sentence) appear before the main clauses of the sentences, but they can also appear after the main clauses.

"*Hondas feel like tin cans compared to Volkswagens*."

"*The exterior of Camry gives it a sleek look compared to Accord*."

"*BMW is outstanding compared to Audi and Lexus*."

In comparison (of | with): function similarly to the preceding phrases.

"*Mini is good in comparison with Smart*."

"*In comparison with BMW, Lexus is a better choice*."

"*In comparison of the iPhone and* (or *to*) *the Lumia, Lumia has a good voice quality*."

Compare (with | to | and | over): Here *compare* is used either as the main verb of the sentence or in the infinitive form. Such sentences are often hard to deal with as the clauses expressing the comparison may not indicate any sentiment or opinion. For instance, in the first example following, the opinion is expressed in the second sentence. This causes difficulty because the compared entities are not in the same sentence. To deal with such sentences, we need discourse-level analysis. In the second example, the sentiment is expressed in the second clause after *and*, and in the third example, the opinion is only implied in the before clause. The fourth example uses an infinitive phrase of *compare* and it does not express any opinion.

"*I drove and compared the BMW and the Lexus. I found the BMW is more fun to drive.* "

"*I compared the BMW and the Lexus and found that the Lexus offers far more features*."

"*I compared the BMW and the Lexus before buying the BMW*."

"*I prepared a spreadsheet to compare the fuel and cost savings between the BMW and the Lexus*."

No comparison | cannot compare. Usually express opinions and are relatively easy to deal with:

"*There is no comparison with the BMW when it comes to the interior space*."

"*The BMW cannot compare with the Audi*."

However, in some cases they express no sentiment and can be hard to spot, for example,

"*You cannot compare BMW and Lexus as they are for different purposes*."

"*I have no comparison results for these two cars*."

8.5 Entity and Aspect Extraction

As mentioned at the beginning of Chapter 6, there are four main approaches to aspect and entity extraction, which is also called *opinion target extraction*. We reproduce them here:

1. Extraction based on frequent nouns and noun phrases.

2. Extraction by exploiting grammatical relations. There are two main types of relations: (i) syntactic dependencies depicting opinion and target relations, and (ii) lexico-syntactic patterns encoding entity and part/attribute relations.

3. Extraction using supervised learning.

4. Extraction using topic models.

For target extraction from comparative sentences, these approaches still apply. In fact, the detailed methods discussed in Chapter 6 (for regular opinion sentences) in the first and fourth approaches can be directly used here with no modifications. The third approach is applicable as well except that the features used for the two types of sentences may be different. The second approach is also applicable except that the relations used for the two types of sentences have differences, but there is also a large intersection between them (see Section 6.2.1). Here we highlight three main differences.

1. Opinion and target relations used in Section 6.2.1 need to be extended because a comparative sentence compares two sets of entities. Thus, there is usually more than one opinion target. For example, in "*Coke is better than Pepsi*," the targets of the comparative opinion (represented by *better*) are *Coke* and *Pepsi*. Clearly this special relation can be exploited for aspect and entity extraction.

2. A comparative sentence contains at least one entity, usually two or more except some special types of comparisons. But for a regular opinion sentence, it may not mention any entity or even a pronoun referring to it. For example, in "*I brought a Lenovo laptop yesterday. The screen is really cool*," the opinion target of the second sentence is *screen* but the sentence does not mention the entity that it belongs to, which is in the first sentence. However, it is unlikely that a comparative sentence does not mention any entity. For example, in "*I brought a Lenovo laptop yesterday. The screen is better than that of Dell*," if the second sentence does not mention *Dell*, it will not be a comparative sentence.

3. Special characteristics of different types of comparisons can be exploited in extraction because they usually have different syntactic forms and thus different dependencies between opinion (or sentiment) expressions and their targets. That is, targets and opinions are connected with their specific relations. For example, we can see from Section 8.4.4, different ways of using *compare* or *comparison* require different relations for extraction.

To consider these observations in entity and aspect extraction using opinion and target relations, we simply need to design additional dependency relations, which are fairly easy to do and we will not discuss them further here. Obviously, these relations can be used as features for supervised learning as well.

8.6 Summary

Although there have been some existing works, comparative opinions have not been studied as extensively as many other topics of sentiment analysis. Apart from identifying comparative sentences and their types as we discussed earlier, several researchers have also worked on the extraction of compared entities, compared aspects, and comparative words. Jindal and Liu (2006b) used label sequential rule mining, which is a supervised learning method based on sequential patterns. Yang and Ko (2011) applied the ME (maximum entropy) and SVM (support vector machines) learning algorithms. Fiszman et al. (2007) attempted to identify entities with more of certain aspects in comparative sentences in biomedical texts, but they did not analyze opinions in comparisons.

In general, standard comparisons involving *–er* and *–est* words and other words functioning similarly to them (e.g., *prefer* and *superior*) are relatively easy to analyze. Two problems are, however, challenging in my opinion. The first problem involves comparative sentences using the word *compare* or *comparison*. Because their use can be very flexible, identifying aspects and/or entities that have been compared and the preferred entity set is not easy. The second problem is that many nonstandard comparison words have multiple senses. In some senses, they express comparison but in some other senses they do not. It is not easy to perform accurate word sense disambiguation. Using simple patterns to perform the task is usually not sufficient. Further research is needed.

3 http://www.cis.upenn.edu/~xtag/release-8.31.98-html/node189.html

9

Opinion Summarization and Search

As discussed in Chapter 2, in most sentiment analysis applications, one needs to study opinions from many people because due to the subjective nature of opinions, looking at only the opinion from a single person is usually not sufficient. To understand a large number of opinions, some form of summary is necessary. Definition 2.14 in Section 2.2 defined a structured opinion summary called *aspect-based summary*, also known as *feature-based summary* in Hu and Liu (2004) and Liu et al. (2005). Much of the opinion summarization research is based on this definition. This form of summary is also widely used in industry. For example, both Microsoft Bing and Google Product Search use this form of summary in their opinion analysis systems.

In general, opinion summarization can be seen as a kind of *multidocument text summarization*. Traditional text summarization has been studied extensively in NLP (Das, 2007). However, an opinion summary is quite different from a conventional single document or multidocument summary (of factual information). The reason is that an opinion summary should (1) be centered on entities and aspects and sentiments about them and (2) be quantitative. Traditional single document summarization produces a short document from a long document by extracting some “important” sentences, while traditional multidocument summarization finds differences among documents and discards repeated information. Neither of them *explicitly* captures different topics/entities and their aspects discussed in the documents, nor do they have a quantitative perspective. The “importance” of a sentence in traditional text summarization is typically defined operationally based on the summarization algorithms and measures used in each system. Opinion summary, on the other hand, can be defined formally in a structured form and represented as structured objects (see Definition 2.14). Even for output opinion summaries that are short text documents, there should still be explicit structures in them.

After discussing summarization, we move the topic of opinion search or retrieval in this chapter. As the general web search has proven to be an extremely valuable service on the web, it is not hard to imagine that opinion search will be of great use as well. However, opinion search is very different from the general web search, and is considerably harder to perform. Ideally, opinion search should return summarized opinions for the user’s search query. Sections 9.6 and 9.7 examine the current algorithms for opinion search, many of which originated from the TREC Blog Track evaluations.

9.1 Aspect-Based Opinion Summarization

Aspect-based opinion summarization has two main characteristics (Hu and Liu, 2004). First, it captures the essence of opinions: opinion targets (entities and their aspects) and sentiments about them. Second, it is quantitative, which means that it gives the number or percentage of people who hold positive or negative opinions about the entities and aspects. The quantitative side is crucial because of the subjective nature of opinions. The resulting opinion summary is a form of structured summary produced from the opinion quintuple in Section 2.1. Figure 9.1 reproduces the opinion summary example in Section 2.2 about a digital camera. The aspect GENERAL represents opinions on the camera entity as a whole. For each aspect (e.g., picture quality), it shows the number of people who hold positive and negative opinions respectively. <Individual review sentences> links to the actual sentences or full reviews or blogs. Because it is a structured form of summary, it can be easily visualized (Liu et al., 2005). Figure 9.2a uses a bar chart to visualize the summary in Figure 9.1. In the figure, each bar above the *X*-axis shows the number of positive opinions about the aspect given at the top. The corresponding bar below the *X*-axis shows the number of negative opinions on the same aspect. Clicking on each bar, we can see the individual sentences and full reviews. Obviously, other forms of visualizations are also possible, for example, pie charts. Comparing opinion summaries of a few entities is even more interesting (Liu et al., 2005). Figure 9.2b shows the visual opinion comparison of two digital cameras. We can see how consumers felt about each of them along different aspect dimensions including the entities (the digital cameras) themselves.

Digital Camera 1:

Aspect: **GENERAL**

Positive:	105	<individual review sentences>
Negative:	12	<individual review sentences>

Aspect: **Picture quality**

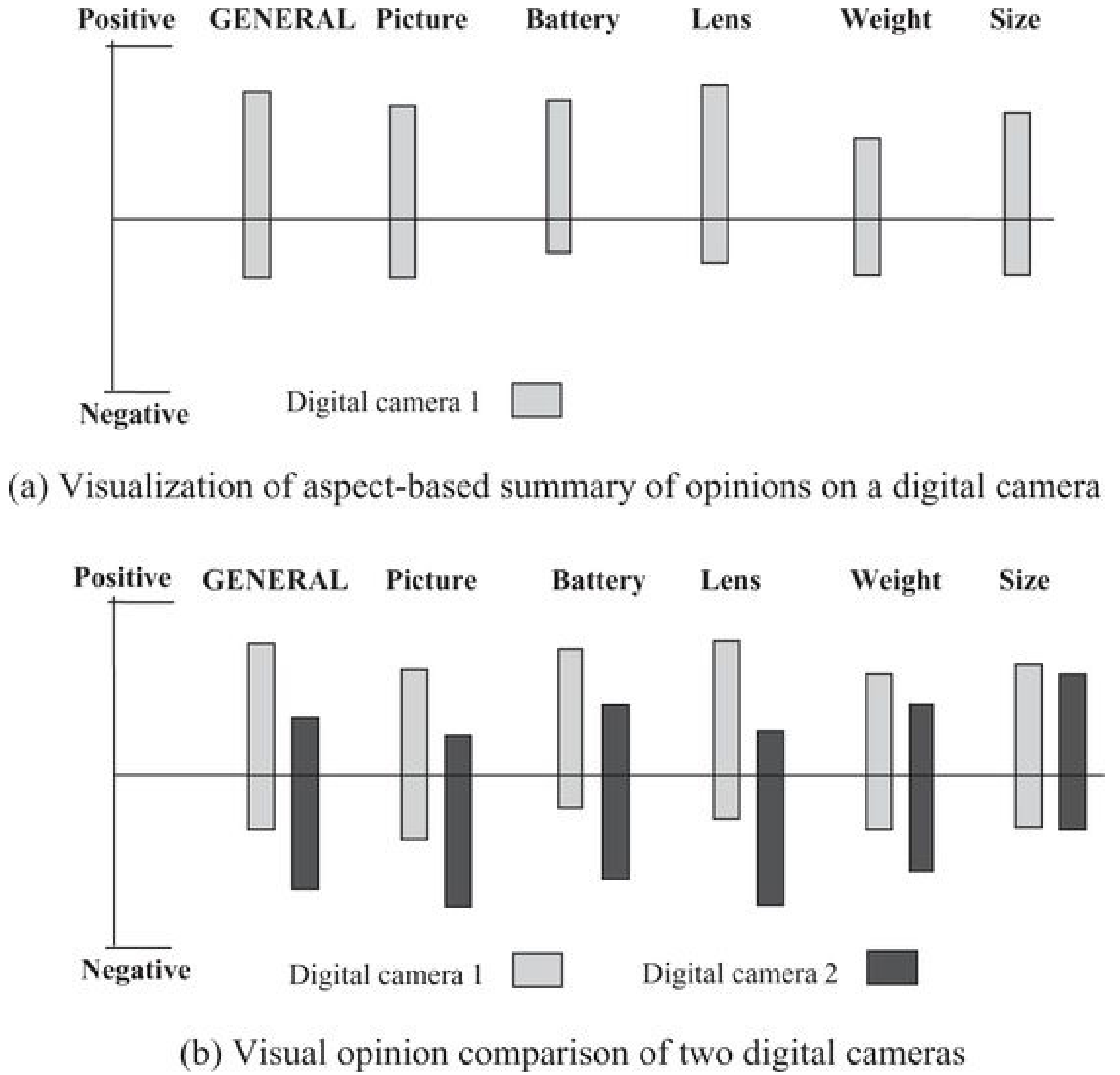
Positive:	95	<individual review sentences>
Negative:	10	<individual review sentences>

Aspect: **Battery life**

Positive:	50	<individual review sentences>
Negative:	9	<individual review sentences>

…

Figure 9.1. An aspect-based opinion summary.



(a) Visualization of aspect-based summary of opinions on a digital camera

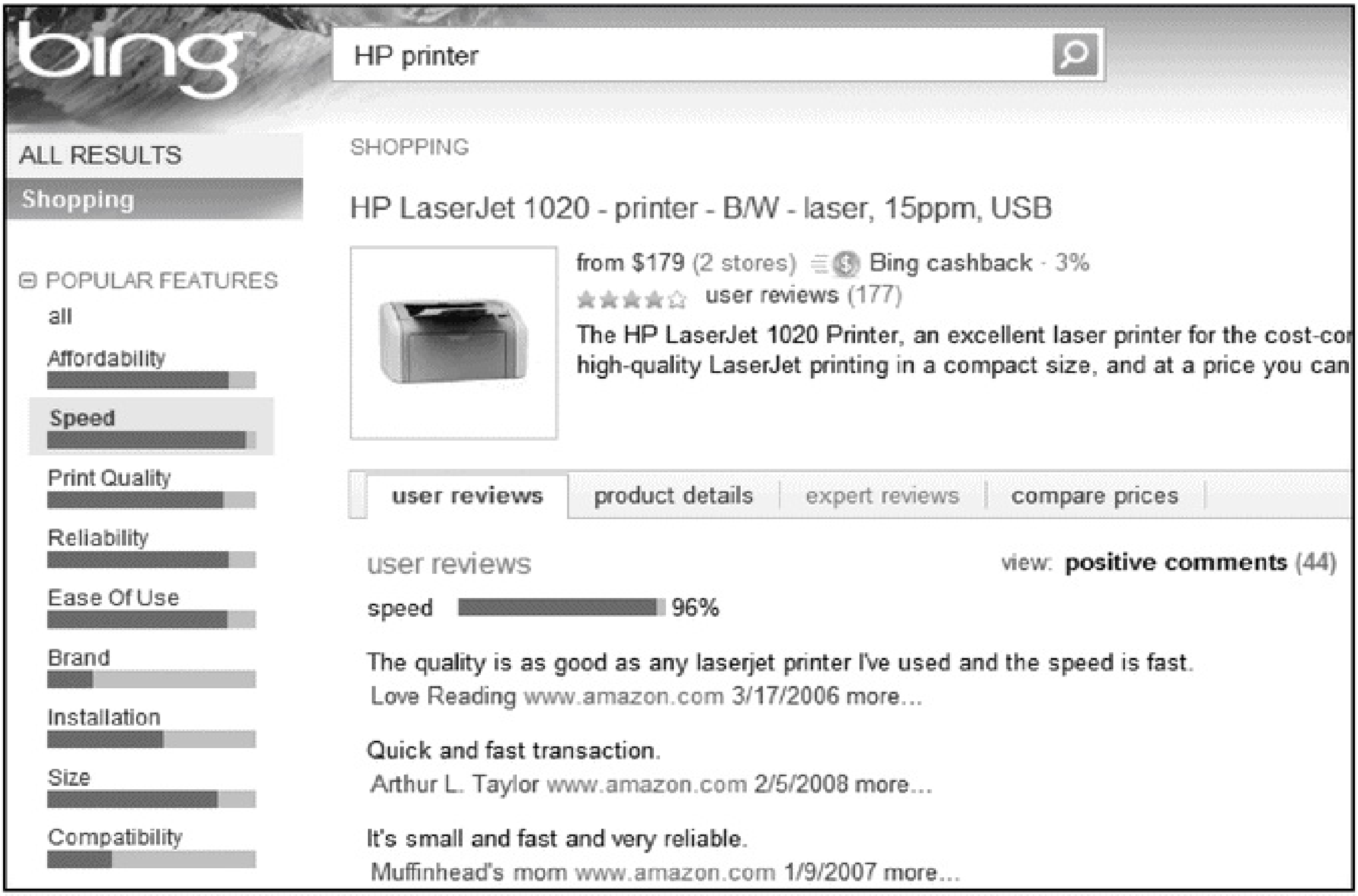
(b) Visual opinion comparison of two digital cameras

Figure 9.2. Visualization of aspect-based summaries of opinions.

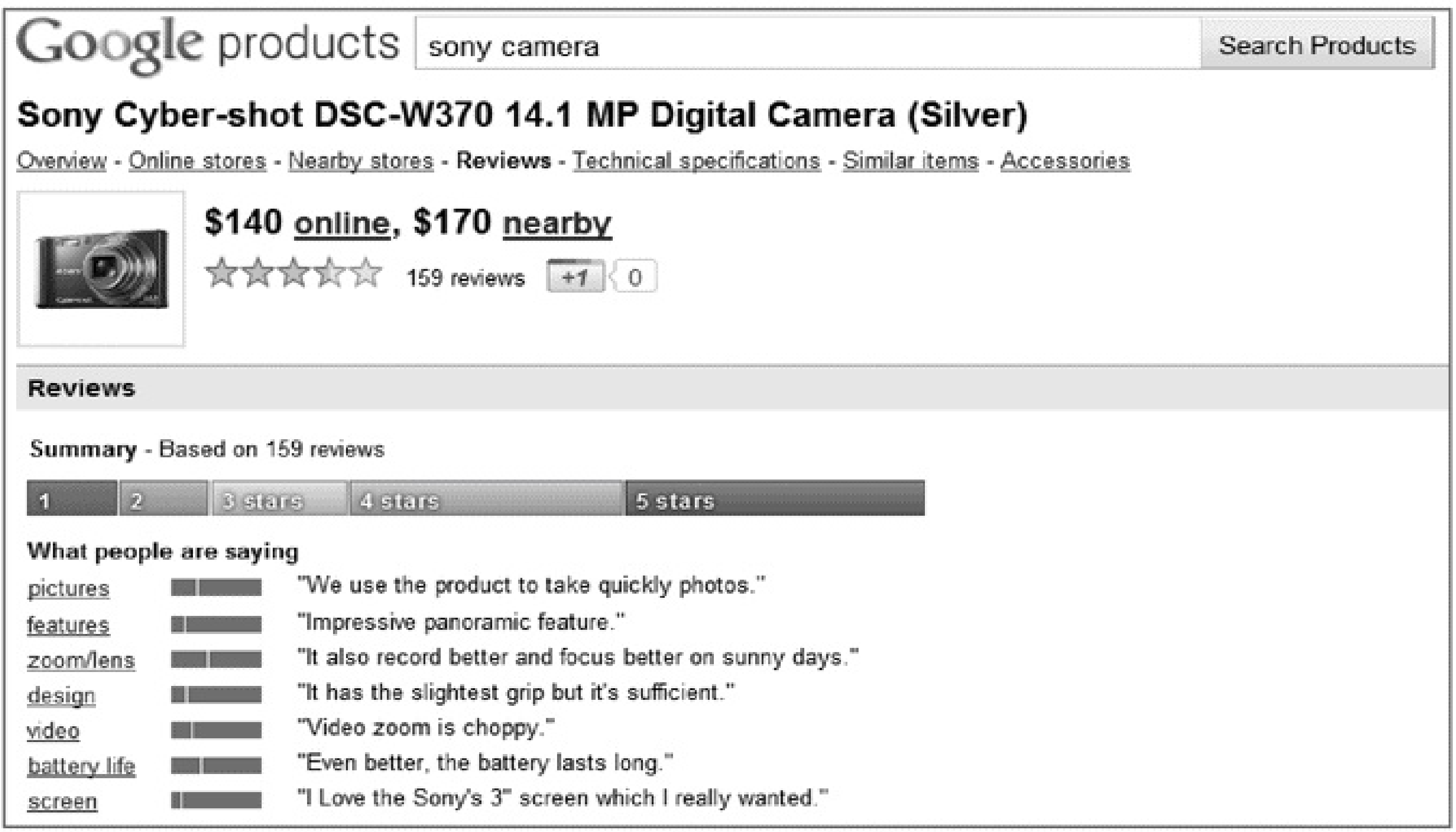
The opinion quintuples in fact allows one to provide many more forms of structured summaries. For example, if time is extracted, one can show the trend of opinions on different aspects. Even without using sentiments, one can see the buzz (or frequency) of mentions of each aspect, which gives the user an idea what aspects people are most concerned about. In fact, a full range of database and OLAP tools can be applied to slice and dice the data for all kinds of qualitative and quantitative analyses. For example, in one practical sentiment analysis application in the automobile domain, opinion quintuples of individual cars were mined first. The user then compared sentiments about small cars, medium sized cars, German cars and Japanese cars, and so on. In addition, the sentiment analysis results were also used as the raw data for further data mining. For example, the user ran a clustering algorithm and found some interesting segments of the market. It was found that one segment of the customers always talked about how beautiful and slick the car looked and how fun it was to drive, while another segment of the customers talked a lot about back seats and trunk spaces. Clearly the first segment consisted of mainly young people, while the second segment consisted mainly of people with families and children. Such insights are extremely useful as they enabled the users to see the opinions of different segments of markets and allowed them to respond accordingly in their marketing and product design processes.

Aspect-based summary has been the main summarization framework used in sentiment analysis research, for example, Zhuang et al. (2006) used it to summarize movie reviews, Ku et al. (2006) used it to summarize Chinese opinion text, and Blair-Goldensohn et al. (2008) used it to summarize service reviews. We will discuss the extensive research on the topic in the next three sections.

The aspect-based summary is also widely used in industry. For example, Figure 9.3a shows the opinion summary about a printer from Microsoft Bing Shopping, where each green bar depicts the percentage of positive opinions about the aspect above the bar. If we click on a bar (e.g., for aspect *speed*), we will see the corresponding opinion sentences. Figure 9.3b shows the summary of opinions about a camera from Google Product Search. Each green (respectively, red) bar shows the percentage of positive (negative) opinions about the aspect on the left. Clicking on an aspect or a bar, the system will also display its corresponding opinion sentences. Unfortunately, neither system can visualize comparison of opinions on multiple products like that in Figure 9.2b, which I believe is a major weakness. Without side-by-side comparison, it is hard for a user to know which product is better.


bing
HP printer
ALL RESULTS
Shopping
POPULAR FEATURES
all
Affordability
Speed
Print Quality
Reliability
Ease Of Use
Brand
Installation
Size
Compatibility
SHOPPING
HP LaserJet 1020 - printer - B/W - laser, 15ppm, USB
from $179 (2 stores) Bing cashback - 3%
user reviews (177)
The HP LaserJet 1020 Printer, an excellent laser printer for the cost-co
high-quality LaserJet printing in a compact size, and at a price you can
user reviews
product details
expert reviews
compare prices
user reviews
view: positive comments (44)
speed 96%
The quality is as good as any laserjet printer I've used and the speed is fast.
Love Reading www.amazon.com 3/17/2006 more...
Quick and fast transaction.
Arthur L. Taylor www.amazon.com 2/5/2008 more...
It's small and fast and very reliable.
Muffinhead's mom www.amazon.com 1/9/2007 more...

(a)


Google products
sony camera
Search Products
Sony Cyber-shot DSC-W370 14.1 MP Digital Camera (Silver)
Overview - Online stores - Nearby stores - Reviews - Technical specifications - Similar items - Accessories
$140 online, $170 nearby
159 reviews
+1
0
Reviews
Summary - Based on 159 reviews
1
2
3 stars
4 stars
5 stars
What people are saying
pictures
"We use the product to take quickly photos."
features
"Impressive panoramic feature."
zoom/lens
"It also record better and focus better on sunny days."
design
"It has the slightest grip but it's sufficient."
video
"Video zoom is choppy."
battery life
"Even better, the battery lasts long."
screen
"I Love the Sony's 3" screen which I really wanted."

(b)

Figure 9.3. Opinion summaries of (a) Bing Shopping and (b) Google Product Search.

9.2 Enhancements to Aspect-Based Summary

Over the years, researchers have proposed several improvements and refinements to the basic aspect-based summary. Carenini et al. (2006) proposed to integrate aspect-based summarization with two traditional text summarization approaches for factual documents, that is, sentence selection (or extraction) and sentence generation. We discuss the integration with the sentence selection approach first. Their system first identifies aspect expressions from reviews of a particular entity (e.g., a product) using the method in Hu and Liu (2004). It then maps the aspect expressions to some given aspect categories organized as an ontology tree for the entity. These aspects in the tree are subsequently scored based on their sentiment strength. Sentences containing aspect expressions are also extracted. Each such sentence is rated based on scores of aspects in the sentence. If multiple sentences have the same sentence rating, a traditional centroid-based sentence selection method is used to break the tie (Radev et al., 2003). All relevant sentences are attached to their corresponding aspects in the ontology. The sentences for each aspect are then selected for the final summary based on sentence scores and aspect positions in the ontology tree.

The integration with the sentence generation approach works similarly. First, a measure is used to score the aspects in the ontology based on their occurrence frequencies, sentiment strengths, and their positions in the ontology. An algorithm is also applied to select aspects in the ontology tree. Positive and negative sentiments are then computed for the aspects. On the basis of the selected aspects and their sentiments, a language generator generates the summary sentences, which can be qualitative and quantitative. A user evaluation was carried out to assess the effectiveness of the two integration approaches. The results showed that they performed equally well, but for different reasons. The sentence selection method gave more varied languages and more details, while the sentence generation approach gives a better sentiment overview of the reviews.

In Tata and Di Eugenio (2010), the authors produced an opinion summary of song reviews similar to that in Hu and Liu (2004), but for each aspect and each sentiment (positive or negative) they first selected a representative sentence for the group. The sentence should mention the fewest aspects (thus the representative sentence is focused). They then ordered the sentences using a given domain ontology by mapping sentences to the ontology nodes. Note that the ontology basically encodes the key domain concepts and their relations. The sentences were ordered and organized into paragraphs following the tree such that they appear in a conceptually coherent fashion.

Lu et al. (2010) also used an online ontology of entities and aspects to organize and summarize opinions. Their method is related to the preceding two, but is also different. Their system first selects aspects that capture major opinions. The selection is done using frequency, opinion coverage (no redundancy), or conditional entropy. It then orders aspects and their corresponding sentences based on a coherence measure, which tries to optimize the ordering so that they best follow the sequences of aspect appearances in their original posts.

Ku et al. (2006) performed blog opinion summarization, and produced two types of summaries, brief and detailed summaries, based on extracted topics (aspects) and sentiments on the topics. For the brief summary, their method picks up the document/article with the largest number of positive or negative sentences and uses its headline to represent the overall summary of positive-topical or negative-topical sentences. For the detailed summary, it lists positive-topical and negative-topical sentences with high sentiment degrees.

Lerman et al. (2009) defined opinion summarization in a slightly different way. Given a set of documents *D* (e.g., reviews) that contains opinions about some entity of interest, the goal of their opinion summarization system is to generate a summary *S* of the entity that is representative of the average opinion and speaks to its important aspects. This paper proposed three different models, all of which choose some set of sentences from a review, to perform summarization of reviews of a product. The first model is called *sentiment match* (SM), which extracts sentences so that the average sentiment of the summary is as close as possible to the average sentiment rating of the reviews of the entity. The second model, called *sentiment match + aspect coverage* (SMAC), builds a summary that trades-off between maximally covering important aspects and matching the overall sentiment of the entity. The third model, called *sentiment-aspect match* (SAM), attempts not only to cover important aspects, but also to cover them with appropriate sentiment. A comprehensive evaluation using human users was conducted to compare the three types of summaries. It was found that although the SAM model was the best, it is not significantly better than the others.

Nishikawa et al. (2010b) presented a more sophisticated summarization technique that generates a traditional text summary by selecting and ordering sentences taken from multiple reviews, considering both informativeness and readability of the final summary. The informativeness was defined as the sum of frequency of each aspect-sentiment pair. Readability was defined as the natural sequence of sentences, which was measured as the sum of the connectivity of all adjacent sentences in the sequence. The problem was then solved through optimization. The authors further studied this problem using an integer linear programming formulation (Nishikawa et al., 2010a). Ganesan et al. (2010) proposed a graphical model based method to generate an abstractive summary of opinions, and Yatani et al. (2011) extracted adjective-noun pairs as the summary.

For more advanced analysis, the summarization should also include the reasons and qualifications for opinions. However, little work has been done on extracting and summarizing opinions at this level. One simple way to include these two types of information in the overall opinion summary is to first discover and cluster reasons and qualifications respectively and the system then presents the main reasons (which represent problems or issues with the product being reviewed) and main qualifications for the opinions. Opinion reasons are fairly frequent but qualifications are rare and also harder to identify. On the visualization, we can still use that in Figure 9.2. When one clicks a positive or negative bar, the system can show the clusters of reasons and qualifications ranked according to the sizes of the clusters.

9.3 Contrastive View Summarization

Several researchers studied the problem of summarizing opinions by finding contrastive viewpoints. For example, a reviewer may give a positive opinion about the voice quality of an iPhone by saying "*The voice quality of the iPhone is really good*," but another reviewer may say the opposite, "*The voice quality of my iPhone is very bad*." Such pairs can give the reader a direct comparative view of different opinions.

This problem was proposed by Kim and Zhai (2009). Given a positive sentence set and a negative sentence set, they performed contrastive opinion summarization by extracting a set of k contrastive sentence pairs from the sets. A pair of opinionated sentences (x, y) is called a *contrastive sentence pair* if sentence x and sentence y are about the same aspect, but have opposite sentiment orientations. The k chosen sentence pairs must also represent both the positive and negative sentence sets well. They formulated the summarization as an optimization problem and solved it based on several similarity functions.

Paul et al. (2010) worked on this problem further. Their algorithm generates a macro multiview summary and a micro multiview summary. A macro multiview summary contains multiple sets of sentences, each representing a different opinion. A micro multiview summary contains a set of pairs of contrastive sentences (each pair consists of two sentences representing two different opinions). The algorithm works in two steps. In the first step, it uses a topic modeling approach to extract both topics (aspects) and sentiments. In the second step, a random walk formulation (similar to PageRank; Page et al., 1999) was employed to score sentences and pairs of sentences from opposite viewpoints based on both their representativeness and their contrastiveness with each other. Along similar lines, Park et al. (2011) reported another method for generating contrasting opposing views in news articles.

In Lerman and McDonald (2009), a different contrastive summarization problem was formulated. They wanted to produce contrastive summaries of opinions about two different products to highlight the differences of opinions about them. Their approach jointly models the two summarization tasks with the objective to explicitly optimize the summaries so that they maximally contract each other.

9.4 Traditional Summarization

Several researchers have also studied opinion summarization in the traditional fashion, for example, producing a short text summary with limited or no explicit consideration for aspects (or topics) and sentiments about them. Beineke et al. (2003) proposed a supervised learning method to select important sentences in reviews. Seki et al. (2006) proposed a paragraph-clustering algorithm for the same task.

Wang and Liu (2011) studied extractive summarization (selecting important sentences) of opinions in conversations. They experimented with both the traditional sentence ranking and graph-based approaches, but also considered additional features such as topic relevance, sentiments, and dialogue structure.

A weakness of such traditional summaries is that they only gave limited or no consideration to target entities and aspects and sentiments about them. Thus, they may select sentences that are not related to sentiments or aspects. Another issue is that such a summary is not quantitative. As we discussed earlier, the quantitative perspective is important in practice because one out of ten people hating something is very different from eight out of ten people hating something.

9.5 Summarization of Comparative Opinions

On the basis of the definition of comparative opinions in Section 8.1, comparisons are essentially preference orders. Thus, a graph-based summary is more appropriate. In the graph, each node is an entity (e.g., a product or a business), and each directed edge between two nodes represents the mined pairwise preference order between the two nodes. The edge can be attached with two pieces of information. The first piece is the specific aspect that has been compared about the two entities and the second piece is the ratio of the comparative positive opinion count and the total number of comparisons that have been made about this aspect. Because multiple aspects may be compared, there could be multiple edges between two nodes, and their edge directions may be different too. The reasons for the comparative opinions and opinion qualifications can also be attached to each edge. However, so far little work has been done on summarization of comparative opinions. Li et al. (2011) made an attempt to study the problem using a similar but simpler approach. Future research or practice should give us a better idea about what might be a good way to summarize and present comparisons.

9.6 Opinion Search

We now turn to the problem of opinion search or retrieval. Like general web search, it is easy to imagine that opinion search will be of great use. Wouldn't it be nice that whenever you want to find opinions about an entity or topic, you just submit a query to an opinion search engine with the name of the entity or topic as the query, and the search engine returns summarized opinions with attached reasons? Unfortunately, this ideal scenario is still far from reality because of many challenges discussed in preceding chapters.

In general, there are at least two types of opinion searches that are interesting in practice:

1. Find public opinions about a particular entity or an aspect of the entity, for example, a particular digital camera or the picture quality of the digital camera, or a political candidate or issue.

2. Find opinions of a particular person or organization (i.e., opinion holder) about a specific entity or an aspect of the entity (or topic), for example, Barack Obama's opinion about abortion. This type of search is particularly relevant to news articles, where individuals or organizations who have expressed opinions are explicitly stated.

For the first type of search, the user simply gives the name of the entity or the name of the aspect together with the name of the entity as the search query. For the second type of search, the user needs to additionally give the name of the opinion holder as the search query.

Similar to general web search, opinion search needs to perform two main tasks: (1) retrieve relevant documents/sentences to the user query and (2) rank the retrieved documents or sentences. However, there are also major differences. On retrieval, opinion search needs to perform two subtasks:

1. Find documents or sentences that are relevant to the query. This is the only task performed in the traditional search.

2. Determine whether the documents or sentences express opinions on the query topic (entity and/or aspect) and whether the opinions are positive or negative. This is the task of sentiment analysis. Traditional search does not perform this sub-task.

As for ranking, traditional web search engines rank web pages based on authority and relevance scores (Liu, 2006, 2011). The basic premise is that the top-ranked pages (ideally the first page) contain sufficient information to satisfy the user's information need. This paradigm is adequate for factual information search because *one fact equals to any number of the same fact*. That is, if the first page contains the required information, there is no need to see the rest of the relevant pages. For opinion search, this paradigm is fine only for the second type of queries because an opinion holder usually has only one opinion about a particular entity or topic, and the opinion is contained in a single document or page. However, for the first type of opinion queries, this paradigm needs to be modified because ranking in opinion search has two objectives. First, it needs to rank those opinionated documents or sentences with high utilities or information contents at the top (see Chapter 13). Second, it needs to reflect the natural distribution of positive and negative opinions. This second objective is important because in most applications the actual proportions of positive and negative opinions are critical pieces of information. Only reading the top-ranked result as in the traditional search is problematic because the top result only represents the opinion of a single opinion holder. Thus, ranking in opinion search needs to capture the natural distribution of positive and negative sentiments of the whole population in a summarized form. One simple solution for this is to produce two rankings, one for positive opinions and one for negative opinions, and also display the numbers of positive and negative opinions.

Providing an aspect-based summary for each opinion search is even better. However, this is an extremely challenging problem. As we have seen, generating aspect-based opinion summary is already very difficult even with given entities and given relevant corpora, let alone for arbitrary query entities or topics from the user and a general corpus containing opinions about all kinds of entities and topics.

9.7 Existing Opinion Retrieval Techniques

Current research in opinion retrieval typically treats the task as a two-stage process. In the first stage, documents are ranked by topic relevance only, which is what a traditional information retrieval or search system does. In the second stage, candidate relevant documents are reranked by their opinion scores. The opinion scores can be acquired by using either a machine learning–based sentiment classifier, such as SVM, or a lexicon-based sentiment classifier using a sentiment lexicon and a score aggregation function that combines sentiment word scores and query term–sentiment word proximity scores. More advanced research models topic relevance and opinion simultaneously, and produces rankings based on their integrated scores.

To give a flavor of opinion search, we present an example system (Zhang and Yu, 2007), which was the winner of the blog track in the 2007 TREC evaluation (http://trec.nist.gov/). The task was exactly opinion search (or retrieval). This system has two components. The first component is for retrieving relevant documents for each query, and the second component is for classifying the retrieved documents as being opinionated or not-opinionated. The opinionated documents are further classified into positive, negative, or mixed (containing both positive and negative opinions).

Retrieval component. This component performs the traditional information retrieval (IR) task. It uses both keywords and concepts. Concepts are named entities (e.g., names of people or organizations) or various types of phrases from dictionaries and other sources (e.g., Wikipedia entries). The strategy for processing a user query is as follows (Zhang and Yu, 2007; Zhang et al., 2008): the algorithm first recognizes and disambiguates the concepts within the user query before broadening the search query with its synonyms. Then, it recognizes concepts in the retrieved documents and also performs pseudo-feedback so that relevant words are automatically extracted from the top-ranked documents to expand the query. Finally, it computes a similarity (or relevance) score of each document with the expanded query using both concepts and keywords.

Opinion classification component. This component performs two tasks: (1) classifying each document into one of the two categories, opinionated and not-opinionated, and (2) classifying each opinionated document as expressing a positive, negative, or mixed opinion. For both tasks, the system uses supervised learning. For the first task, it obtains a large amount of opinionated (subjective) training data from review sites such as rateitall.com and epinions.com. The data are also collected from different domains involving consumer goods and services as well as government policies and political viewpoints. The not-opinionated training data are obtained from sites that give objective information such as Wikipedia. From these training data, a SVM classifier is constructed.

This classifier is then applied to each retrieved document as follows. The document is first partitioned into sentences. The SVM classifier then classifies each sentence as opinionated or not-opinionated. If a sentence is classified to be opinionated, its strength, as determined by SVM, is also noted. A document is regarded as opinionated if there is at least one sentence that is classified as opinionated. To ensure that the opinion of the sentence is directed at the query topic, the system requires enough query concepts/words to be found in its vicinity. The totality of the opinionated sentences and their strengths in a document together with the document's similarity with the query is used to rank the document.

To determine whether an opinionated document expresses a positive, negative or mixed opinion, a second classifier is constructed using reviews from review sites containing review ratings (e.g., rateitall.com) as the training data. A low rating indicates a negative opinion while a high rating indicates a positive opinion. Using positive and negative reviews as training data, a sentiment classifier is built to classify each document as expressing a positive, negative, or mixed opinion.

There are also other approaches to opinion retrieval in TREC evaluations. The readers are encouraged to read the papers at the TREC website (http://trec.nist.gov/). For a summary of TREC evaluations, please refer to the overview papers of the 2006 TREC blog track (Ounis et al., 2006), the 2007 TREC blog track (Macdonald et al., 2007), and the 2008 TREC blog track (Ounis et al., 2008). In what follows, I discuss research published in some other forums.

Eguchi and Lavrenko (2006) proposed a sentiment retrieval technique based on generative language modeling. In their approach, the user first provides a set of query terms representing a particular topic of interest and the sentiment polarity (orientation) of interest represented either as a set of seed sentiment words or a particular sentiment orientation (positive or negative). Instead of treating topic relevance and sentiment classification as two separate problems, their language modeling approach combines sentiment relevance models and topic relevance models with model parameters estimated from the training data, considering the topic dependence of the sentiment. Their experiments showed that explicitly modeling the dependency between topic (or aspect) and sentiment produced better retrieval results than treating them independently. A similar approach was also proposed by Huang and Croft (2009), which scores the relevance of a document using a topic relevance model and an opinion relevance model. Both these works took a linear combination of topic relevance and sentiment relevance for the final ranking. Zhang and Ye (2008) used the product of the two relevance scores. The relevance formulation is also based on language modeling.

Na et al. (2009) used a lexicon-based approach for opinion retrieval. They also attempted to deal with the domain-dependent lexicon construction issue. A relevant feedback style learning for generating query-specific sentiment lexicon was proposed, which made use of a set of top-ranked documents in response to a query.

Liu et al. (2009) explored various lexical and sentiment features and different learning algorithms to identify opinionated blogs. They also presented results for the strategy that combines both the opinion analysis and the retrieval components for retrieving relevant and opinionated blogs. Li et al. (2010) took a different approach. Their algorithm first finds topic and sentiment word pairs from each sentence of a document, and then builds a bipartite graph to link such pairs with the documents that contain the pairs. The graph-based ranking algorithm HITS (Kleinberg, 1999) was applied to rank the documents, where documents were considered as authorities and pairs were considered as hubs. Each link connecting a pair and a document is weighted based on the contribution of the pair to the document.

In Pang and Lee (2008), a simple method was proposed for review search, which only re-ranks the top *k* topic-based search results by using an *idiosyncrasy* measure defined on the rarity of terms appeared in the initial search results. The rationale for the measure was explained in the paper. The assumption was that the search engine has already found good results and only reranking is needed to put reviews at the top. The method is unsupervised and does not use any pre-existing lexicon.

9.8 Summary

Unlike traditional text summarization, which produces short abstracts from long documents, opinion summarization needs to identify aspects and sentiments and to be quantitative (giving the proportions of positive and negative opinions). So far, a great deal of research has been done to produce structured summaries based on the aspect-based summarization framework. In some applications, human users also like to have readable summaries. Structured summaries are clearly not suitable for human reading. Although several researchers have attempted to address the readability issue, the existing work is still not mature. One possible option is to generate natural language sentences based on the structured summary in Section 9.1 using some language templates. For instance, the first bar in Figure 9.2b can be written as “70% of the people are positive about digital camera 1 as a whole.” This, however, may not be the best sentence for people’s reading pleasure. We expect future research to produce more human readable opinion summaries that are also quantitative about aspects and sentiments. However, we should note that opinion summarization research cannot progress alone. It critically depends on results and techniques from other areas of the research on sentiment analysis, for example, aspect and entity extraction and aspect-based sentiment classification. All these directions go hand-in-hand.

About opinion search, it will be very useful if a web search engine such as Google or Microsoft Bing can provide a general opinion search service. Both Google and Microsoft Bing already produce opinion summaries for reviews of some products, but their coverage is still limited. For those not covered entities and topics, it is not easy to find opinions about them because their opinions are scattered all over the Internet. Finding and extracting such opinions are formidable tasks because of the proliferation of diverse sites and the difficulty of identifying opinions that are relevant to the searched entities or topics. Much further research is needed.

10

Analysis of Debates and Comments

Opinion documents come in many different forms. So far, we have implicitly assumed that individual documents are independent of each other or have no relationships. In this chapter, we move on to two social media contexts that involve extensive interactions of their participants, that is, debates/discussions and comments, which are also full of expressions of sentiments and opinions. However, the key characteristic of the documents in such media forms is that they are not independent of each other, which is in contrast to standalone documents such as reviews and blog posts. Interactive exchanges of discussions among participants make these media forms much richer for analysis. The interactions can be seen as relationships or links among participants and also among posts. Thus, we not only can perform sentiment analysis as we have discussed in previous chapters, but also carry out additional types of analyses that are characteristic of interactions, for example, grouping people into camps, discovering contentious issues of debates, mining agreement and disagreement expressions, discovering pairwise arguing nature, and so on. Because debates are exchanges of arguments and reasoning among participants who may be engaged in some kind of deliberation to achieve a common goal, it is interesting to study whether each participant in online debate forums indeed gives reasoned arguments with justifiable claims via constructive debates or just exhibits dogmatism and egotistic clashes of ideologies. These tasks are important for many fields of social science such as political science and communications. Central to these tasks are the sentiment of agreement and disagreement, which are instrumental to these analyses. These additional types of analyses are the focus of this chapter.

Comments are posts that comment on online articles (e.g., news articles, blog posts, and reviews), videos, images, and so on. We use comments about online articles in our study in this chapter. Comments typically contain many types of information, for example, views and opinions from the readers of the article about the article and/or its subject matter, questions to the author of the article or to other readers, and discussions among readers and between readers and the author of the article. Hence, comments are a mixture of reviews (of the article), debates/discussions, and questions and answers. In other words, they contain more types of dialogue acts than debates/discussions. Although in general the topic of the article can be anything, an article on a controversial topic often generates a large number of comments. This chapter studies the existing mining and analysis research about debates and comments. It covers both the traditional supervised classification approach to solving some specific problems and probabilistic modeling approaches to capturing both the rich content and the complex user interactions.

10.1 Recognizing Stances in Debates

One of the interesting issues in debate analysis is to identify the stances of the participants. Two main variations of the problem have been attempted by researchers. Given a debate/discussion topic, for example, "*Do you support tax increase*?" and a set of debate posts from a set of participants,

1. classify the participants into some predefined groups, for example, those who take a for-increase stance and those who take an against-increase stance.

2. classify the posts into some predefined groups, for example, those that are for-increase and those that are against-increase.

Most techniques exploited the interactions among participants to model the problem as a graph and use graph theoretic algorithms to perform the classification task. For example, in Agrawal et al. (2003), a graph theoretic algorithm was proposed to categorize newsgroup discussion participants of a topic into two classes: those who are "for" the topic and those who are "against" the topic. It thus solves the first problem. The interesting feature of this work is that the text content of the discussions is completely ignored. The authors observed that quoting and replying activities usually show disagreement with previous authors, which are used as clues for grouping. The graph is constructed as follows. Each participant forms a node and each edge (i, j) between node i and node j represents that participant i has responded to a post by participant j. The algorithm then tried to bipartition the graph into two subsets F (for) and A (against) of participants. To solve the problem, the two sets are associated with a cut function, $f(F, A)$, which is the number of edges crossing from F to A. It was shown that the optimum choice of F and A maximizes $f(F, A)$, which is the classic *maximum cut* problem. However, to solve the problem more efficiently, a spectral partitioning algorithm was used instead to partition the graph into two groups (or camps).

An instance of the second problem was attempted in Thomas et al. (2006). The technique aims to determine from the transcripts of U. S. Congressional floor debates whether each speech represents support for or opposition to a proposed piece of legislation. This work integrates two factors in the classification: (1) each individual speech segment (analogous to a debate post in social media) classification based on traditional n-gram features and (2) the relationships among labels of speech segments which are characteristic of conversations. The whole classification problem was modeled as a graph. Each node represents a speech segment and each link represents a relationship constraint with a weight. The algorithm has three steps. The first step trains a SVM classifier using unigrams to classify each speech segment. The second step adds links to the graph by setting some constraints between nodes. Two types of constraints are used. The first type is that speech segments from the same speaker should be labeled the same. The second type is about different-speaker agreement. In a debate, a speaker may refer to another speaker and express agreement or disagreement with her. Thus the system needs to classify agreement and disagreement, which is done with another SVM classifier based on the surround text where the referenced speaker was mentioned. The class labels (agree and disagree) are determined based on whether the two persons voted the same way or not. The SVM classification scores are used to add more links to the graph. The final step solves an optimization problem by finding graph minimum cuts.

Murakami and Raymond (2010) proposed another graph-based method that exploits the reply relationship and some local information to build the graph. The local information between two participants includes the number of agree, disagree and neutral pairs in their exchanges. The three numbers are combined linearly to produce the link weight between two participants. The graph is then partitioned using a maximum cut algorithm to separate supporting and opposing participants. This work thus solves the first problem.

The earlier work in Galley et al. (2004) classified posts into agreement, disagreement, backchannel and other classes. It also exploited the relationships (called dependencies in the paper) among posts along with many other traditional features in a Bayesian network-based classification method. Bayesian networks facilitate the encoding of dependencies. An example relationship is that if speaker B disagrees with A, B is likely to disagree with A in his or her next speech addressing A.

These methods basically used the relational information between posts and between participants in addition to traditional features to solve the problems. They can all be seen as instances of *collective classification* (Sen et al., 2008), which is a relational learning framework for modeling and solving such problems. Several existing learning algorithms exist for collective classification, which work on a graph $G = (V, E)$, where $V = \{V_1,\ldots, V_n\}$ is a set of nodes and each node V_i is a random variable with a value domain, which is the set of class labels $C = \{C_1, .., C_k\}$. Each node typically is also associated with a set of features $F = \{F_1, .., F_m\}$. E is a set of edges and each edge (V_i, V_j) represents a relationship. V is further divided into two subsets of nodes: L, labeled nodes, and U, unlabeled nodes. The task is to predict the label of each unlabeled node in U ($\subseteq V$). One of the simplest machine learning algorithms for solving this problem is ICA (iterative classification algorithm). Unlike traditional instance-based classification, which only has features about each instance or example, the feature set for a node in ICA includes additionally a set of relational features which are computed based on the neighbors of the node and its relationships with the neighbors. The algorithm runs iteratively because the labels of the nodes and the relational features can change in the classification process. We have described the ICA method in Section 6.4. Apart from ICA, *Markov random fields* (Kindermann and Snell, 1980) using the inference method of *loopy belief propagation* and the *Mean-field* method can also be applied to the problem. In Burfoot et al. (2011), a comparative study was performed to compare these and the minimum cut method used in Thomas et al. (2006) based on the congressional voting data. The results show that Markov random fields and mean-field give better results.

Somasundaran and Wiebe (2010) took the traditional supervised learning approach to solving the first problem of classifying stances of participants, but used sentiment lexicon and arguing expression features. Arguing expression features had not been used prior to this paper. The types of features used in the paper are as follows:

> *Arguing-lexicon features*. These features are produced as follows: An arguing subjectivity-annotated corpus (Wilson and Wiebe, 2005) is first used to construct an arguing lexicon. Then for each sentence of a post, the algorithm finds all positive and negative arguing expressions and determines the primary polarity or orientation. After that it attaches each content word (noun, verb, adjective and adverb) with *ap* (for positive polarity) or *an* (for negative polarity).
>
> *Modal verb features for arguing*. Modal verbs such as *must*, *should*, and *ought* are usually good indicators of arguing. For every modal in a sentence, three features are created by combining the modal word with its subject and object in three ways.
>
> *Sentiment-based features*. It uses the subjectivity lexicon of Wilson et al. (2005), which not only contain positive and negative sentiment words but also many neutral subjective words such as *absolutely*, *amplify*, *believe*, and *think*.

Apart from supervised learning, unsupervised learning approaches can be used to solve the problems too. Such an approach is proposed in Somasundaran and Wiebe (2009), which primarily used sentiment analysis to identify user stances in discussions about products, which are different from ideological discussions. For each side, it first mines the web to discover opinion and target pairs that are associated with a preference for that side. This information and some discourse information are then combined in an integer linear programming framework to arrive at stance classifications.

Abu-Jbara et al. (2012) attempted a related but slightly different problem. They grouped the discussion participants into subgroups. Their technique is also based on sentiment analysis and unsupervised. Its key idea is to find opinion (or attitude) and target pairs. The target of an opinion can be an entity or another participant (or discussant). Two methods are used to find targets. The first method finds frequent noun phrases similar to one of the methods in Hu and Liu (2004). The second method uses a named entity recognition system to identify named entities. The opinion target pair is produced based on dependency relations similar to that in Zhuang et al. (2006) and Qiu et al. (2011). Each participant is then represented with his attitude profile, a feature vector consisting of counts of positive/negative attitudes expressed by the discussant toward each of the targets. With the vectors, clustering is applied to find groups. Further work reported in Abu-Jbara et al. (2013) performed the task of identifying how the participants in a discussion split into subgroups with contrasting opinions.

Other related work studying dialogue and discourse in discussions includes authority recognition (Mayfield and Rose, 2011), participant characteristics classification based on their posting contributions (Lui and Baldwin, 2010), dialogue act segmentation and classification (Boyer et al., 2011; Morbini and Sagae, 2011), dialogue acts classification (Kim et al., 2010), and thread discourse structure (including interpost links and dialogue acts) prediction (Wang et al., 2011). These tasks, however, are not related to sentiment. In the next section, we will see that dialogue acts and topics can be modeled in a single framework, which also helps identify language expressions that are indicative of these dialogue acts.

10.2 Modeling Debates/Discussions

Online debate/discussion forums allow people with common interests to freely ask and answer questions, to express their views and opinions on any subject matter, and to discuss issues of common interests. A large part of such discussions is about social, political, and religious issues. On such issues, there are often heated discussions/debates, that is, people agree or disagree and argue with one another. Such ideological discussions on a myriad of social and political issues have practical implications in the fields of communication and political science as they give social scientists an opportunity to study real-life discussions/debates on almost any issue and to analyze the behaviors of participants in a large scale. In this section, we discuss modeling of this form of interactive social media (Mukherjee and Liu, 2012; Mukherjee et al., 2013). Given a set of discussion/debate posts, we aim to perform the following tasks:

1. Discover expressions that people often use to express *agreement* (e.g., "*I agree*" and "*you're right*") and *disagreement* (e.g., "*I disagree*" and "*you speak nonsense*"). This will help produce a lexicon of agreement and disagreement (or contention) expressions, which is useful for many tasks of debate/discussion analysis.

2. Discover contentious topics or issues, which have the most disagreements among participants. This is important because a large part of social media is about discussions/debates of contentious issues. The application of contentious issues is also abundant. For example, in a political election, they can separate voters into different camps and determine the voters' political leanings or orientations. It is thus important for political candidates to know such issues.

3. Discover the nature of interactions between each pair of participants who have engaged in discussions or debates on certain issues. By *nature of interaction*, we mean whether the two participants mostly agree or disagree with each other in their exchanges.

4. Identify tolerant and intolerant participants in debates/discussions. Tolerance is a psycholinguistic phenomenon of discussions, and an important concept in the field of communications. It is a sub-facet of deliberation which refers to critical thinking and the exchange of rational arguments on an issue among participants that seek to achieve consensus/solution (Habermas, 1984).

Although agreement and disagreement expressions are distinct from traditional sentiment expressions (words and phrases) such as *good*, *excellent*, *bad*, and *horrible*, agreement and disagreement clearly express a kind of sentiment. They are usually emitted during an interactive exchange of arguments.

We then introduce the concept of *AD-sentiment* (for *Agreement Disagreement sentiment*) and regard analysis of debates as an extension to the traditional sentiment analysis. The polarity of agreement expressions is defined as *positive* and the polarity of disagreement expressions is defined as *negative*. Agreement and disagreement expressions are thus *AD-sentiment expressions*, or *AD-expressions* for short. AD-expressions are instrumental for the analysis of debates.

Three statistical or graphical models were proposed to perform the aforementioned tasks in Mukherjee and Liu (2012) and Mukherjee et al. (2013). The first model, called the joint topic-expression (JTE) model, jointly models both discussion topics and AD-expressions. It thus provides a general framework for discovering discussion topics and AD-expressions simultaneously. Its generative process separates topics and AD-expressions by using maximum entropy priors to guide the separation. However, this model does not consider a key characteristic of discussions/debates: authors quoting or mentioning the claims/views of other authors and expressing contention or agreement on those claims/views. That is, there are interactions among authors and topics through the reply-to relation. To consider the reply-to relation, JTE was extended to JTE-R. Furthermore, another model (called JTE-P) was also proposed to consider author-pair structures.

10.2.1 JTE Model

The JTE model jointly model topics and AD-expressions. It belongs to the family of generative models for text where words and phrases (n-grams) are viewed as random variables. Each document is viewed as a bag of n-grams and each n-gram (word/phrase) takes one value from a predefined vocabulary. Up to 4-grams, that is, *n* = 1, 2, 3, 4, were used in JTE. Note that topics in most topic models like LDA are usually unigram distributions over words and assume words to be exchangeable at the word level. Arguably, this offers a great computational advantage over more complex models taking word order into account for discovering significant n-grams (Wallach, 2006). The JTE model enhances the expressiveness by considering n-grams and preserving the advantages of exchangeable modeling (rather than modeling n-gram word order). Thus, both words and n-gram phrases are considered in the vocabulary. For notational convenience, from now on we use *terms* to denote both *words* (unigrams) and *phrases* (n-grams). We denote the entries in the vocabulary by $v_{1...V}$, where *V* is the number of unique terms in the vocabulary. The corpus (document collection) of study is comprised of $d_{1...D}$ documents. A document (e.g., debate/discussion post) *d* is represented as a vector of terms $\boldsymbol{w_d}$ with N_d entries. *W* is the bag of all observed terms in the corpus with cardinality $|W| = \sum_d N_d$. *Z* denotes the topic assignments of all terms in all documents. Note that here we use different notations than those in Section 6.6 just to conform to the notations used in their original papers (Mukherjee and Liu, 2012; Mukherjee et al., 2013). For example, *W* is ***w*** and *Z* is ***z*** in Section 6.6.1 respectively.

The JTE model is motivated by the joint occurrence of AD-expression types (i.e., *agreement* and *disagreement*) and topics in debate posts. A typical debate post mentions a few topics (using semantically related topical terms) and expresses some viewpoints with one or more AD-expression types (using semantically related agreement and/or disagreement expressions). This observation motivates the generative process of the model where documents are represented as random mixtures of latent topics and AD-expression types. Each topic or AD-expression type is characterized by a distribution over terms. Assume we have *t* = 1,…, *T* topics and *e* = 1,…, *E* expression types in the corpus. In the case of discussion/debate forums, based on reading of posts, it was hypothesized in Mukherjee and Liu (2012) that *E* = 2, as in such forums, one mostly finds two expression types: agreement and disagreement. However, the JTE and other models are general and can be used with any number of expression types. Let $\psi_{d,j}$ denote the probability of $w_{d,j}$ being a topical term with $r_{d,j} \in \{\hat{t}, \hat{e}\}$ denoting the binary indicator variable (topic or AD-expression) for the *j*th term of *d*, $w_{d,j}$. $z_{d,j}$ denotes the appropriate topic or AD-expression type index to which $w_{d,j}$ belongs. JTE parameterizes multinomials over topics using a matrix $\Theta^T_{D \times T}$ whose elements $\theta^T_{d,t}$ signify the probability of document *d* exhibiting topic *t*. For simplicity of notation, we will drop the latter subscript (*t* in this case) when convenient and use θ^T_d to stand for the *d*th row of Θ^T. Similarly, we define multinomials over AD-expression types using a matrix $\Theta^E_{D \times E}$. The multinomials over terms associated with each topic are parameterized by a matrix $\Phi^T_{T \times V}$, whose elements $\varphi^T_{t,v}$ denote the probability of generating *v* from topic *t*. Likewise, multinomials over terms associated with each AD-expression type are parameterized by a matrix $\Phi^E_{E \times V}$. We now define the generative process of JTE (see Figure 10.1 for plate notation of JTE).

1. For each AD-expression type *e*, draw $\varphi^E_e \sim Dir(\beta_E)$

2. For each topic *t*, draw $\varphi^T_t \sim Dir(\beta_T)$

3. For each forum discussion post $d \in \{1 \ldots D\}$:

i. Draw $\theta^E_d \sim Dir(\alpha_E)$

ii. Draw $\theta^T_d \sim Dir(\alpha_T)$

iii. For each term $w_{d,j}$, $j \in \{1 \ldots N_d\}$:

a. Set $\psi_{d,j} \leftarrow MaxEnt(x_{d,j}; \lambda)$

b. Draw $r_{d,j} \sim Bernoulli(\psi_{d,j})$

c. if ($r_{d,j} = \hat{e}$) // $w_{d,j}$ is an AD-expression term

Draw $z_{d,j} \sim Mult(\theta_d^E)$

else // $r_{d,j} = \hat{t}$, $w_{d,j}$ is a topical term

Draw $z_{d,j} \sim Mult(\theta_d^T)$

d. Emit $w_{d,j} \sim Mult(\varphi_{z_{d,j}}^{r_{d,j}})$

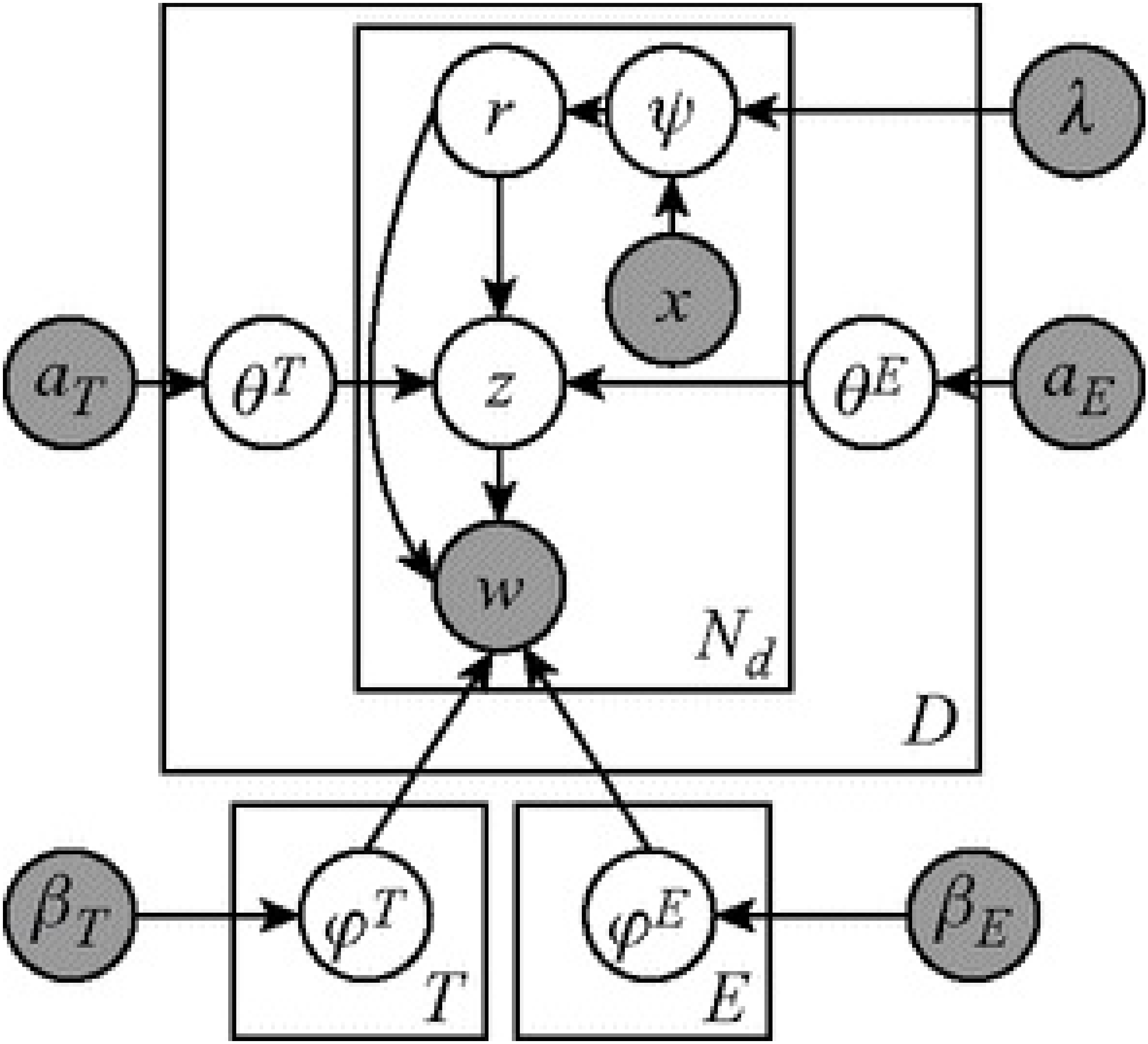


Figure 10.1. The JTE model in the plate notation. Shaded and unshaded nodes indicate observed and latent variables, respectively.

The maximum entropy (Max-Ent) model was used to set $\psi_{d,j}$. The Max-Ent parameters can be learned from a small number of labeled topical and AD-expression terms which serve as good priors, similar to that in Zhao et al. (2010). The idea is motivated by the following observation: topical and AD-expression terms usually play different syntactic roles in a sentence. Topical terms (e.g. *U. S. Senate*, *sea level*, *marriage*, *income tax*) tend to be nouns and noun phrases while AD-expression terms (e.g., *I refute*, *how can you say*, *probably agree*) usually contain pronouns, verbs, wh-determiners, and modals. To utilize POS tag information, we place $\psi_{d,j}$ (the prior over the indicator variable $r_{d,j}$) in the word plate (see Figure 10.1) and draw it from a Max-Ent model conditioned on the observed context $x_{d,j}$ associated with $w_{d,j}$ and the learned Max-Ent parameters λ based on a set of feature functions defined on $x_{d,j}$. $x_{d,j}$ can encode arbitrary contextual information that may be discriminative. In Mukherjee and Liu (2012), the authors used the previous, current, and next POS tags and lexemes of the term $w_{d,j}$, that is, $x_{d,j} = [POS_{w_{d,j-1}}, POS_{w_{d,j}}, POS_{w_{d,j+1}}, w_{d,j-1}, w_{d,j}, w_{d,j+1}]$. For phrasal terms (n-grams), all POS tags and lexemes of $w_{d,j}$ are included. To learn the JTE model from data, exact inference is not possible. Approximate inference using collapsed Gibbs sampling (Griffiths and Steyvers, 2004) was employed. In what follows, we first give the joint distribution and then the Gibbs sampler.

To derive the joint distribution, we factor the joint according to the conditional distributions (causalities) governed by the Bayesian network of the proposed generative model (*R* denotes the topical ($\hat{t}$) or *AD*-expression ($\hat{e}$) assignments of all terms in the corpus).

$$P(W, Z, R) = P(W|Z, R) \times P(Z|R) \times P(R) \tag{10.1}$$

As a collapsed Gibbs sampler is used, θ and φ are integrated out to give the joint as follows.

$$\begin{aligned} P(W, Z, R) = &\left[\prod_{t=1}^{T} \frac{B\left(n_t^{TV} + \beta_T\right)}{B(\beta_T)} \times \prod_{e=1}^{E} \frac{B\left(n_e^{EV} + \beta_E\right)}{B(\beta_E)}\right] \\ &\times \left[\prod_{d=1}^{D} \left(\frac{B\left(n_d^{DT} + \alpha_T\right)}{B(\alpha_T)} \times \frac{B\left(n_d^{DE} + \alpha_E\right)}{B(\alpha_E)}\right)\right] \\ &\times \left[\prod_{d=1}^{D} \prod_{j=1}^{N_d} p(r_{d,j}|\psi_{d,j})\right] \end{aligned} \tag{10.2}$$

where

$$p(r_{d,j}|\psi_{d,j}) = (\psi_{d,j,\hat{t}})^u (\psi_{d,j,\hat{e}})^{1-u}, u = \begin{cases} 1, r_{d,j} = \hat{t} \\ 0, r_{d,j} = \hat{e} \end{cases}$$

, and the outcome probabilities of the Max-Ent model are given by (*y* is the prediction/class variable):

$$\psi_{d,j,\hat{t}} = p(y = \hat{t}|x_{d,j})$$
$$\psi_{d,j,\hat{e}} = p(y = \hat{e}|x_{d,j})$$
$$p(y|x_{d,j}) = \frac{\exp\left(\sum_{i=1}^{n} \lambda_i f_i\left(x_{d,j}, y\right)\right)}{\sum_{y \in \{\hat{t},\hat{e}\}} \exp\left(\sum_{i=1}^{n} \lambda_i f_i\left(x_{d,j}, y\right)\right)}$$

$\lambda_{1\ldots n}$ are the parameters of the learned Max-Ent model corresponding to the *n* binary feature functions $f_{1\ldots n}$ from Max-Ent. $n_{t,v}^{TV}$ and $n_{e,v}^{EV}$ denote the number of times term *v* was assigned to topic *t* and expression type *e* respectively. *B*(·) is the multinomial Beta function $B(\vec{x}) = \frac{\prod_{i=1}^{\dim(\vec{x})} \Gamma(x_i)}{\Gamma(\sum_{i=1}^{\dim(\vec{x})} x_i)}$. $n_{d,t}^{DT}$ and $n_{d,e}^{DE}$ denote the number of terms in document *d* that were assigned to topic *t* and AD-expression type *e* respectively. n_t^{TV}, n_e^{EV}, n_d^{DT}, and n_d^{DE} denote the corresponding row vectors.

Posterior inference is done using Gibbs sampling, which is a form of Markov Chain Monte Carlo (MCMC) method where a Markov chain is constructed to have a particular stationary distribution. In our case, we want to construct a Markov chain which converges to the posterior distribution over *R* and *Z* conditioned on the observed data. We only need to sample *z* and *r* as we use collapsed Gibbs sampling and the dependencies of θ and φ have already been integrated out analytically in the joint. Denoting the random variables {*w*, *z*, *r*} by singular subscripts $\{w_k, z_k, r_k\}$, $k_{1\ldots K}$, $K = \sum_d N_d$, a single iteration consists of performing the following sampling:

$$p(z_k = t, r_k = \hat{t}|Z_{\neg k}, W_{\neg k}, R_{\neg k}, w_k = v) \propto \frac{n_{d,t\ \neg k}^{DT} + \alpha_T}{n_{d,(\cdot)\neg k}^{DT} + T\alpha_T} \times \frac{n_{t,v\ \neg k}^{TV} + \beta_T}{n_{t,(\cdot)\neg k}^{TV} + V\beta_T} \times \frac{\exp\left(\sum_{i=1}^{n} \lambda_i f_i(x_{d,j}, \hat{t})\right)}{\sum_{y \in \{\hat{t},\hat{e}\}} \exp\left(\sum_{i=1}^{n} \lambda_i f_i(x_{d,j}, y)\right)} \quad (10.3$$

$$p\left(z_k = e, r_k = \hat{e} \mid Z_{\neg k}, W_{\neg k}, R_{\neg k}, w_k = v\right) \propto \frac{n^{DE}_{d,e\ \neg k} + \alpha_E}{n^{DE}_{d,(\cdot)\neg k} + E\alpha_E} \times \frac{n^{EV}_{e,v\ \neg k} + \beta_E}{n^{EV}_{e,(\cdot)\neg k} + V\beta_E} \times \frac{\exp\left(\sum_{i=1}^{n} \lambda_i f_i(x_{d,j}, \hat{e})\right)}{\sum_{y \in \{\hat{i}, \hat{e}\}} \exp\left(\sum_{i=1}^{n} \lambda_i f_i(x_{d,j}, y)\right)} \quad (10.4$$

where $k = (d, j)$ denotes the jth term of document d and the subscript $\neg k$ denotes assignments excluding the term at k. Omission of a latter index denoted by $(\cdot)$ represents the marginalized sum over the latter index. The conditional probabilities in Equation (10.3) and Equation (10.4) were derived by applying the chain rule on the joint distribution. A blocked sampler was employed where r and z were sampled jointly, as this improves convergence and reduces autocorrelation of the Gibbs sampler (Rosen-Zvi et al., 2004).

Here we give a list of disagreement or AD-expressions and a list of agreement expressions discovered by JTE from a debate data set.

Contention expressions, $\Phi^{E}_{Contention}$**.** *Disagree, I don't, oppose, I disagree, reject, I reject, I refute, I refuse, doubt, nonsense, I contest, dispute, completely disagree, don't accept, don't agree, your claim isn't, incorrect, hogwash, ridiculous, I would disagree, false, I don't buy your, I really doubt, your nonsense, can you prove, argument fails, you fail to, your assertions, bullshit, sheer nonsense, doesn't make sense, why do you, you have no clue, how can you say, do you even, absolute nonsense, contradict yourself, absolutely not, you don't understand*, and so on.

Agreement expressions, $\Phi^{E}_{Agreement}$**.** *Agree, correct, yes, true, accept, I agree, right, indeed correct, I accept, are right, valid, I concede, is valid, you are right, would agree, agree completely, yes indeed, you're correct, valid point, proves, do accept, support, agree with you, I do support, rightly said, absolutely, completely agree, well put, very true, well said, personally agree, exactly, very well put, absolutely correct, kudos, acknowledge, point taken, partially agree, agree entirely*, and so on.

10.2.2 JTE-R Model: Encoding Reply Relations

The JTE model does not consider interactions among participants, which contain rich information that can be exploited in modeling. We now improve JTE by encoding the reply-to relations as authors usually reply to each other's viewpoints by explicitly mentioning the user name using @name, and/or by quoting others' posts. For easy presentation, we refer both cases as *quoting* from now on. Considering reply-to relations, the new model is called JTE-R (Figure 10.2). This model is based on the following observation:

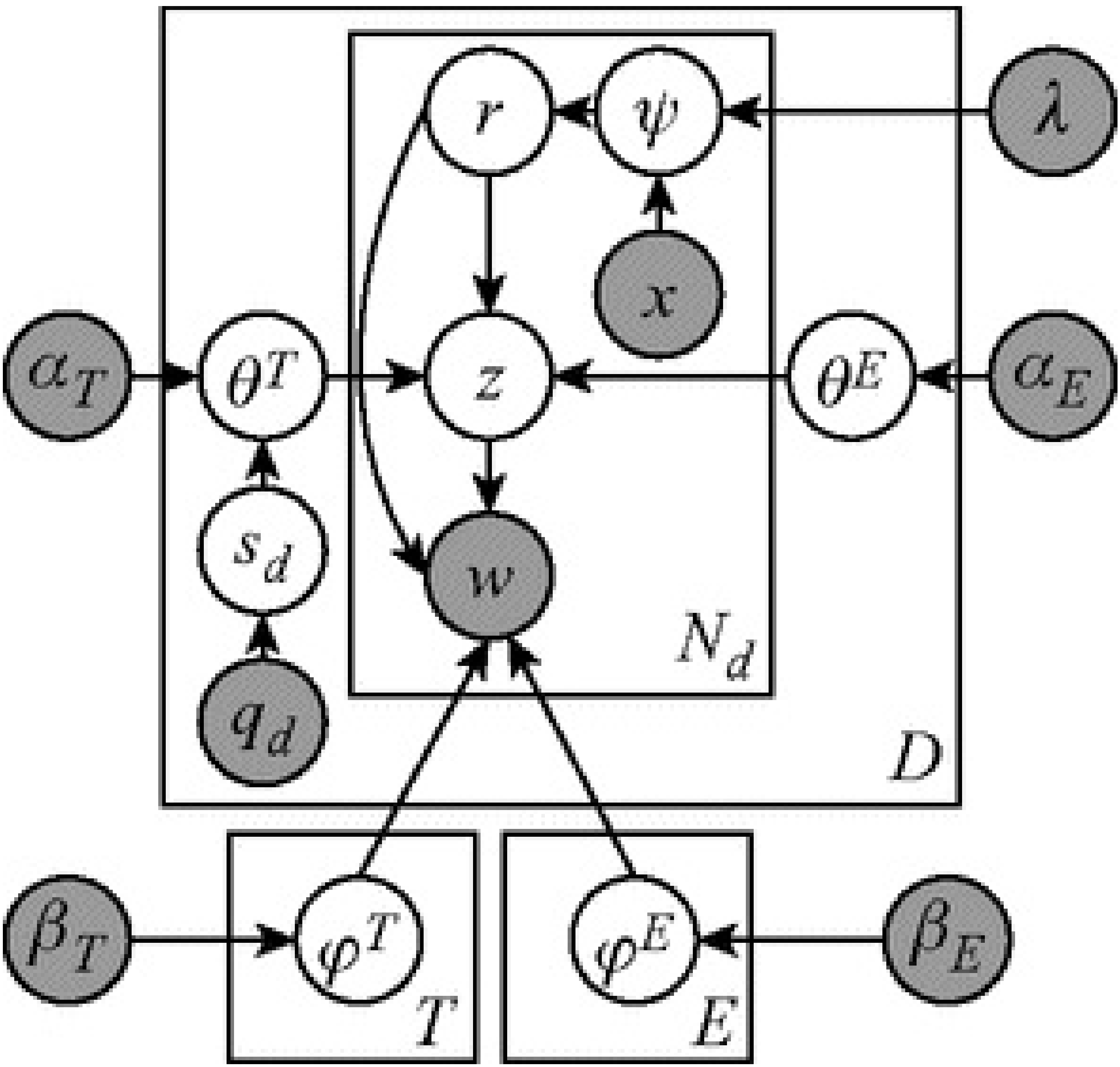


Figure 10.2. The JTE-R model.

Observation: Whenever a post *d* replies to the viewpoints in some other posts by quoting them, *d* and the posts quoted by *d* should have similar topic distributions.

This observation indicates that the JTE-R model needs to depart from typical topic models where there is no topical interaction among documents, that is, documents are treated as being independent of one another. Let q_d be the set of posts quoted by post *d*. Clearly q_d is observed. To encode this "reply-to" relation into JTE-R, the key challenge is to somehow constrain the topic distribution of *d*, θ_d^T to be similar to the topic distributions of posts in q_d. Specifically, it is how to constrain θ_d^T to be similar to $\theta_{d'}^T$, where $d' \in q_d$ (i.e., constraining topic assignments to documents) during inference while the topic distributions of both θ_d^T and $\theta_{d'}^T$, $d' \in q_d$ are latent and unknown a priori. To solve our problem, Mukherjee and Liu (2012) exploited the following salient features of the Dirichlet distribution:

1. Because $\theta_d^T \sim Dir(\alpha_T)$, we have $\sum_t \theta_{d,t}^T$ = 1. Thus, it suffices that θ_d^T can act as a base measure for Dirichlet distributions of the same order.

2. Also, the expected probability mass associated with each dimension of the Dirichlet distribution is proportional to the corresponding component of its base measure. That is, taking moments on $(X_1 \ldots X_n) \sim Dir(\alpha_1 \ldots \alpha_n)$, we get $E[X_i]$ = $\frac{\alpha_i}{\Sigma\alpha_i}$. Thus, $E[X_i] \propto \alpha_i$

Thus, to constrain a post *d*'s topic distribution to be similar to the posts that it replies/quotes (i.e. posts in q_d), we need functional base measures, which govern the expected mass associated with each topical dimension in θ_d^T. One way to employ functional base measures is to draw $\theta_d^T \sim Dir(\alpha_T s_d)$, where $s_d = \sum_{d' \in q_d} \theta_{d'}^T / |q_d|$ (the expected topical distribution of posts in q_d). For posts which do not quote any other post, we simply draw

$\theta_d^T \sim Dir(\alpha_T)$. For a topic model with functional Dirichlet base measures, the sampling distribution is more complicated due to the topic interaction of the current post and quoted posts. Specifically, the document-topic distribution, θ_d^T is no longer a simple predictive distribution, that is, when sampling z_k^d, the implication of each quoted document related to *d* by reply-to relations and their topic assignments must be considered because the sampling distribution for z_k^d in document *d* must consider its effect on the joint probability of the entire model. Unfortunately, this too can be computationally expensive for large corpora. To circumvent this issue, it is possible to hierarchically sample documents based on the reply-to relation network using sequential Monte Carlo (Canini et al., 2009), or to approximate the true Gibbs sampling distribution by updating the original smoothing parameter (α_T) to reflect the expected topic distributions of quoted documents ($s_{d,t}\alpha_T$), where $s_{d,t}$ is the *t*th component of the base measure, s_d which is computed at runtime during sampling. The latter approach is taken in Mukherjee and Liu (2012) (see Equation (10.5)). Experiments show that this approximation performs well empirically. The approximate Gibbs distribution for JTE-R while sampling $z_k^d = t$ is given by

$$p\left(z_k = t, r_k = \hat{t} | Z_{\neg k}, W_{\neg k}, R_{\neg k}, w_k = v\right) \propto \frac{n_{d,t}^{DT}{}_{\neg k} + s_{d,t}\alpha_T}{\sum_{t=1}^{T}\left(n_{d,t}^{DT}{}_{\neg k} + s_{d,t}\alpha_T\right)} \times \frac{n_{t,v}^{TV}{}_{\neg k} + \beta_T}{n_{t,(\cdot)\neg k}^{TV} + V\beta_T} \times \frac{\exp\left(\sum_{i=1}^{n}\lambda_i f_i(x_{d,j}, \hat{t})\right)}{\sum_{y\in\{\hat{t},\hat{e}\}}\exp\left(\sum_{i=1}^{n}\lambda_i f_i(x_{d,j}, y)\right)} \quad (10.5$$

Discovering points of contention. On the basis of the model results, we can identify points of contention, which are topical terms on which contentions or disagreements have been expressed. The JTE and JTE-R models can be employed in the following manner with the estimated θ_d^T. Given a contentious post *d*, the algorithm first selects the top *m* topics that are mentioned in *d* according to its topic distribution, θ_d^T. Let T_d denote the set of these top *m* topics in *d*. Then, for each disagreement expression $e \in d \cap \varphi_{Disagreemnt}^E$, we emit the topical terms of topics in T_d appearing within a word window of *h* from *e* in *d*. More precisely, we emit the set $H = \{w | w \in d \cap \varphi_t{}^T, t \in T_d, |posi(w) - posi(e)| \leq h\}$, where *posi*(·) returns the position index of the word/phrase in a document *d*. To compute the intersection $d \cap \varphi_t^T$ (and also $d \cap \varphi_{Disagreemnt}^E$), we need a threshold. This is so because the Dirichlet distribution has a smoothing effect which assigns some nonzero probability mass to every term in the vocabulary for each topic *t*. So for computing the intersection, we considered only terms in φ_t^T which have $p(v|t) = \varphi_{t,v}^T$ > 0.001 as probability masses lower than 0.001 are more due to the smoothing effect of the Dirichlet distribution than to a true correlation. In an actual application, the values for *m* and *h* can be set according to the user's need. In the experiment, *m* = 3 and *h* = 5 were used, which are reasonable because a post normally does not talk about many topics (*m*), and the contention points (topical terms) should appear quite close to the contentious or disagreement expressions. The JTE-R model was shown to produce better results (points of contention) than the JTE model.

10.2.3 JTE-P Model: Encoding Pair Structures

JTE-R builds over JTE by encoding reply-to relations to constrain a post to have similar topic distributions to those it quotes. An alternative strategy is to make θ^T and θ^E author-pair specific, which can be used to estimate pairwise interaction nature. The idea is motivated by the following observation.

Observation. When authors reply to others' viewpoints (by @name or quoting other authors' posts), they typically direct their own topical viewpoints with contentious (or disagreeing) or agreeing expressions to those authors. Such exchanges can go back and forth between pairs of authors. The discussion topics and AD-expressions emitted are thus caused by the author-pairs' topical interests and their nature of interactions.

Let a_d be the author of a post *d*, and $b_d = [b_{1...g}]$ be the list of *target authors* (we will also call them *targets* for short) to whom a_d replies to or quotes in *d*. The pairs of the form *p* = (a_d, *c*), *c* ∈ b_d essentially shapes both the topics and AD-expressions emitted in *d* as contention or agreement on topical viewpoints are almost always directed toward certain target authors. For example, if *c* claims something, a_d quotes the claim in his post *d* and disagrees/agrees by emitting AD-expressions like "*you have no clue,*" "*yes, I agree,*" "*I don't think,*" and so on. Clearly this pair structure is an important feature of discussion/debate forums. Each pair has its unique and shared topical interests and interaction nature (by which we mean contention/disagreement or agreement). Thus, it is appropriate to condition θ^T and θ^E over author-pairs. Standard topic models do not consider this piece of information.

The JTE model was extended to incorporate the pair structure. The new model is called JTE-P, which conditions the multinomial distributions over topics and AD-expression types (θ^T, θ^E) on authors and targets as pairs rather than on documents as in JTE and JTE-R. In its generative process, for each post, the author a_d and the set of targets b_d are observed. To generate each term $w_{d,j}$, a target, $c \sim Uni(b_d)$, is chosen at uniform from b_d forming a pair *p* = (a_d, *c*). Then, depending on the switch variable $r_{d,j}$, a topic or an expression type index *z* is chosen from a multinomial over topic distribution θ_p^T or AD-expression type distribution

θ_p^E, where the subscript *p* denotes the fact that the distributions are specific to the author-target pair *p* which shape topics and AD-expressions. Finally, the term is emitted by sampling from topic or AD-expression specific multinomial distribution $\varphi_{z_{d,j}}^{r_{d,j}}$.

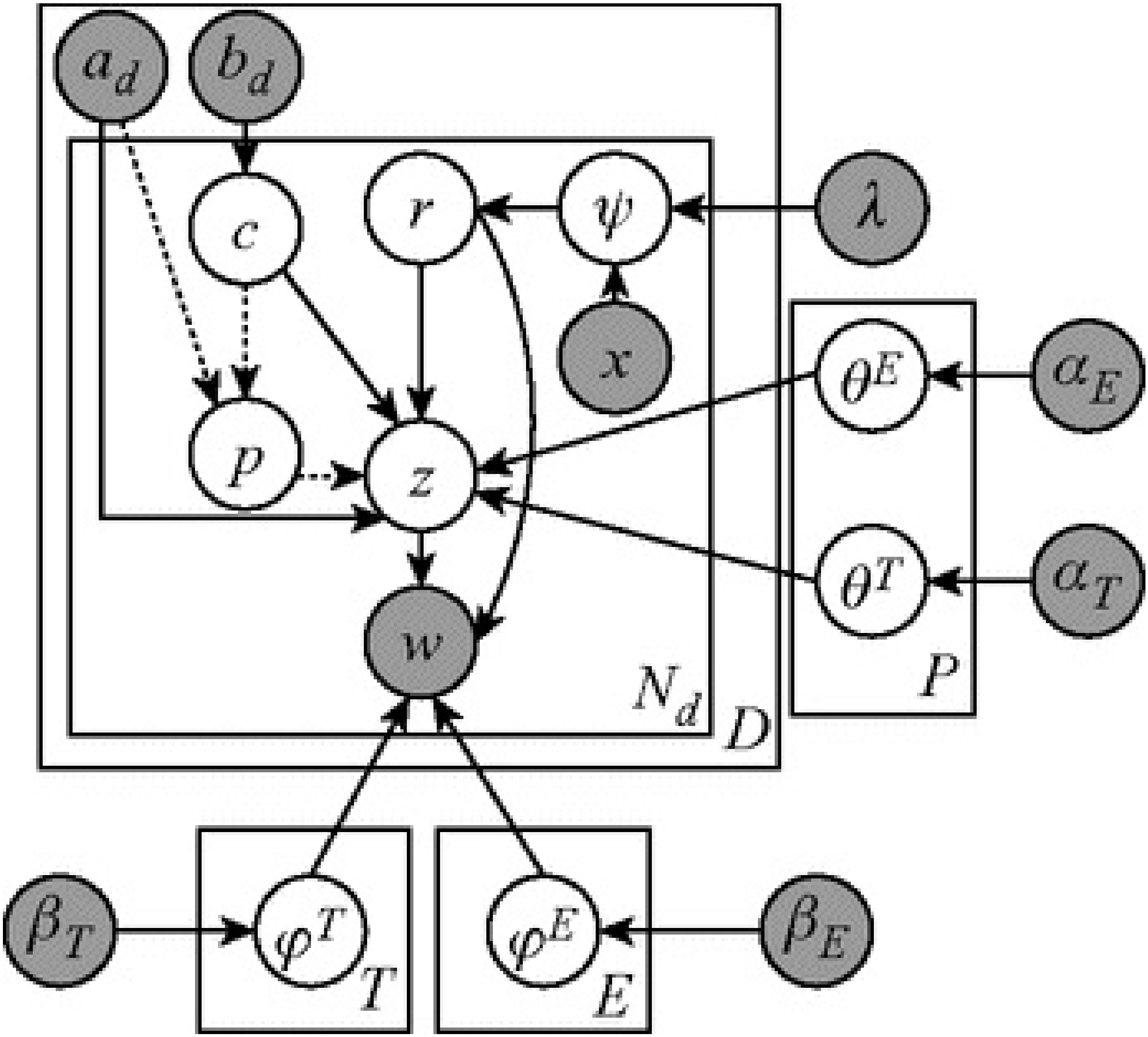


Figure 10.3. The JTE-P model. Note that the pair variable *p* is introduced for derivational convenience, and thus its causalities are shown by dotted arrows.

The graphical model in plate notation corresponding to the preceding process is shown in Figure 10.3. Clearly, in JTE-P, the discovery of topics and AD-expressions are guided by the pair structure of reply-to relations from which the collection of posts was generated. For posterior inference, we again use Gibbs sampling. Note that as a_d is observed, sampling c is equivalent to sampling the pair $p = (a_d, c)$. Its Gibbs sampler is given by

$$p\left(z_k = t, p_k = p, r_k = \hat{t} \mid Z_{\neg k}, W_{\neg k}, P_{\neg k}, R_{\neg k}, w_k = v\right) \propto \frac{1}{|b_d|} \times \frac{n^{PT}_{p,t\,\neg k} + \alpha_T}{n^{PT}_{p,(\cdot)\neg k} + T\alpha_T} \times \frac{n^{TV}_{t,v\,\neg k} + \beta_T}{n^{TV}_{t,(\cdot)\neg k} + V\beta_T} \times \frac{\exp\left(\sum_{i=1}^{n} \lambda_i f_i(x_{d,j}, \hat{t})\right)}{\sum_{y \in \{\hat{t}, \hat{e}\}} \exp\left(\sum_{i=1}^{n} \lambda_i f_i(x_{d,j}, y)\right)} \quad (10.6$$

$$p(z_k = e, p_k = p, r_k = \hat{e} \mid Z_{\neg k}, W_{\neg k}, P_{\neg k}, R_{\neg k}, w_k = v) \propto \frac{1}{|b_d|} \times \frac{n^{PE}_{p,e\,\neg k} + \alpha_E}{n^{PE}_{p,(\cdot)\neg k} + E\alpha_E} \times \frac{n^{EV}_{e,v\,\neg k} + \beta_E}{n^{EV}_{e,(\cdot)\neg k} + V\beta_E} \times \frac{\exp\left(\sum_{i=1}^{n} \lambda_i f_i(x_{d,j}, \hat{e})\right)}{\sum_{y \in \{\hat{t}, \hat{e}\}} \exp\left(\sum_{i=1}^{n} \lambda_i f_i(x_{d,j}, y)\right)} \quad (10.7$$

where $n^{PT}_{p,t}$ and $n^{PE}_{p,e}$ denote the number of times the pair p was assigned to topic t and expression type e respectively. As JTE-P assumes that each pair has a specific topic and expression distribution, we see that Equations (10.6) and (10.7) share topics and expression types across pairs. It is also worthwhile to note that given A authors, there are $\binom{A}{2}$ possible pairs. However, the actual number of pairs (i.e., where the authors have communicated at least once) is much less than $\binom{A}{2}$. The experimental data used in Mukherjee and Liu (2012) consists of 1824 authors and 7684 actual pairs.

Classify pair interaction nature. The model posterior on θ^E_p for JTE-P actually gives an estimate of the overall interaction nature of a pair, that is, the probability masses assigned to expression types, $e = Ag$ (Agreement) and $e = DisAg$ (Disagreement). As $\theta^E_p \sim Dir(\alpha_E)$, we have $\theta^E_{p,e=Ag} + \theta^E_{p,e=DisAg} = 1$. Hence, if the probability mass assigned to any one of the expression types (agreement, disagreement) > 0.5 then according to the model posterior, that expression type is dominant, that is, if $\theta^{E}_{p,Ag}$ > 0.5, the pair is agreeing else disagreeing. However, this approach is not the best. In Mukherjee and Liu (2013), a supervised learning approach was adopted, which gave better results. The authors randomly sampled 500 pairs from their data for labeling. The manual labeling resulted in 320 disagreeing and 152 agreeing pairs. The rest of the pairs were hard to decide by human labelers and not used in the evaluation. The features were the top 2000 AD-expressions from φ^{E}. 5-fold cross-validation using SVM achieved an F-score of 0.78 for agreement and 0.89 for disagreement.

10.2.4 Analysis of Tolerance in Online Discussions

We now discuss a different and important concept of debate, the psycholinguistic phenomenon of *tolerance*. Tolerance is a sub-facet of *deliberation*, which refers to critical thinking and exchange of rational arguments on an issue among participants that seek to achieve consensus/solution (Habermas, 1984).

Perhaps the most widely accepted definition of tolerance is that of Gastil (2005, 2007), who defined tolerance as a means to engage (in written or spoken communication) in critical thinking, judicious argument, sound reasoning, and justifiable claims through constructive discussion as opposed to mere coercion/egotistic clashes of ideologies. Mukherjee et al. (2013) adopted this definition, and also employed the following characteristics of tolerance (known as "code of conduct") (Gutmann and Thompson, 1996; Crocker, 2005) in judging whether a debate participant is tolerant.

> *Reciprocity*. Each member (or participant) offers proposals and justifications in terms that others could understand and accept.
>
> *Publicity*. Each member engages in a process that is transparent to all and each member knows with whom he is agreeing or disagreeing.
>
> *Accountability*. Each member gives acceptable and sound reasons to others on the various claims or proposals suggested by him.
>
> *Mutual respect and civic integrity*. Each member's speech should be morally acceptable, that is, using proper language irrespective of agreement or disagreement of views.

Although the issue of tolerance has been actively researched in the field of communications for the past two decades and in multiple dimensions, existing studies are typically qualitative and focus on theorizing the socio-linguistic aspects of tolerance (Mukherjee et al., 2013).

With the rapid growth of social media, the large volumes of online discussions/debates offer a golden opportunity to investigate people's implicit psyche in discussions quantitatively based on the real-life data, that is, their tolerance levels and their arguing nature, which are of fundamental interest to several fields such as communications, marketing, politics, and sociology (Moxey and Sanford, 2000; Dahlgren, 2005; Gastil, 2005). Communication and political scholars are hopeful that technologies capable of identifying people's tolerance levels on social issues (often discussed in online forums) can provide statistics that is vital to predicting political outcomes in elections and in tailoring voting campaigns and agendas to maximize winning chances (Dahlgren, 2002).

Mukherjee et al. (2013) studied the problem of classifying tolerant and intolerant participants in discussions. For their classification experiments, they manually labeled 436 participants from a political domain and 501 participants from a religion domain as tolerant or intolerant based on their posts in the debate forum volconvo.com. The guidelines for labeling are the “code of conduct” described earlier. Owing to the complex and interactive nature of debates/discussions, the traditional n-gram features are not sufficient for accurate classification. Mukherjee et al. (2013) proposed a generative model called Debate Topic Model (DTM) to discover some key pieces of information. DTM is a variation of the JTE model. These pieces of information are used to generate a set of novel features from the estimated latent variables of DTM capable of capturing authors’ tolerance or intolerance psyche during discussions. These features include, word and POS n-grams, factor expressions that are indicative of tolerance and intolerance, AD-expressions, overall arguing nature of the participant, behavioral response, equality of speech, and topic shift. The features are then used in learning to identify tolerant and intolerant authors. These features are quite involved as there are not surface features that can be directly extracted from the text or the posting behavior. Instead, most of them need various posteriors of the DMT model to define them. Interested readers are encouraged to refer to the paper for detailed explanations of the features and their formulas. The final classification was done using SVM. The paper found that the set of features is highly effective and outperforms several baseline feature sets.

10.3 Modeling Comments

We now turn to modeling of comments. This section is based on the work of Mukherjee and Liu (2012), which models comments of online reviews. Online reviews enable consumers to evaluate the products and services that they have used. These reviews are also used by other consumers and businesses as a valuable source of opinions. However, reviews only give the evaluations and experiences of the reviewers. This is problematic because a reviewer may not be an expert of the product and may misuse the product or make other mistakes. Reviews may also miss opinions on certain aspects of the product that are interesting to readers. Some reviewers may even write fake reviews to promote or demote some products, which is called *opinion spamming* (Jindal and Liu, 2008). To improve the online review system and the user experience, many review hosting sites allow readers to write comments about reviews. However, many reviews receive a large number of comments. It is difficult for a reader to read them to get a gist of them, so an automated comment analysis system will be very helpful. Review comments mainly contain the following information:

Thumbs-up or thumbs-down: Some readers may comment on whether they find the review useful in helping them make purchase decisions.

Agreement or disagreement. Some readers who comment on a review for a product may be users of the product themselves. They can state whether they agree or disagree with the review. Such comments are valuable as they provide a second opinion, which may even help identify fake reviews because a genuine user often can easily spot reviewers who have never used the product.

Question and answer. A commenter may ask for clarifications or for opinions about some aspects of the product that are not covered in the review.

Similar to debate modeling, here we want to model comment topics and different types of expressions that indicate different types of comment posts:

1. Thumbs-up (e.g., “review helped me”)

2. Thumbs-down (e.g., “poor review”)

3. Question (e.g., “how to”)

4. Answer acknowledgment (e.g., “thank you for clarifying”). Note that no expression for answer is used because there are usually no specific phrases indicating that a post answers a question except possibly starting with the name of the person who asked the question. However, there are typical phrases for acknowledging answers, thus *answer acknowledgment* expressions.

5. Disagreement (contention) (e.g., “I disagree”)

6. Agreement (e.g., “I agree”).

These expressions are called the *comment expressions* (or *C-expressions*). The JTE model can actually be used for comment modeling as well. The only difference is that C-expressions have six types (E = 6) while the debate expressions have only two types (E = 2). Thus, JTE also provides a model for extracting these six pieces of information and comment topics. Its generative process separates topics and C-expression types (6 of them) also by using a switch variable and treats posts as random mixtures over latent topics and C-expression types. Maximum entropy priors are again used to guide topic/C-expression switching. The topics in the comment context are usually product aspects.

The extracted C-expressions and topics from review comments are very useful in practice. First of all, C-expressions enable accurate comment classification. The thumbs-up, thumbs-down, and disagreeing posts can give us a good evaluation of the review quality and credibility. For example, a review with many *disagreeing* and *thumbs-down* comments is dubious. Second, the extracted C-expressions and topics help identify the key product aspects that trouble people in disagreements and in questions. With these pieces of information, comments for a review can be summarized. The summary may include, but not limited to, the following:

1. percentage of people who give the review thumbs-up or thumbs-down

2. percentage of people who agree or disagree (or contend) with the reviewer

3. contentious (disagreed) aspects (or topics)

4. aspects of the product that people have many questions.

These summaries are related to, but also different from, other comment summarization works that summarize comments based on topics and clustering in relation to their associated articles (Hu et al., 2008; Khabiri et al., 2011; Ma et al., 2012).

10.4 Summary

In this chapter, we studied some current techniques for mining and analyzing debates/discussions, and comments, which are important social media forms. Existing research is still in its early stage, and mainly done in computer science. I believe that for this area of research to flourish, we need the participation of social scientists because they are the ones who truly understand the problems and their implications, and can set meaningful research agendas. I have been fortunate to have the opportunity to collaborate with some social science researchers. Through the collaborations, I realized that there is so much to be done. In what follows, I use politics as an example to describe some research issues that are interesting to political scientists. Their current analytic methods are still primitive and mainly based on keyword search and manual coding and analysis, which cannot keep up with the rapid growth of online political discussions and participations.

Political scientists are interested in knowing the dynamics of how online conversation elevates issues, perspectives, and participants. They are also interested in understanding how the changing scope and means of participation influence the political agenda, public attitudes and preferences, and the resolution of conflicts. More specific to this chapter, they want to analyze many features of debates and discussions, for example, positions taken, contentious issues, frames/interpretations used to describe issues, beliefs about the implications of policies, and so on, and to examine the dynamics of interaction and the nature of exchange among participants. They believe that the Internet seems to hold the potential to invigorate public discussions of controversial issues, but it is important to study whether web publics engage in the hallmark features of deliberation: Does conversation move toward consensus on particular understandings or interpretations of issues? Do participants of opposing positions exhibit tolerance toward diverse perspectives? In other words, to what extent do partisan publics seem willing to bridge political groups and engage in healthy intergroup political discussions? They also want to have some insight on why certain ideas gain popularity and why some individuals attain greater celebrity online. The analysis of large-scale data sets about debates, discussions, and comments can also help them understand the nature of the competition among arguments and claims in politics, in particular the extent to which popularity and durability are related to the source of ideas, their content and framing, and the context in which they are expressed. The knowledge gained in such analyses can help politicians, political organizations, think tanks, and the government better understand the dynamics of online preference formation, enabling more informed policy decisions through speedy data processing of public opinions toward social, political, and economic issues.

Several existing works in computer science have ventured into some of these areas. I have discussed them in this chapter, but they are still quite preliminary and much more research remains to be done. We can see that there is a tremendous scope for collaboration with social scientists to conduct fundamental and impactful research. Although I just used political science as an example, I have no doubt that related studies will also be of great utility to many other fields of social sciences.

11

Mining Intentions

Before performing an action, we almost always have the intention to perform the action first. In many cases, we also talk about or write about our intentions. Although the concept of intention has been investigated in philosophy and psychology, researchers in these fields are usually not concerned with the language used to express intentions or how to infer intentions from written language computationally, which is our objective in this chapter. Studying intention computationally is just beginning, and our understanding of the problem is still limited.

Intention and sentiment are generally regarded as two different concepts. They are, however, closely related, which we will discuss in Section 11.1. Mining intentions also has many practical applications. For example, if we find that a large number of Twitter posts say something like "*I am dying to see the Life of Pi*," we can predict that the movie is going to do well at the box office. If one wrote "*I am looking for a car to replace my old Ford Focus*, a*ny suggestions?*" the person clearly wants to buy a car and a car dealer can quickly recommend the person some new car models. If the dealer also has reviews of these cars, these reviews can be shown to this potential buyer in persuasion at the same time. Mining intention information is also useful to social media hosting sites, which often use their user-generated content (posts) for advertising. If user intentions can be recognized automatically, advertising can be made intention based and should therefore be much more targeted and effective. This chapter is organized as follows. Section 11.1 defines the intention mining problem. Section 11.2 studies an existing method for identifying intention posts in social media based on transfer learning. Section 11.3 suggests a simple method to mine fine-grained intentions of any kind in a massive scale from any social media site.

11.1 Problem of Intention Mining

This section defines the concept of *intention*. Two definitions are presented, one *dictionary definition* for human understanding and one *structured definition* for computer to identify the core components of an intention to operationalize the task of intention mining.

> **Definition 11.1 (Intention):** *Intention* has two main meanings or senses:[4]

1. A course of action that a person or a group of persons intends to follow.

2. The goal or purpose behind a specific action or set of actions.

The intentions expressed in the following sentences have the first meaning:

"*I really want to buy an iPhone 5*"

"*I am in the market for a new car*"

The intentions expressed in the following sentences have the second meaning:

"*He bought this car just to please his girlfriend*."

"*This policy is to help the smart kids*."

For the second type, some intentions may be hidden, especially unethical intentions, for example,

"*I love this car and it is definitely the best car ever.*"

The author of this sentence may have either one of the two intentions: (1) to provide an honest opinion about the car and (2) to promote the car by writing a fake review.

In this chapter, we focus on the first sense of intention partly because there are more commercial interests in the first sense and partly because the intention in the second sense may be hidden and its analysis is highly subjective. In Chapter 12, we will deal with hidden intentions of reviews by detecting fake or deceptive reviews. From now on, when we use the word intention we refer to its first sense/meaning.

Although intention and sentiment are different concepts, they are related in several ways. First, many intention sentences express sentiments or emotions, for example,

"*I am dying to see the Life of Pi*."

"*I am going to join the PROTEST in the city square tomorrow*!!!!!!"

The intention in the first sentence is emotional and the author is likely to have a positive sentiment about the movie *Life of Pi*. The second sentence is emotional too because the author capitalized every letter of *protest* and used multiple exclamation marks. He clearly supports the protest. We call the intentions expressed in these two sentences *emotional intentions*. Second, when one expresses a desire to get a specific item one usually has a positive impression about the item, for example,

"*I want to buy an iPhone 5*."

Although this sentence shows no sign of sentiment or emotion explicitly, it should be safe to infer from this sentence that the person has a positive impression about the *iPhone 5* because she has the desire to purchase it. In fact, these two cases represent the *sentiment of desire*, which is different from the traditional evaluation or appraisal type of sentiment because the sentence authors have not had the firsthand experiences with the entities. Such sentiment of desire is important for many applications. For example, they can be used to assess how successful a marketing campaign is in arousing people's buying interests or how many people may be enthusiastic voters of a political candidate.

One interesting thing to note is that in the preceding example sentences, the author wants to buy a specific product, *iPhone 5*, which we call the intention target. It is also possible that the intention target is not specific, for example,

"*I need to get a new camera*," and

"*I am in the market for a new car*."

In these cases, it is not clear whether the authors have any sentiment attached or not. We call the intentions implied in the preceding three sentences the *rational intentions*, which may or may not imply any sentiment.

Third, some evaluative opinions are expressed as intentions, for example,

"*I want to throw this camera out of the window*," and

"*I am going to return this camera to the shop*."

The author of the first sentence may not literally mean to throw the camera out of the window, but it is a figure of speech expressing a strong negative sentiment about the camera. This kind of "pseudo" intention is quite common in opinion documents.

We are now ready to provide a structured definition of intention, which will help operationalize the task of intention mining from text.

Definition 11.2 (Intention): An intention is a quintuple:

(intended-action, intention-target, intention-intensity, holder, time),

where *intended-action* is the action that is intended, *intention-target* is the object of the intention, *intention-intensity* is the intensity of the intention, for example, rational intention or emotional intention, *holder* is the person or the group of persons who has the intention, and *time* is the time when the intention is posted.

For example, in "*I plan to buy a camera*," the holder is *I*, the intended-action is *to buy*, the intention-target is *a camera*, and intention-intensity is *rational*. Following are some remarks about this definition:

1. All five components are useful, although the first and the second are probably more important in practice, and form the core of an intention. The intended action is crucial because different actions mean very different things, for example, *to buy* and *to fix* a computer have completely different implications. Similarly, the target of intention is also important. For example, *to buy* a *computer* is very different from *to buy* a *camera* for applications. The holder is also useful because the author's own intention is more meaningful to an application than someone else's intention described by the author. For example, "*I plan to buy a new car*" and "*my friend plans to buy a new car*" mean quite different things to advertisers because the author may or may not have any influence on her friend. Thus, showing an advertisement to the author may have little effect. Clearly, the intention intensity and time of intention are useful too.

2. The intention target can be specific (e.g., *iPhone 5*) or nonspecific (e.g., *a smart phone*), which also has implications to applications. For example, in advertising, the two types of targets need different advertising actions. Thus discovering such information is useful.

3. The scales of intention-intensity can be designed according to the application need. In the above discussions, we used two scales, *rational intention* and *emotional intention*, which are analogous to rational and emotion evaluations in Section 2.1.3.

The following definition distinguishes explicit and implicit intentions.

Definition 11.3 (Explicit intention and implicit intention): An *explicit intention* is an intention explicitly stated in the text. An *implicit intension* is one that may be implied or inferred from the text. An implicit intention is uncertain.

For example, the sentence "*I want to buy a new phone*" explicitly expresses a buying intention. The sentence "*How long is the battery life of an iPhone*?" may or may not suggest an implicit intention of buying an iPhone. This sentence clearly has the explicit intention of finding out the battery life of an iPhone. Many interrogative sentences actually have two intentions, an *explicit intention* of getting an answer to the question, and an *implicit intention* of doing something based on the answer. Of course, both intentions of a question sentence can be explicit, for example, “*Anyone knows where I can buy an iPhone?*” The author wants to find a store and also wants to buy an iPhone. Because an explicit intention does not mean absolute certainty, there is no clear demarcation between explicit and implicit intentions. Their judgment is based on commonsense and pragmatics.

Intention mining can be seen as an instance of the information extraction problem (Sarawagi, 2008; Hobbs and Riloff, 2010). Traditional supervised sequence learning methods such as conditional random fields (CRFs) (Lafferty et al., 2001) and hidden Markov models (HMMs) (Rabiner, 1989) can be applied. Pattern-based methods are also applicable because most intention sentences are indicated by some linguistic patterns as we can see from the preceding example sentences. A preliminary study by my group shows that using a set of manually compiled linguistic patterns on a forum discussion corpus we can find buying intentions with a recall of 95% and a precision of about 30%.

The next section discusses an intention mining study based on machine learning, which aims to identify social media posts expressing some intentions of interest (Chen et al., 2013). The task is called *intention classification*. It can be considered as one step toward solving the intention mining problem because extracting individual components of intentions should be done only in the intention posts. There is also a start-up company called Aiaioo Labs that uses intention analysis for business applications. They presented a demonstration at the Coling-2012 conference (Carlos and Yalamanchi, 2012). However, neither of these systems extracts the intention components in the quintuple definition.

11.2 Intention Classification

In Chen et al. (2013c), intention classification is formulated as a two-class classification problem. *Intention posts* (positive class) are defined as posts that explicitly express a particular intention of interest. The other posts are treated as *nonintention posts* (negative class), although some of these posts may express some other kinds of intentions. In their experiments, the positive class was the intention *to buy*.

An important characteristic of this problem makes it amenable to transfer learning. For a particular kind of intention such as the buying intention, the ways to express the intention in different application domains are very similar. This idea can be exploited to build a classifier based on labeled data in other domains and apply it to any new/target domain without labeling training data in the new/target domain. This problem, however, also has two difficulties that make it hard for existing general transfer learning methods:

1. In an intention post, the intention is typically expressed in only one or two sentences while most sentences do not express intention. Additionally, words/phrases that indicate intentions are limited compared to other types of expressions. This means that the set of shared features in different domains is small. Because most transfer learning methods try to extract and exploit these shared features, a small number of such features can make it hard for the methods to find them accurately, which in turn can result in weak classifiers.

2. As mentioned earlier, in different domains, the ways to express the same intention are often quite similar. Thus only the positive (or intention) features are shared among different domains, while features indicating the negative (nonintention) class in different domains can be quite diverse. This gives a feature imbalance problem, that is, the shared features mostly indicate the positive class, which also makes it difficult for a general transfer learning method to work accurately.

Chen et al. (2013c) proposed a specific transfer learning (or domain adaptation) method for intention classification, called Co-Class, to deal with these difficulties. The algorithm works by using labeled data from one or more domains, called the *source domains* or *source data*, to help classify the *target domain* data, which have no labels.

To deal with the first problem, Co-Class avoids it by using a naïve Bayes–based EM (Nigam et al., 2000) like algorithm to iteratively transfer from the source domains to the target domain while exploiting feature selection in the target domain to focus on the important features in the target domain. Co-Class is also inspired by Co-Training (Blum et al., 2004) as it builds two classifiers and makes them work together on the target data. The algorithm starts by first building a classifier *h* using the labeled data combined from all source domains, and then applying the classifier to classify the unlabeled target (domain) data. On the basis of the target data labeled or classified by *h*, it performs a feature selection on the target data. The selected set of features is used to build two classifiers, one (h_S) from the labeled source data and one (h_T) from the target data which has been labeled by *h*. The two classifiers (h_S and h_T) then work together to perform classification on the target data. The process runs iteratively until the labels assigned to the target data stabilize. Because in each iteration, both classifiers are built using the same set of features selected from the target domain, the process is forced to focus on the target domain and the knowledge in the source domains thus transfers gradually/iteratively to the target domain.

The detailed Co-Class algorithm is given in Figure 11.1. First, it selects a feature set Δ from the labeled source data D_L to build an initial naïve Bayes classifier *h* (lines 1 and 2). The feature selection is based on information gain (IG) (Yang and Pedersen, 1997). After that, *h* classifies each document in the target data D_U to obtain its predicted class (lines 3–5). A new target data set D_P is produced in line 6, which is D_U with added class labels (predicted in line 4). Line 8 selects a set of new features Δ from D_P. Two naïve Bayes classifiers, h_L and h_P, are then built using the source data D_L and predicted target data D_P respectively with the same set of features Δ (lines 9–10). Lines 11–13 classify each target domain document d_i again using the two classifiers. $\Phi\left(h_L(d_i), h_P(d_i)\right)$ is the aggregation function to combine the results of two classifiers. It is defined as

$$\Phi\left(h_L(d_i), h_P(d_i)\right) = \begin{cases} + & h_L(d_i) = h_P(d_i) = + \\ - & Otherwise \end{cases}$$

The function Φ assigns the positive class to the document d_i if both classifiers classify it as positive. Otherwise, it is classified as negative. This is a crucial step for dealing with the second problem of feature imbalance, that is, strong positive features and weak negative features. This function restricts the positive class to require both classifiers to give positive predictions. After the algorithm converges, the classification results of the target domain data are the class labels produced in line 12 of the last iteration.

Finally, we note that, although the study of intention mining from full text documents has just started, many researchers have studied the problem of *user* (or *query*) *intent classification* in web search. Their task is to classify each query submitted to a search engine to determine what the user is searching for and/or whether she has a commercial intention such as to buy and to sell. Such intents are typically highly implicit because people usually do not issue a search query like "*I want to buy a digital camera*." Instead, they may just type the keywords "*digital camera*." Current classification methods use user keyword queries, click-through data, and external data sources such as Wikipedia to build machine learning models for classification (Chen et al., 2002; Dai et al., 2006; Shen et al., 2006; Li et al., 2008; Arguello et al., 2009; Hu et al., 2009). The intentions discussed in this chapter are different as they are explicitly stated in full text documents.

Algorithm Co-Class

Input: Labeled data D_L and unlabeled data D_U

Select a feature set Δ based on IG from D_L;
Learn an initial naïve Bayes classifier h from D_L based on Δ;
for each document d_i in D_U **do**
    $c_i = h(d_i)$; // predict the class of d_i using h
end
Produce data D_P based on the predicted classed of D_U;
repeat
    Select a new feature set Δ from D_P;
    Build a naïve Bayes classifier h_L using Δ and D_L;
    Build a naïve Bayes classifier h_P using Δ and D_P;
    for each document d_i in D_U **do**
        $c_i = \Phi(h_L(d_i), h_P(d_i))$; // Aggregate function
    end
    Produce data D_P based on the predicted class of D_U;
until the predicted classes of D_U stabilize

Figure 11.1. The Co-Class algorithm.

11.3 Fine-Grained Mining of Intentions

As mentioned earlier, little research has been done on fine-grained mining of intention components as defined in Section 11.1. In this section, we suggest a simple approach to performing this detailed level of mining on a social media platform, which usually has a massive amount of data or user posts.

On a typical social media platform such as Twitter or Facebook, people consciously or unconsciously express their intentions all the time. If you issue the search query "*I want to buy*" to the Twitter search engine, you will find a large number of Twitter posts (tweets) that express the desire or intention to buy all kinds of products. If you issue the query "*I want to watch*," you will find a large number of people who want to watch all kinds of movies and TV shows. If you issue some variations of these queries, you will get even more of such intention posts. Knowing user intentions can help merchants and advertisers promote their products and services online more accurately. It can also save time and effort for the users or post authors because they do not have to find the needed information, products or services, using a general search engine such as Google and browsing a large number of returned pages in the convention manner, because merchants or advertisers can directly respond to user intentions by showing them relevant products and services.

The preceding search queries suggest a simple pattern matching based method to mine fine-grained intentions. This search or pattern matching based approach is reasonable because an earlier study showed that using manually crafted patterns can yield a very high recall of 95% in identifying intention sentences. Owing to a huge number of posts at any social media site, search is perhaps the most efficient method to get relevant information. However, because of the low precision of only about 30%, we need more than just search. Search also cannot extract intention targets and other needed information. We thus suggest the following simple approach:

1. Use a set of manually crafted patterns to extract candidate intention sentences. As the types of intentions can be very broad (e.g., intentions to buy, to watch, to go, to eat, and to stay) the patterns should reflect the desired intentions of the application user.

2. Manually label some training intention and nonintention sentences from the search result to build a classifier. The classifier will classify the future candidate intention sentences to find those truly intentional sentences.

3. Extract intention targets from intention sentences using a supervised sequence learning method such as CRF. We do not need to extract intention type because the patterns already include the information about the intention type. For example, if we use the pattern "*I want to buy*" or its variations such as "*I plan to purchase*" and "*I intend to buy*" to find buying intention posts, we already know the intention type, that is, *to buy*. Thus, we only need to extract intention targets in this step.

If an application also needs intention holders and times when intentions are expressed, they can be extracted as well. They are usually the authors of the posts and the times when the posts are made, which are simple to extract from the posting pages of any social media site.

This approach has not been tested or validated using real-life experiments. Hopefully someone will build a system based on the approach in the near future. One can also couple this system with an application. For example, once fine-grained intentions are extracted, the site advertisers can provide the intention holders (or the authors) their needed products or services. For example, if I want to eat French food, I post "*I want to eat French food this evening*" on Twitter. Twitter immediately recognizes my intention and gives me the information about the local French restaurants and the customer reviews of the restaurants. Technically, it is already possible to build such a system.

This simple approach can be employed to do large scale or massive intention mining on one or multiple social media sites because both the search (pattern matching) and classification can be done very efficiently. With a wide range of applications, this may represent a good business opportunity for social media sites and their advertisers.

11.4 Summary

Intention has a tremendous potential for commercial applications. Advertising and recommendation are perhaps the two most direct applications. On social media platforms such as Twitter, Facebook, and discussion forums, people express their intentions constantly. However, the research on intention mining is just starting. This chapter discussed a machine learning approach to discovering intention posts. We are still unable to do fine-grained mining of intention components as defined in Definition 11.2 in Section 11.1. A simple pattern-based approach has been suggested to mine intentions at the fine-grained level. The mining can be carried out at a massive scale because it is easy to design patterns for all possible domains. Finally, we note that this chapter only studied explicit intentions. The topic of recognizing implicit intentions has not been touched because it is much harder to do due to the highly subjective nature of the problem and the difficulty of evaluation.

4 http://www.thefreedictionary.com/.

12

Detecting Fake or Deceptive Opinions

Opinions from social media are increasingly used by individuals and organizations for making purchase decisions, making choices at elections, and for marketing and product design. Positive opinions often mean profits and fame for businesses and individuals. This, unfortunately, gives strong incentives for imposters to game the system by posting *fake reviews* or *opinions* to promote or to discredit some target products, services, organizations, individuals, and even ideas without disclosing their true intentions, or the person or organization that they are secretly working for. Such individuals are called *opinion spammers* and their activities are called *opinion spamming* (Jindal and Liu, 2007, 2008). An opinion spammer is also called a *shill*, a *plant*, or a *stooge* in the social media environment, and opinion spamming is also called *shilling* or *astroturfing*. Opinion spamming not only can hurt consumers and damage businesses, but also can warp opinions and mobilize masses into positions counter to legal or ethical mores. This can be frightening, especially when spamming is about opinions on social and political issues. It is safe to say that as opinions in social media are increasingly used in practice, opinion spamming is becoming more and more sophisticated, which presents a major challenge for their detection. However, they must be detected to ensure that the social media continues to be a trusted source of public opinions, rather than being full of fakes, lies, and deceptions. The good news is that both the industry and the research community have made tremendous progress in combating opinion spamming. I am aware that several major review hosting sites are able to detect a good proportion of fake reviews and fake reviewers. These efforts have already acted as a deterrent to opinion spamming and made it difficult for inexperienced spammers to succeed. However, the problem is still huge and a great deal of research is needed.

Spam detection in general has been studied in many fields. Web spam and e-mail spam are perhaps the two most widely studied types of spam. Opinion spam is, however, very different. There are two main types of web spam, that is, *link spam* and *content spam* (Liu, 2006, 2011; Castillo and Davison, 2010). Link spam is spam on hyperlinks, which hardly exist in online reviews. Although advertising links are common in Twitter and forum discussions, they are relatively easy to detect, and are not considered as opinion spam. Content spam adds popular (but irrelevant) words in target web pages to fool search engines into making them relevant to many search queries, but this hardly occurs in opinion posts because opinion posts are for human beings to read rather than for machines to consume. It thus does not make sense to add irrelevant words. E-mail spam refers to unsolicited explicit advertisements. Opinion spam, especially these aimed at promoting some target products and services, can be thought of as some form of advertisement. However, they are highly implicit and pretend to be honest opinions from real users or customers. This leads us to the major challenge of opinion spam detection:

> *Challenge of opinion spam detection.* Unlike other forms of spam, it is very hard, if not impossible, to recognize fake opinions by manually reading them. This makes it difficult to find gold-standard data to help design and evaluate detection algorithms. For other forms of spam, one can recognize them fairly easily.

In fact, in the extreme case, it is logically impossible to recognize spam by simply reading it. For example, one can write a truthful review for a good restaurant and post it as a fake review for a bad restaurant to promote it. There is no way to detect this fake review without considering information beyond the review text itself simply because the same review cannot be both truthful and fake at the same time. Following are three example reviews. Can you, as a reader, figure out which reviews are fake? The answer is at the end of the chapter.

> *Review 1.* I want to make this review in order to comment on the excellent service that my mother and I received on the Serenade of the Seas, a cruise line for Royal Caribbean. There was a lot of things to do in the morning and afternoon portion for the 7 days that we were on the ship. We went to 6 different islands and saw some amazing sites! It was definitely worth the effort of planning beforehand. The dinner service was 5 star for sure. One of our main waiters, Muhammad was one of the nicest people I have ever met. However, I am not one for clubbing, drinking, or gambling, so the nights were pretty slow for me because there was not much else to do. Either than that, I recommend the Serenade to anyone who is looking for excellent service, excellent food, and a week full of amazing day-activities!

> *Review 2.* This movie starring big names – Tom Hanks, Sandra Bullock, Viola Davis, and John Goodman – is one of the most emotionally endearing films of 2012. While some might argue that this film was "too Hollywood" and others might see the film solely because of the cast, it is Thomas Horn's performance as young Oskar that is deserving of awards. The story is about a 9-year-old boy on a journey to make sense of his father's tragic death in the 9/11 attacks on the World Trade Center. Oskar is a bright and nervous adventurer calmed only by the rattle of a tambourine in his ear. "I got tested once to see if I had Asperger's disease," the boy offers in explain of his odd behavior. "The tests weren't definitive." One year after the tragedy, Oskar

finds a key in his father's closest and thus begins a quest to find the missing lock. Oskar's battle to control his emotional anxiety and form and mend relationships proves difficult, even with his mother. "If the sun were to explode, you wouldn't even know about it for eight minutes," Oskar narrates. "For eight minutes, the world would still be bright and it would still feel warm." Those fleeting eight minutes Oskar has left of his father make for two hours and nine minutes of Extremely Emotional and Incredibly Inspiring film. Leaving the theater, emotionally drained, it is a wonder where a movie like this has been. We saw Fahrenheit 9/11 and United 93, but finally here is the story of a New York family's struggle to understand why on "the worst day" innocent people would die. I highly recommend this movie as a must see.

Review 3. High Points: Guacamole burger was quite tall; clam chowder was tasty. The decor was pretty good, but not worth the downsides. Low Points: Noisy, noisy, noisy. The appetizers weren't very good at all. And the service kind of lagged. A cross between Las Vegas and Disney world, but on the cheesy side. This Cafe is a place where you eat inside a plastic rain forest. The walls are lined with fake trees, plants, and wildlife, including animatronic animals. A flowing waterfall makes sure that you won't hear the conversations of your neighbors without yelling. I could see it being fun for a child's birthday party (there were several that occurred during our meal), but not a place to go if you're looking for a good meal.

I am sure that you would agree with me that it is really hard to decide. This chapter uses the context of online reviews to study the opinion spam detection problem. Not much research has been done in the contexts of other forms of social media. However, the ideas described in the chapter are applicable to other forms of social media such as forum discussions, blogs, and microblogs. Of course, each of these forms also has its special characteristics or features that can be exploited in the detection process. For example, for microblogs, social network structures are quite useful for detection. Likewise, each of them also has specific challenges that do not exist in reviews. Review ratings, for instance, are quite helpful in detecting fake reviews, but such ratings are not available in other social media forms. If sentiment ratings are needed in a detection algorithm, then an accurate sentiment analysis system is required.

In recent years, numerous high-profile fake review cases have been reported in the news media. In some cases, fake reviewers even bluntly admitted that they wrote a large number of fake reviews. Most cases involve businesses (even highly reputable ones) paying people to write fake reviews for them to promote their products/services and/or to discredit their competitors. Fake reviews are thus not only harmful to consumers, but also to businesses. I personally know some fake negative reviews causing real griefs to businesses. Such reviews are especially damaging for small businesses as they usually have only a few reviews. Even one nasty fake review can potentially destroy a small business.

Increasingly, consumers are also becoming wary of fake reviews. The Google Trend chart for the query “fake review” (Figure 12.1) clearly shows a growing concern about fake reviews from the general public. This chapter examines this problem and presents the current state-of-the-art detection algorithms.

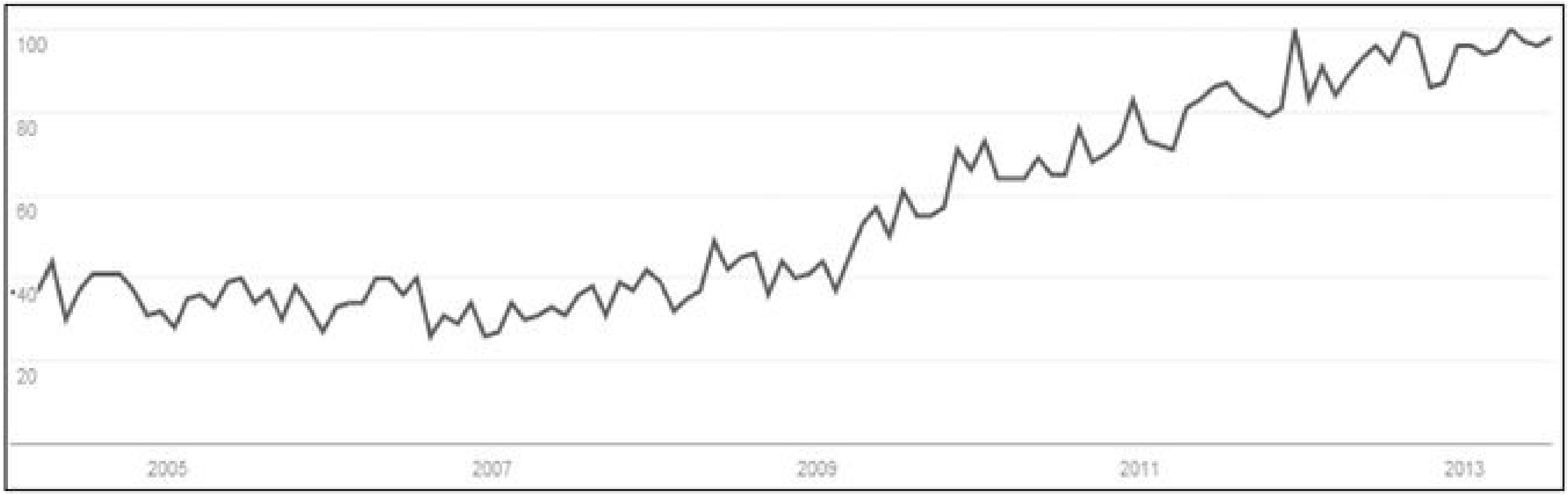


Figure 12.1. The Google Trend result of the search query “fake review.”

12.1 Different Types of Spam

According to Jindal and Liu (2008), there are three main types of spam reviews:

Type 1 (fake reviews). These are untruthful reviews that are written not based on the reviewers' genuine experiences of using the products or services, but are written with hidden motives. They often contain undeserving positive opinions about some target entities (products or services) to promote the entities and/or unjust or false negative opinions about some other entities to damage their reputations.

Type 2 (reviews about brands only). These reviews do not comment on the specific products or services that they are supposed to review, but only comment on the brands or the manufacturers of the products. Although they may be genuine, they are considered as spam as they are not targeted at the specific products and are often biased. For example, a review for a specific HP printer says "*I hate HP. I never buy any of their products*."

Type 3 (nonreviews). These are not reviews. There are two subtypes: (1) advertisements and (2) irrelevant texts containing no opinions (e.g., questions, answers, and random texts). Strictly speaking, they are not opinion spam as they do not give user opinions.

It has been shown in Jindal and Liu (2008) that types 2 and 3 spam reviews are rare and relatively easy to detect using supervised learning. Even if they are not detected, it is not a major problem because human readers can easily spot them during reading. This chapter thus focuses on type 1 spam, fake reviews.

12.1.1 Harmful Fake Reviews

Not all fake reviews are equally harmful. Table 12.1 gives a conceptual view of different kinds of fake reviews. Here we assume we know the true quality of the product. The objective of fake reviews in regions 1, 3 and 5 is to promote the product. Although opinions expressed in region 1 may be true, the reviewers do not disclose their conflicts of interest or hidden motives. The goal of fake reviews in regions 2, 4, and 6 is to damage the reputation of the product. Although opinions in the reviews of region 6 may be true, the reviewers have malicious intensions. Fake reviews in regions 1 and 6 are not damaging, but fake reviews in regions 2, 3, 4, and 5 are very harmful. Thus, fake review detection algorithms should focus on identifying reviews in these regions. Some existing detection algorithms have already used this idea by employing some rating deviation features. Note that fake neutral reviews category is not included in Table 12.1 because such fake reviews hardly serve the purpose of spamming and therefore seldom occur.

Table 12.1. Fake review versus product quality

	Fake positive review	**Fake negative review**
Good quality product	**1**	**2**
Average quality product	**3**	**4**
Poor quality product	5	6

By separating regions 1 and 6 from regions 2, 3, 4, and 5, we also want to stress that those damaging fake reviews are only a subset of all fake reviews. Fake reviews in regions 2, 3, 4, and 5 are all harmful to consumers, but only those reviews in regions 2 and 4 are damaging to businesses. Because no one knows the percentage of harmful fake reviews and no one can tell which reviews should belong to which regions, it is hard to assess how much real damage has been done by fake reviews.

However, we must note that although reviews in regions 1 and 6 do not harm consumers, they do create an unfair advantage for the product that their reviewers are trying to promote. That is why when some businesses are caught buying fake reviews, they justify their actions by claiming defense against others who are also engaging in the same activity. After all, it is well known that positive reviews help sales. These unethical activities do create an unhealthy environment that can potentially render online reviews completely useless in the long run because they largely become either implicit or hidden advertisements for products/services, or weapons for businesses to attack each other.

12.1.2 Types of Spammers and Spamming

Fake reviews may be written by many types of people, for example, friends and family, business owners and employees, competitors, freelance fake review writers, businesses that provide fake review writing services, dismissed former employees, unhappy current employees, even genuine customers (who are given some benefits by businesses in exchange for writing positive reviews for the businesses), and so on. In other forms of social media, public or private agencies may employ people to post messages to secretly influence social media conversations and to spread lies and disinformation.

We categorize fake reviewers or opinion spammers into two main categories, professional fake reviewers and nonprofessional fake reviewers:

Professional fake reviewers. They write a large number of fake reviews and get paid to do so. They may work as freelance fake review writers or work for companies that write fake reviews as part of their businesses. Professional reviewers are often easier to catch because they write a large number of fake reviews, which can leave linguistic and behavioral patterns easily discoverable by data mining algorithms. However, the issue is that by the time they are caught, the damage might have already been done because it takes some time and possibly many fake reviews for the system to detect abnormal writing styles and behavioral patterns. Thus, it is important to discover the patterns as soon as possible, which is challenging. To make matters worse, once an account of a fake reviewer is detected for spamming activities, the fake reviewer simply abandons the account, registers another account, and starts again from the new account.

Nonprofessional fake reviewers. These people do not write many fake reviews and often are not paid. They write mainly to help themselves, their businesses, or their friends. These people include friends and family of a business, business owners and their employees, competitors, dismissed former employees, unhappy current employees, and genuine customers who are given some incentives to write. They write fake reviews (1) to promote their own products and services or those of their friends', (2) to discredit their competitors, and (3) to hurt their former or current employers and their businesses. There are also some fake reviewers who just write for fun.

Because nonprofessional fake reviewers do not write many reviews, they may not have the same patterns as professional reviewers. However, this is not to say that there is no pattern about them. For example, someone frequently checked a restaurant review page without writing anything. Then, one day, when the person saw a negative review appeared on the page, he quickly wrote a strong positive review. Clearly this positive review is suspicious because the person could be the restaurant owner or someone closely associated with the restaurant who wrote the positive review to mitigate the impact of the negative review.

In fact, there is another group of people on the borderline. These people were normal reviewers or even influencers who had contributed many genuine reviews and in the process had built up their reputation. However, due to their reputations, they are approached by some businesses and are asked to promote their products for financial rewards. Some of these reviewers then started to spam for these businesses. Then their body of reviews contains a mixture of genuine and fake reviews. Some even sell their accounts to spammers.

We can also categorize spamming into two main types, individual spamming and group spamming (Mukherjee et al., 2011; Mukherjee et al., 2012). They have different characteristics that can be exploited to facilitate their detection.

Individual spamming. A spammer does not work with anyone. He just writes fake reviews himself using a single account (or userid), for example, the author of a book.

Group spamming. A group of spammers or accounts who knowingly or unknowingly work together to promote or demote some products or services. Group spamming is mainly carried out by professional review writers or fake review writing businesses. However, nonprofessional spammers may do it too. Group spammers mainly work in the follow two models or some ad hoc mixture of the models.

1. A group of spammers (persons) works in collusion to promote a target entity and/or to damage the reputation of another. The individual spammers in the group may or may not know each other or each other's activities. For example, a book author asks a group of friends to write positive reviews for one of his new books. The friends may not know each other's activity, and they are normally not professional spammers.

2. A single person or organization registers multiple accounts (each with a different userid) and spam using these accounts. These multiple accounts (or userids) behave just like a group working in collusion. This is called *sock puppeting*. In the case of an organization, there are different sub-models, that is, multiple people posting from these accounts, one person in charge of several accounts, or a mixture of both. Some so-called reputation management companies and government agencies work in this way.

Group spamming is highly damaging because due to the sheer number of members in a group, it can take total control of the sentiment on a product and completely mislead potential customers, especially at the beginning of a product launch. Although group spammers can also be seen as many individual spammers, group spamming has some distinctive characteristics that can give them away as we will see in Section 12.6.

Clearly a spammer might work individually sometimes and as a member of a group some other times. He may also be a genuine reviewer on occasion because he also purchases products as a consumer and may write reviews about them based on his true experiences. All these complicated situations make opinion spamming a very challenging problem to solve.

12.1.3 Types of Data, Features, and Detection

There are three main types of data that can be used for review spam detection:

Review content. The actual text content of each review including its title. From the content, we can extract *linguistic features* such as word and POS n-grams and other syntactic, semantic, and stylistic clues for deceptions and lies. However, linguistic features are often not sufficient because one can fairly easily craft a fake review that is just like a genuine one. In the extreme case, one can write a fake positive review for a bad restaurant based on one's true experience in a good restaurant.

Meta-data about each review. The data such as the star rating given to each review, userid of the reviewer, review-id, the time/date when the review was posted, the number of helpfulness votes, and the total number of votes. From these pieces of data, many features can be generated. For example, we can compute the number of reviews written by a reviewer in a day. If the number is too large, the reviewer is suspicious. From the review ratings and product information, we may find that a reviewer wrote only positive reviews for a brand and only negative reviews for a competing brand. In Section 12.4, we will see that many such features/patterns can be mined automatically using data mining algorithms.

Web usage data. Every website records the activities that a person performs on the website. The types of data include the sequence of clicks, the time when each click is made, how much time a user stays on a page, the time taken to write a review, and so on. Such data are also called the *side information*. They are collected automatically by the web application server representing the fine-grained navigational behavior of visitors. Specifically, each hit against the server, corresponding to an HTTP request, generates a single entry in the server access logs. Each log entry (depending on the log format) may contain fields such as the time and date of the request, the IP address of the client, the resource requested, possible parameters used in invoking a web application, status of the request, HTTP method used, the user agent (browser and operating system type and version), the referring web resource, and, if available, client-side cookies which uniquely identifies a repeat visitor. Using the IP address information, it is also possible to find the approximate geo-location of the user's computer. From such raw web usage data, many types of abnormal *behavioral patterns* of reviewers and their reviews can be defined and mined. For example, we may find that multiple userids from the same computer posted multiple positive reviews for a product. These reviews are clearly suspicious. Also, if the positive reviews for a hotel are all from the nearby area of the hotel, they are also not trustworthy. If a person monitors the review page of a business constantly and writes a positive review, the person is also suspicious because she cares about the business on the page too much. She may be the business owner.

Product information. Information about the entity being reviewed, for example, product brand, model, type/category, and description. These pieces of information can be exploited to generate abnormal patterns of reviewers and reviews.

Sales information. This mainly includes business-related information such as the sales volume and the sales rank of a product in each period of time. This information is useful for spam detection because the number of products sold should be roughly correlated to the number of reviews posted. If a product is not selling well but has many positive reviews, it is hard to believe. Here the product can also means a business or a service.

These types of data not only can be used individually to generate useful features but can also be combined to produce more powerful features for spam detection. Furthermore, many of these features can be discovered automatically using rule mining (Section 12.4).

We can also classify the preceding data into *public data* and *site private data*.

Public data. The data displayed on the review pages of the hosting site, for example, review content, review meta-data, and possibly some available product information.

Site private data. The data that the site collects but is not displayed on their review pages for public viewing. Such data mainly include web usage data, product data, and sales data.

Due to privacy concerns of review hosting companies, none of the published algorithms has used any site private data so far. All algorithms are based on the public data.

Different types of detection. Existing research has studied three types of detection, namely, *fake review detection*, *fake reviewer detection*, and *fake reviewer group detection*. These tasks are closely related to each other as fake reviews are written by fake reviewers and fake reviewers can also form fake reviewer groups. Thus, one type of detection can help the other types of detection. Clearly each type also has its own special characteristics that can be exploited in detection algorithms.

In the next four sections, we focus on detecting individual fake reviews and reviewers, and in Section 12.6, we examine the detection of fake reviewer groups.

12.1.4 Fake Reviews versus Conventional Lies

Fake reviews can be seen as a special form of deception (Newman et al., 2003; Hancock et al., 2007; Pennebaker et al., 2007; Vrij, 2008; Zhou et al., 2008; Mihalcea and Strapparava, 2009). Conventional deception usually refers to lies about some facts or personal feelings. Researchers have identified many deception signals in text. Many are specific to particular situations and domains, but some are broad signals across domains. Generally, lying/deception communications are characterized by the use of fewer first-person personal pronouns, more negative emotion words, fewer "exclusive" words, and more motion/action words (Newman et al., 2003). The justification for these findings is summarized under three main psychological mindsets exhibited in deception:

Detachment. Several researchers (Knapp and Comaden, 1979; Newman et al., 2003; Vrij, 2008) have hypothesized that liars often try to avoid statements of ownership either to "dissociate" themselves from their words or due to the lack of personal experiences. This results in fewer uses of first-person pronouns such as *I*, *me*, *my*, and so on, but with more use of third-person pronouns such as *she*, *he*, and *they*. In some data, they may also use fewer third-person pronouns (Newman et al., 2003).

Liars feeling guilty. Liars may feel discomfort and guilty either about lying or about the topic they are discussing (Knapp and Comaden, 1979; Vrij, 2008). This is often translated to deceptive communications characterized by the use of more negative emotion words (e.g., *hate*, *worthless*, *sad*).

Lowering cognitive complexity. Liars need to make up false stories, which is a highly complicated cognitive task (Knapp et al., 1974; Vrij, 2008). Owing to the difficulty of fabricating a story, lies typically exhibit two additional characteristics:

1. *Using fewer exclusive words such as but*, *except*, *without*. Sentences using such words often require a person to know the intricate details of a task or situation. Without true experiences, it is hard to know such details and thus to use these words.

2. *Using more motion verbs*. Because lies are fabricated, due to the cognitive complexity in making a believable story, the easiest thing to do is to describe some actions using motion words such as *walk*, *move*, *go*. It is much harder to create detailed evaluation and judgment as they need to consume significantly more cognitive resources without one's experiencing the situation firsthand.

Although fake reviews are related to conventional deception/lying, writing such reviews is a somewhat different cognitive process than lying about facts and feelings in the conventional sense due to the nature of fake reviews.

- In conventional deception, liars tend to use fewer first-person pronouns to “detach” themselves from lies. However, fake reviewers behave completely differently. They actually like to use more first-person pronouns such as *I*, *me*, *my*, *we*, *us*, and so on, rather than third-person pronouns to make their reviews sound more convincing and to give readers the impression that their reviews are based on their true experiences and evaluations. We call this “*attachment*” as opposed to “detachment” in conventional lies.
- Conventional liars may “feel guilty” and thus use more negative emotion words. Fake reviewers may not have such guilty feelings due to different states of mind and practical scenarios. They often have resolute motivations of inflicting spam. The use of positive/negative opinion or emotion words is entirely contingent upon the fact whether they are writing positive/negative fake reviews. Additionally, in many cases, fake reviews may not be lies. For example, one wrote a book and pretended to be a reader and wrote a review to promote the book. The review might be the true feeling of the author. Also, many fake reviewers might have never used the reviewed products/services, but simply tried to give positive or negative opinions. They are not lying about any facts they know or their true feelings.

However, fake reviews and conventional lies also have similarities. The frequency of action/motion words does seem to be higher in fake reviews than in truthful reviews based on the study in Mukherjee et al. (2013), which is the same as for conventional lies. This is not surprising because writing fake reviews is also a complex and demanding cognitive task. For the same reason, fake reviewers tend to use more general opinion words such as *great*, *good*, *wonderful*, and so on, rather than specific opinion words to evaluate specific features of products and services based on their actual performances.

To further analyze, we can also coarsely classify fake reviewers into two categories, those who know the products or businesses well (e.g., business owners and their employees) and those who do not know the products or the businesses well (e.g., professional reviewers who are paid to write). Their writings can be quite different. Unfortunately, there is still no reported study about their linguistic style or word usage differences. On the basis of my general observations, I find that fake reviews from business owners and their employees often sound too knowledgeable about the business and thus read like advertisements, while fake reviews from paid reviewers who know little about the businesses often contain empty praises and lack depth or details. However, if one puts enough time and effort, crafting a fake review that is just like a genuine review is not hard. One simple and effective way is to write a fake review for a product/service by recalling a true experience of using a similar product/service.

12.2 Supervised Fake Review Detection

Fake review detection can be naturally formulated as a classification problem with two classes, *fake* and *nonfake*. Supervised learning is thus applicable. However, as we described earlier, the key difficulty is that it is very hard, if not impossible, to recognize fake reviews reliably by manually reading them because a spammer can carefully craft a fake review that is just like any genuine review (Jindal and Liu, 2008). Owing to this difficulty, there is no reliable fake review and nonfake review data set available to train a machine learning model to recognize fake reviews. Despite these difficulties, several supervised detection algorithms have been proposed and evaluated in various ways. This section discusses three such methods. In the next section, we describe a supervised learning experiment using the filtered and unfiltered reviews from Yelp.com.

Because there is no labeled training data for learning, Jindal and Liu (2008) exploited duplicate reviews. In their study of 5.8 million reviews and 2.14 million reviewers from Amazon.com, a large number of duplicate and near-duplicate reviews were found indicating that review spam was widespread. Because writing new reviews can be taxing, many spammers use the same reviews or slightly modified reviews for different products. These duplicates and near-duplicates can be divided into four categories:

1. Duplicates from the same reviewer-id on the same product

2. Duplicates from different reviewer-ids on the same product

3. Duplicates from the same reviewer-id on different products

4. Duplicates from different reviewer-ids on different products

The first type of duplicates can be the results of reviewers mistakenly clicking the review submit button multiple times (which can be easily checked based on the submission dates). However, the last three types of duplicates are most likely to be fake. Thus Jindal and Liu used the last three types of duplicates as fake reviews and the rest of the reviews as nonfake reviews in the training data for machine learning. They employed three sets of features for learning:

Review-centric features. These are features about each review. Example features include length of title, length of review, percentage of positive and negative sentiment words in the review, cosine similarity of the review and the product description, percentage of brand name mentions, percentages of numerals, capitals and all capital words in the review, and the number of helpfulness votes. In many review sites (e.g., Amazon.com), readers can provide feedback to each review by answering the question "*Do you find this review helpful?*"

Reviewer-centric features. These are features about each reviewer. Example features include the average rating given by the reviewer, the mean and the standard deviation in ratings of the reviewer, the ratio of the number of reviews that this reviewer wrote which were the first reviews of products to the total number of reviews that he has written, and the ratio of the number of cases in which he was the only reviewer.

Product-centric features. These features are about each product. Example features include the price of the product, the sales rank of the product (amazon.com assigns a sales rank to each product according to its sales volume), and the mean and the standard deviation of review ratings of the product.

Logistic regression was used for model building. Experimental results showed some tentative but interesting results:

- Negative outlier reviews (ratings with large negative deviations from the average rating of a product) tend to be heavily spammed. Positive outlier reviews are less spammed.
- Reviews that are the only reviews of some products are likely to be spam. This can be explained by the tendency of a seller promoting its unpopular products with fake reviews.
- Top-ranked reviewers are more likely to be fake reviewers. Amazon.com gives a rank to each reviewer based on its proprietary method. Analysis showed that top-ranked reviewers generally have written a large number of reviews. People who write a large number of reviews are natural suspects. Some top reviewers had written thousands or even tens of thousands of reviews, which is unlikely for an ordinary consumer.
- Fake reviews can get good feedback and genuine reviews can get bad feedback. This shows that if the quality of a review is defined based on helpfulness feedback, people can be fooled by fake reviews because spammers can easily craft a sophisticated review that can receive many helpful feedback.
- Products of lower sales ranks are more likely to be spammed. This indicates that spam activities seem to be limited to low selling products. This is intuitive, as it is difficult to damage the reputation of a popular product, while an unpopular product needs a reputation promotion.

It should be stressed again that these results are tentative because (1) it is not confirmed that the three types of duplicates are definitely fake and (2) many fake reviews are not duplicates and they are considered as nonfake reviews in model building in Jindal and Liu (2008).

Li et al. (2011) made another supervised learning attempt to identify fake reviews. In their case, a manually labeled fake review corpus was built using Epinions reviews. In Epinions, after a review is posted, users can evaluate the review by giving it a helpfulness score. They can also write comments about the reviews. The authors manually labeled a set of fake and nonfake reviews by reading the reviews and the comments. For learning, several types of features were proposed, which are similar to those in Jindal and Liu (2008) with some additions, for example, subjective and objective features, positive and negative features, reviewer's profile, authority score computed using PageRank (Page et al., 1999), and so on. For learning, they used naïve Bayes classification which gave promising results. The authors also experimented with semi-supervised learning exploiting the idea that a spammer tends to write many fake reviews.

In Ott et al. (2011), supervised learning was also employed. In this case, the authors used Amazon Mechanical Turk (AMT) to crowdsource fake hotel reviews of twenty hotels. Several provisions were made to ensure the quality of the fake reviews. For example, they only allowed each Turker (an anonymous online worker) to make a single submission, Turkers must be in the United States, and so on. The Turkers were also given the scenario that they worked in the hotels and their bosses asked them to write fake reviews to promote the hotels. Each Turker was paid US$1 per review. Four hundred fake positive reviews were crafted using AMT for twenty popular Chicago hotels. Four hundred positive reviews from Tripadvisor.com for the same twenty Chicago hotels were used as nonfake reviews. The authors tried several classification approaches used in related tasks such as genre identification, psycholinguistic deception detection, and text classification. All these tasks have some existing features proposed by researchers. Their experiments showed that text classification performed the best using only unigrams and bigrams based on the 50/50 fake and nonfake class distribution. Traditional features for deceptions (Newman et al., 2003; Hancock et al., 2007; Pennebaker et al., 2007; Vrij, 2008; Zhou et al., 2008; Mihalcea and Strapparava, 2009) did not do well. This work reported 89.6% of accuracy using only word bigram features under the balanced class distribution. Feng et al. (2012) used some deep syntax rule–based features to boost the accuracy to 91.2%. Deep syntax-based features are lexicalized (e.g., PRP → "you") and un-lexicalized (e.g., NP2 → NP3 SBAR) production rules involving immediate or grandparent nodes of Probabilistic Context Free Grammar (PCFG) sentence parse trees. A similar work was also reported in Xu and Zhao (2012).

This very high accuracy using only word n-gram features is surprising and encouraging. It shows that while writing fake reviews, fake reviewers do exhibit some linguistic differences from genuine reviewers. However, like the previous studies, a weakness of this study is its evaluation data, which is still not perfect. Although the reviews crafted using AMT are fake, they are not *real* "fake reviews” on a commercial website as the Turkers do not know the hotels well and are also not likely to have the same psychological states of mind when they wrote fake reviews as those of authors of real fake reviews who have real business interests to promote. If a real fake reviewer is a business owner, he knows the business very well and is able to write with sufficient details, rather than just give glowing praises to the business. He will also be very careful in writing to ensure that the review sounds genuine and is not easily spotted as fake by readers. Consequently, their writings may be very different. Furthermore, using the balanced data of 50% fake and 50% nonfake for training and testing does not reflect the true distribution of the real-life situation. The class distribution can have a significant impact on the precision of the detected fake reviews.

12.3 Supervised Yelp Data Experiment

Yelp.com is a large hosting site of online reviews about businesses. To ensure the credibility and trustworthiness of its reviews, Yelp uses a review filtering algorithm to filter suspicious reviews to prevent them from showing up on the businesses' pages. According to Yelp's CEO, Jeremy Stoppelman, the filtering algorithm has evolved over the years and is still constantly being improved by Yelp engineers (Stoppelman, 2009). Yelp also stated that the filter might catch some false positives, and was ready to accept the cost of filtering a few legitimate reviews than the infinitely high cost of not having an algorithm at all which would render it a *lassez-faire* review site that people would stop using (Luther, 2010; Holloway, 2011). Yelp purposely does not reveal the clues that go into its filtering algorithm as doing so can lessen the filter's effectiveness (Luther, 2010) because fake reviewers can change their strategies in writing.

Because Yelp has performed filtering since its launch in 2005 and also made its filtered reviews public, it shows that Yelp is confident about its filtering accuracy. Yelp's filter has also been claimed to be accurate by a study reported in BusinessWeek (Weise, 2011). My own group had a firsthand experience too. We knew that there were several fake reviews for a business based on some insider information, and these reviews were all filtered by Yelp. Thus, we believe that Yelp's filtering is at least reasonably reliable. Its filtered and unfiltered reviews are probably the closest to the ground truth labels (fake and nonfake) available in the real-life setting. I am also aware that the Chinese Internet company Dianping.com has a similar filtering system. Apart from filtering, the Dianping system also provides evidences to reviewers who complain that their "genuine" reviews were filtered.

Yelp does not actually delete those filtered reviews but puts them in a filtered list, which is publicly available. Mukherjee et al. (2013) crawled both filtered and unfiltered reviews for 85 hotels and 130 restaurants in the Chicago area and conducted an experiment using supervised learning to try to reverse engineer Yelp's filter algorithm. In their experiment, those filtered reviews are treated as fake and those unfiltered as nonfake. This gives a two-class classification problem. The experiments generated some interesting results. The paper also analyzed the quality of the Yelp data set and showed that the filtered reviews were strongly correlated with abnormal spamming behaviors (Section 12.3.2), which again renders confidence in the quality of fake and nonfake labels identified by Yelp.

12.3.1 Supervised Learning Using Linguistic Features

There are generally two types of features that can be used in classification: *linguistic features* and *behavioral features*. Linguistic features are about the review text content, while behavioral features are about behaviors of reviewers and their reviews. This subsection describes the experiment results using only linguistic features.

Because Ott et al. (2011) showed that unigrams and bigrams performed the best using the AMT generated hotel review data with an accuracy of 89.6%, Mukherjee et al. (2013) experimented with unigrams and bigrams using the Yelp data (only positive reviews about popular Chicago hotels and restaurants) with exactly the same experimental settings. Both papers used SVM as the classifier. However, Yelp hotel data yielded only 67.6% in accuracy and Yelp restaurant data yielded only 67.9% in accuracy (Table 12.2). Note that Ott et al. (2011) only used hotel reviews in their evaluation. These results show that (1) n-gram features are indeed useful and (2) fake review detection in the real-life setting is considerably harder than using the AMT data. Because both papers used 50% fake and 50% nonfake reviews in training and testing, by chance the accuracy should be 50%.

Table 12.2. SVM five-fold cross-validation accuracy results for the hotel and restaurant domains

Feature setting	Hotel accuracy	Restaurant accuracy
Unigram	67.6	67.9
Bigram	64.9	68.5

An interesting and intriguing question is: What exactly is the difference between the AMT fake reviews and Yelp fake reviews, and how can we find and characterize the difference? Mukherjee et al. (2013) proposed a principled method based on the information theoretic measure, KL-divergence and its asymmetric property. The author found the following:

1. The word distributions of fake reviews generated using AMT and nonfake reviews from Tripadvisor are widely different, meaning that a large number of words in the two sets have very different frequencies. That is, Turkers tend to use different words from those of genuine reviewers. This may be because Turkers did not know the hotels well and/or they did not put their hearts into writing their fake reviews. So Turkers did not do a good job at “faking.” This explains why the AMT generated fake reviews are easy to classify.

2. However, for the real Yelp data, the frequency distributions of a large majority of words in both fake and nonfake reviews are very similar. This means that fake reviewers on Yelp have done a good job at faking because they used similar words as those genuine (nonfake) reviewers to make their reviews sound convincing. However, the asymmetry of KL-divergence shows that a small number of words in fake reviews have much higher frequencies than in nonfake reviews. Those high-frequency words imply pretense and deception. This indicates that Yelp fake reviewers have *overdone* it in making their reviews sound genuine. The combination of the two findings explains why the accuracy is better than 50% (random guessing) but much lower than that for the AMT data.

The next interesting question is: Is it possible to improve the classification accuracy on the real-life Yelp data? Mukherjee et al. (2013) proposed a set of behavioral features of reviewers and their reviews. This set of features gave a large margin of improvement.

12.3.2 Supervised Learning Using Behavioral Features

Because linguistic features did not perform well on Yelp reviews, a set of reviewer and review behavioral features was proposed and tried in Mukherjee et al. (2013). These features helped improve classification accuracy dramatically. For the behavioral study, the authors crawled profiles of all reviewers in the hotel and restaurant domain data. The features are as follows:

1. *Maximum number of reviews (MNR)*. This is the number of reviews posted by a reviewer in a day.

2. *Percentage of positive reviews (PR)*. This is the percentage of positive (4 or 5 stars) reviews written by a reviewer in the data.

3. *Review length (RL)*. This is the length in word count of each review. As opinion spamming involves writing fake experiences, there is probably not much to write or at least a (paid) spammer probably does not want to invest too much time in writing.

4. *Reviewer deviation (RD)*. This feature is computed as follows: We first compute the absolute rating deviation of a review from other reviews based on their star ratings on the same business. Then, we compute the average deviation of the reviewer by taking the mean of all rating deviations over all his reviews.

5. *Maximum content similarity (MCS)*. Crafting a new fake review every time is time consuming. This feature computes the MCS (using the cosine similarity) between any two reviews of a reviewer.

Each review in the data is then represented by these five behavioral features of its reviewer. Note that there are various other pieces of meta-data that can be extracted from Yelp to generate more features, for example, friendship and fan relations, compliments, and usefulness votes, percentage of previous reviews filtered, and so on. However, using these features for classification is not fair because they are somewhat directly or indirectly affected by Yelp's filtering, for example, if a review is filtered, its chance of getting usefulness votes, compliments, friend and fan requests reduce automatically. The preceding features are not affected or minimally affected by Yelp's filtering. The results are reported in Table 12.3, which used much larger data sets including all hotels and restaurants. We can observe that behavioral features (BF) improve the classification dramatically over linguistic n-grams features. Adding linguistic features is useful for the restaurant domain to some extent, but makes little difference for the hotel domain. This paper then concluded that Yelp might be using behavioral clues in their filtering algorithm. Note that this does not say that Yelp uses supervised learning. The paper also did an in-depth analysis of Yelp reviews against the preceding behaviors and claimed that Yelp's filtering has a good precision, but it is not clear what the recall is.

Table 12.3. SVM five-fold cross-validation classification results in accuracy across behavioral features (BF) and n-gram features in two domains: Hotel and Restaurant

Feature setting	Hotel accuracy	Restaurant accuracy
Unigrams	65.6	66.9
Bigrams	64.4	67.8
Behavioral Features (BF)	83.2	82.8
Unigrams + BF	83.6	84.1
Bigrams + BF	84.8	86.1

12.4 Automated Discovery of Abnormal Patterns

Owing to the difficulty of manual labeling of training examples, most of the published algorithms do not use any labeled fake or nonfake data. In this and the next few sections, we discuss several of these approaches. In this section, we focus on a specific approach that formulates the problem of finding fake reviewers or spammers and many other kinds of abnormalities as a data mining task of discovering unexpected class association rules (Jindal et al., 2010). Specifically, this method is based on automated rule mining and a probabilistic definition of suspicious review and reviewer patterns represented as unexpected rules. The method is general as the different types of unexpectedness are defined on a general form of rules and thus can be used in any domain. This method is also interesting in the sense that it discovers unexpected patterns automatically without the need to manually design abnormal patterns or scenarios and write corresponding specific codes.

12.4.1 Class Association Rules

Class association rules are a special type of association rules with a fixed class attribute (Liu et al., 1998). The data for mining class association rules (CARs) consists of a set of data records, which are described by a set of normal attributes $A = \{A_1, \ldots, A_n\}$ and a class attribute $C = \{c_1, \ldots, c_m\}$ of m discrete values, called *class labels*. A CAR rule is of the form: $X \rightarrow c_i$, where X is a set of conditions from the attributes in A and c_i is a class label in C. Such a rule computes the conditional probability $\Pr(c_i|X)$ (called *confidence*) and the joint probability $\Pr(X, c_i)$ (called *support*). Note that CARs were originally design for supervised learning due to the known class labels. However, in this study, CAR mining is not used as a supervised learning method for fake review detection because the class labels here are not fake and nonfake and are not employed for prediction.

For the spam detection application, one form of data for CAR mining can be as follows: Each review forms a data record with a set of attributes, for example, *reviewer-id*, *product-category*, *IP-address*, *e-mail-address*, *brand-id*, *product-id*, and *a class*. Note that IP-address and e-mail-address (of the reviewer) are usually site private data. The class is the sentiment of the reviewer about the product, that is, *positive*, *negative*, or *neutral* based on the review rating. In most review sites (e.g., amazon.com), each review has a rating between 1 (lowest) and 5 (highest) assigned by its reviewer. Ratings of 4 or 5 are assigned the positive class, 3 the neutral class, and 1 or 2 the negative class. A discovered CAR rule could be that a reviewer (reviewer-1) gives all positive ratings to a brand (brand-1) of products:

$$\text{reviewer-1, brand} - 1 \rightarrow \text{positive (supportCount = 10; confidence = 100\%)},$$

where supportCount is the number of positive reviews from reviewer-1 on brand-1.

Before going further, we note that the preceding data are just an example. In an application, any attribute can serve as the class attribute. It is also possible not to use any class attribute. In that case, the problem is reduced to mining conventional association rules (Agrawal and Srikant, 1994). Then we may find all kinds of interesting rules. For example, we may find that multiple review-ids share a single e-mail (which is highly suspicious), a particular reviewer-id has multiple reviews for a single product, a particular reviewer-id reviewed only products of a single product category, and many more.

We now use the preceding example data to find unexpected rules based on the work in Jindal et al. (2010). To find something unexpected, we need to first define what is expected. The definition begins by assuming that the class prior probabilities ($\Pr(c_i)$) is known, which is easily computed from the data automatically. The priors give the natural distribution of the data to begin with. Two additional principles govern the definition of expectations:

1. Given no prior knowledge, we expect that the data attributes and classes have no relationships, that is, they are statistically independent. This is justified as it allows us to find those patterns that show strong relationships.

2. We use shorter rules (with fewer conditions) to compute the expectations of longer rules. This is also logical due to two reasons. First, it enables the user to see interesting short rules first. Second, more importantly, unexpected shorter rules may be the cause of abnormality in some longer rules, but not the other way around. Thus, knowing such short rules, the longer rules may no longer be unexpected.

On the basis of these two principles, we begin with the discussion of unexpectedness of one-condition rules, and then two-condition rules. For multicondition rules, see Jindal et al. (2010).

12.4.2 Unexpectedness of One-Condition Rules

Four types of unexpectedness are defined in Jindal et al. (2010). This subsection discusses the unexpectedness of one-condition rules, which are rules with only a single condition, that is, an attribute value pair, $A_j = v_{jk}$.

1. *Confidence unexpectedness*. To simplify the notation, we use a single value v_{jk} ($v_{jk} \in dom(A_j)$) to denote the kth value of attribute A_j. A one-condition rule is thus of the form: $v_{jk} \rightarrow c_i$. The expected confidence of the rule is defined as follows:

Expectation: Because we consider one-condition rules, we use the information from zero-condition rules to define expectations:

$$\rightarrow c_i,$$

which is the class prior probability of c_i, that is, $\Pr(c_i)$. Given $\Pr(c_i)$ and no other knowledge, we should expect that attribute values and the classes are independent. Thus, the confidence ($\Pr(c_i \mid v_{jk})$) of the preceding rule ($v_{jk} \rightarrow c_i$) is expected to be $\Pr(c_i)$. We use $E(\Pr(c_i \mid v_{jk}))$ to denote the expected confidence, that is,

$$E(\Pr(c_i \mid v_{jk})) = \Pr(c_i). \tag{12.1}$$

Confidence unexpectedness (Cu). Confidence unexpectedness of a rule is defined as the ratio of the deviation of the actual confidence to the expected confidence. Let the actual confidence of the rule be $\Pr(c_i \mid v_{jk})$. We use $Cu(v_{jk} \rightarrow c_i)$ to denote the unexpectedness of the rule $v_{jk} \rightarrow c_i$.

$$Cu(v_{jk} \rightarrow c_i) = \frac{\Pr(c_i \mid v_{jk}) - E(\Pr(c_i \mid v_{jk}))}{E(\Pr(c_i \mid v_{jk}))} \tag{12.2}$$

The unexpectedness values can be used to rank rules. For example, if 20% of the reviews in the data are negative ($\Pr(negative) = 20\%$), but a particular reviewer's reviews are all negative, then this reviewer is quite unexpected and suspicious. Note that the unexpectedness value can be positive or negative. In applications, rules with positive unexpectedness are often more useful. Other rules can be discarded if not needed.

2. *Support unexpectedness*. The confidence measure does not consider the proportion of data records involved. We therefore need support unexpectedness.

Expectation: Given no knowledge, we expect that an attribute value and each class are independent. Thus, we have $\Pr(v_{jk}, c_i)) = \Pr(v_{jk})\Pr(c_i)$. $\Pr(c_i)$ is known, but not $\Pr(v_{jk})$. It is reasonable to expect that it is the average probability of all values of A_j. Thus we have ($\Pr(v_{jk})$ is unknown to the user, but can be computed),

$$E(\Pr(v_{jk}, c_i)) = \Pr(c_i)\frac{\sum_{a=1}^{|A_j|}\Pr(v_{ja})}{|A_j|} \tag{12.3}$$

Support unexpectedness (Su). Support unexpectedness of a rule is defined as follows:

$$Su(v_{jk} \to c_i) = \frac{\Pr(v_{jk}, c_i) - E(\Pr(v_{jk}, c_i))}{E(\Pr(v_{jk}, c_i))} \tag{12.4}$$

This definition of *Su* (Equations (12.3) and (12.4)) is reasonable as it ranks those rules with high supports highly, which is what we want. For example, on average each reviewer wrote two negative reviews, but some reviewers wrote hundreds of negative reviews. These reviewers are suspicious, and are at least worth further investigation.

3. *Attribute distribution unexpectedness*. Confidence or support unexpectedness considers only a single rule. In many cases, a group of rules together shows an interesting scenario. Here we define an unexpectedness metric based on all values of an attribute and a class, which thus covers multiple rules. This unexpectedness shows how skewed the data records are for the class, that is, whether the data records of the class concentrate on only a few values of the attribute or if they spread evenly to all values, which is expected given no prior knowledge. For example, we may find that most positive reviews for a brand of products are from only one reviewer even though there are a large number of reviewers who have reviewed the products of the brand. This reviewer is clearly a spammer suspect. We use supports (or joint probabilities) to define attribute distribution unexpectedness. Let the attribute be A_j and the class of interest be c_i. The attribute distribution of A_j with respect to class c_i is denoted by:

$A_j \to c_i$

It represents all the rules, $v_{jk} \to c_i$, $k = 1, 2, \ldots, |A_j|$, where $|A_j|$ is the total number of values of attribute A_j.

Expectation: We can use the expected value of $\Pr(v_{jk}, c_i)$ computed earlier (Equation (12.3)) for our purpose here.

Attribute distribution unexpectedness (ADu). It is defined as the sum of normalized support deviations of all values of A_j.

$$ADu(A_j \to c_i) = \sum_{v_{jk}: v_{jk} \in dom(A_j) \wedge Dev > 0} \frac{Dev(v_{jk})}{\Pr(c_i)} \tag{12.5}$$

where

$$Dev(v_{jk}) = \Pr(v_{jk}, c_i) - E(\Pr(v_{jk}, c_i)) \tag{12.6}$$

We use $\Pr(c_i)$ in Equation (12.5) because $\sum_{k=1}^{|A_j|} \Pr(v_{jk}, c_i) = \Pr(c_i)$. Note that in this definition, negative deviations are not utilized because positive and negative deviations ($Dev(v_{jk})$) are symmetric or equal because $\Pr(c_i)$ is constant and $\sum_{k=1}^{|A_j|} \Pr(v_{jk}, c_i) = \Pr(c_i)$. Thus, considering one side is sufficient.

4. *Attribute unexpectedness.* In this case, we want to discover how the values of an attribute can predict the classes. This is denoted by

$A_j \rightarrow C$,

where A_j represents all its values and C represents all classes. Given no knowledge, our expectation is that A_j and C are independent. In the ideal case (or the most unexpected case), every rule $v_{jk} \rightarrow c_i$ has 100% confidence. Then, the values of A_j can predict the classes in C completely.

Conceptually, the idea is the same as measuring the discriminative power of each attribute in classification learning. Hence the *informaiton gain* (IG) measure can be used for the purpose (Quinlan, 1993). The expected information is computed based on entropy. Given no knowledge, the entropy of the original data D is (note that $\Pr(c_i)$ is the confidence of the zero-condition rule on class c_i):

$$entropy(D) = -\sum_{i=1}^{m} \Pr(c_i) \log \Pr(c_i) \tag{12.7}$$

Expectation: The expectation is the entropy of the data D:

$$E(A_j \rightarrow C) = entropy(D)$$

Attribute unexpectedness (Au). Attribute unexpectedness is defined as the information gained by adding the attribute A_j. After adding A_j, we obtain the following entropy:

$$entropy_{A_j}(D) = -\sum_{k=1}^{|A_j|} \frac{|D_k|}{|D|} entropy(D_k) \tag{12.8}$$

Based on the values of A_j, the data set D is partitioned into $|A_j|$ subsets, D_1, D_2,…, $D_{|A_i|}$ (i.e., each subset has a particular value of A_j). The unexpectedness is thus computed with (which is the IG measure (Quinlan, 1993)):

$$Au(A_j \rightarrow C) = entropy(D) - entropy_{A_j}(D) \tag{12.9}$$

12.4.3 Unexpectedness of Two-Condition Rules

We now consider two-condition rules. Although we can still assume that the expected confidence of a rule is the class prior probability as for one-condition rules, it is no longer appropriate because a two-condition rule is made up of two one-condition rules. It is possible that the unexpectedness of a two-condition rule is caused by a one-condition rule. Let us use confidence unexpectedness as an example. We have a data set with two classes and each class has 50% of the data, that is, the class prior probabilities are equal, $\Pr(c_1) = \Pr(c_2) = 0.5$. For a rule $v_1 \to c_1$ with 100% confidence ($\Pr(c_1 \mid v_1) = 1$), it is highly unexpected based on Equation (12.2). Now let us look at a two-condition rule, $v_1, v_2 \to c_1$, which clearly also has 100% confidence (i.e., $\Pr(c_1 \mid v_1, v_2) = 1$). If we assume no knowledge, its expected confidence should be 50%. Then, we say that this rule is highly unexpected. However, because we know $v_1 \to c_1$ has a 100% confidence, the 100% confidence for the rule $v_1, v_2 \to c_1$ is completely expected. The 100% confidence of rule $v_1 \to c_1$ is the cause for rule, $v_1, v_2 \to c_1$, to have the 100% confidence. With the knowledge of one-condition rules, we define different types of unexpectedness of two-condition rules of the form:

$$v_{jk}, v_{gh} \to c_i.$$

1. *Confidence unexpectedness*. We first compute the expected confidence of the two-condition rule based on two one-condition rules:

$$v_{jk} \to c_i \quad \text{and} \quad v_{gh} \to c_i$$

Expectation: Given the confidences of the two rules, $\Pr(c_i \mid v_{jk})$ and $\Pr(c_i \mid v_{gh})$, we compute the expected probability of $\Pr(c_i \mid v_{jk}, v_{gh})$ using the Bayes's rule and obtain:

$$\Pr(c_i \mid v_{jk}, v_{gh}) = \frac{\Pr(v_{jk}, v_{gh} \mid c_i)\Pr(c_i)}{\sum_{r=1}^{m} \Pr(v_{jk}, v_{gh} \mid c_r)\Pr(c_r)} \tag{12.10}$$

The first term of the numerator can be further written as

$$\Pr(v_{jk}, v_{gh} \mid c_i) = \Pr(v_{jk} \mid v_{gh}, c_i)\Pr(v_{gh} \mid c_i) \tag{12.11}$$

Conditional independence assumption. With no prior knowledge, it is reasonable to expect that all attributes are conditionally independent given class c_i. Formally, we expect that

$$\Pr(v_{jk} \mid v_{gh}, c_i) = \Pr(v_{jk} \mid c_i) \tag{12.12}$$

On the basis of Equation (12.10), the expected value of $\Pr(c_i \mid v_{jk}, v_{gh})$ is:

$$E(\Pr(c_i \mid v_{jk}, v_{gh})) = \frac{\Pr(v_{jk} \mid c_i)\Pr(v_{gh} \mid c_i)\Pr(c_i)}{\sum_{r=1}^{m}\Pr(v_{jk} \mid c_r)\Pr(v_{gh} \mid c_r)\Pr(c_r)} \tag{12.13}$$

Because we know $\Pr(c_i \mid v_{jk})$ and $\Pr(c_i \mid v_{gh})$, we finally have:

$$E(\Pr(c_i \mid v_{jk}, v_{gh})) = \frac{\Pr(c_i \mid v_{jk})\Pr(c_i \mid v_{gh})}{\Pr(c_i)\sum_{r=1}^{m}\frac{\Pr(c_r \mid v_{jk})\Pr(c_r \mid v_{gh})}{\Pr(c_r)}} \tag{12.14}$$

Confidence unexpectedness (Cu). Cu is define as follows:

$$Cu(v_{jk}, v_{gh} \rightarrow c_i) = \frac{\Pr(c_i \mid v_{jk}, v_{gh}) - E(\Pr(c_i \mid v_{jk}, v_{gh}))}{E(\Pr(c_i \mid v_{jk}, v_{gh}))} \tag{12.15}$$

Using this measure, one can find reviewers who give all high ratings to products of a brand, but most other reviewers are generally negative about the brand.

2. *Support unexpectedness*. The expected support of $v_{jk}, v_{gh} \rightarrow c_i$ is computed first.

Expectation: The expected support $\Pr(v_{jk}, v_{gh}, c_i)$ is computed based on the following:

$$\Pr(v_{jk}, v_{gh}, c_i) = \Pr(c_i \mid v_{jk}, v_{gh})\Pr(v_{jk}, v_{gh}) \tag{12.16}$$

Using the conditional independence assumption, we know the value for $\Pr(c_i \mid v_{jk}, v_{gh})$. Let us compute the value for $\Pr(v_{jk}, v_{gh})$ based on the same assumption:

$$\Pr(v_{jk}, v_{gh}) = \Pr(v_{jk})\Pr(v_{gh})\sum_{r=1}^{m}\frac{\Pr(c_r \mid v_{jk})\Pr(c_r \mid v_{gh})}{\Pr(c_r)} \tag{12.17}$$

By combining Equations (12.10) and (12.17), we obtain,

$$E(\Pr(v_{jk}, v_{gh}, c_i)) = \frac{\Pr(v_{jk}, c_i)\Pr(v_{gh}, c_i)}{\Pr(c_i)} \tag{12.18}$$

Support unexpectedness (Su). It is computed as follows:

$$Su(v_{jk}, v_{gh} \rightarrow c_i) = \frac{\Pr(v_{jk}, v_{gh}, c_i) - E(\Pr(v_{jk}, v_{gh}, c_i))}{E(\Pr(v_{jk}, v_{gh}, c_i))} \tag{12.19}$$

Using this measure, one can find reviewers who write multiple positive reviews for a single product, while other reviewers only write one review.

3. *Attribute distribution unexpectedness*. Because for two-condition rules, two attributes are involved, to compute attribute distribution unexpectedness, we need to fix an attribute. Without loss of generality, we assume v_{jk} is fixed, and include (or vary) all the values of attribute A_g. We thus compute the unexpectedness of:

$$v_{jk}, A_g \rightarrow c_i$$

This attribute distribution represents all rules, v_{jk}, $v_{gh} \rightarrow c_i$, $h = 1, 2,\ldots, |A_g|$, where $|A_g|$ is the number of possible values of attribute A_g.

Expectation: We can make use of the expected value of $\Pr(v_{jk}, v_{gh}, c_i)$ computed in Equation (12.18).

Attribute distribution unexpectedness (ADu). It is defined as follows:

$$ADu(v_{jk}, A_g \rightarrow c_i) = \sum_{v_{gh}: v_{gh} \in dom(A_g) \wedge Dev > 0} \frac{Dev(v_{gh})}{\Pr(v_{jk}, c_i)} \tag{12.20}$$

where

$$Dev(v_{gh}) = \Pr(v_{jk}, v_{gh}, c_i) - E(\Pr(v_{jk}, v_{gh}, c_i))$$

Using this measure, we can find that most positive reviews for a brand of products are written by only one reviewer even though there are a large number of reviewers who have reviewed the products of the brand.

4. *Attribute unexpectedness*. In this case, we compute the unexpectedness of an attribute given a constraint, which is of the form:

$$v_{jk}, A_g \rightarrow C.$$

Using this measure, one can find reviewers (constraint) who wrote only positive reviews for one brand and only negative reviews for another brand,

Rule1: reviewer-1, brand-1 → positive (confidence = 100%)

Rule2: reviewer-1, brand-2 → negative (confidence = 100%)

12.5 Model-Based Behavioral Analysis

This section describes several model-based methods from simple behavioral models to sophisticated graph models and Bayesian probabilistic models. They all make use of behaviors of reviewers and their reviews to detect fake reviews and reviewers.

We should note that all behaviors studied in published papers are based on the public data displayed on review pages of their respective review hosting sites. The private data collected by each review hosting site are not visible to the general public, but are very useful and perhaps even more useful than the public data, for spam detection. For example, if multiple userids from the same IP address posted a number of positive reviews for a product, then these userids are suspicious. If the positive reviews for a hotel are all from the nearby area of the hotel, they are also doubtful. If the site private data are available, they can be incorporated into existing approaches with no or minimum changes to the models.

12.5.1 Spam Detection Based on Atypical Behaviors

The first technique is from Lim et al. (2010), which identified several unusual reviewer behavior models based on different review patterns that suggest spamming. Each model assigns a numeric spamming behavior score to a reviewer by measuring the extent to which the reviewer practices spamming behavior of the type. All the scores are then combined to produce the final spam score. Thus, this method focuses on finding spammers or fake reviewers rather than fake reviews. The spamming behavior models are as follows:

1. *Targeting products.* To game a review system, it is hypothesized that a spammer will direct most of his efforts toward promoting or victimizing a few target products. He is expected to monitor the products closely and mitigate the ratings by writing fake reviews when time is appropriate.

2. *Targeting groups.* This spam behavior model defines the pattern of spammers manipulating ratings of a set of products sharing some attribute(s) within a short span of time. For example, a spammer may target several products of a brand within a few hours. This pattern of ratings saves the spammers' time as they do not need to log on to the review system many times. To achieve the maximum impact, the ratings given to these target groups of products are either very high or very low.

3. *General rating deviation.* A genuine reviewer is expected to give ratings similar to other raters of the same product. As spammers attempt to promote or demote some products, their ratings typically deviate a great deal from those of other reviewers.

4. *Early rating deviation.* Early deviation captures the behavior of a spammer contributing a fake review soon after product launch. Such reviews are likely to attract attention from other reviewers, allowing spammers to affect the views of subsequent reviewers.

Wu et al. (2010) proposed an unsupervised method to detect fake reviews based on a distortion criterion. The idea is that fake reviews will distort the overall popularity ranking for a collection of entities. Deleting a set of reviews chosen at random should not overly disrupt the ranked list of entities, while deleting fake reviews should significantly alter or distort the ranking of entities to reveal the "true" ranking. This distortion can be measured by comparing popularity rankings before and after deletion using rank correlation. Along similar lines, Feng et al. (2012) proposed a review rating distribution analysis based detection method for each product.

12.5.2 Spam Detection Using Review Graph

In Wang et al. (2011), a graph-based method was proposed for detecting spam in store or merchant reviews. Such reviews describe purchase experiences and evaluations of stores. This study was based on a snapshot of all reviews from resellerratings.com crawled on Oct. 6th, 2010. After removing stores with no reviews, there were 343603 reviewers who wrote 408470 reviews for 14561 stores.

Although one can borrow some clues from product review spammer detection algorithms, their clues are insufficient for the store review context. For example, it is unusual for a person to post multiple reviews to the same product, but it can be normal for a person to post more than one review to the same store due to multiple purchasing experiences. Also, it can be normal to have near-duplicate reviews from one reviewer for multiple stores because unlike different products, different stores basically provide the same type of services. Therefore, features or clues proposed in approaches for detecting fake product reviews and reviewers are not all appropriate for detecting spammers of store reviews. Thus, there is a need to look for a more sophisticated and complementary framework.

Wang et al. proposed a heterogeneous review graph-based approach. The graph consists of three types of nodes, that is, reviewers, reviews, and stores, to capture their relationships and to model spamming clues. A reviewer node has a link to each review that he wrote. A review node has a link to a store node if the review is about that store. A store is connected to a reviewer via this reviewer's review about the store. Each node is also attached with a set of features. For example, a store node has features about its average rating, its number of reviews, and so on. Based on the review graph, three concepts were defined and computed, that is, the *trustiness* of reviewers, the *honesty* of reviews, and the *reliability* of stores. A reviewer is more trustworthy if she has written more honest reviews; a store is more reliable if it has more positive reviews from trustworthy reviewers; and a review is more honest if it is supported by many other honest reviews. Furthermore, if the honesty of a review goes down, it affects the reviewer's trustiness, which in turn has an impact on the store she reviewed. These intertwined relations are revealed in the review graph and defined mathematically. An iterative computation method was proposed to compute the three values, which were then used to rank reviewers, stores and reviews. Those top-ranked reviewers, stores and reviews are likely to be involved in review spamming. The evaluation was done using human judges by comparing with scores of stores at *Better Business Bureau* (BBB), which is a well-known corporation in USA that gathers reports on business reliability and alerts the public to business or consumer scams. In Akoglu et al. (2013), another graph-based method was proposed to solve a similar problem. The method is based on Markov Random Fields (MRF).

12.5.3 Spam Detection Using Bayesian Models

Most existing detection algorithms are based on different heuristics or hinge on ad hoc fake and nonfake labels for model building. Mukherjee et al. (2013) proposed a theoretical model to formulate the task as a clustering problem in the unsupervised Bayesian framework. The Bayesian setting enables modeling of *spamicity* of reviewers as latent with a set of observed behavioral features. The proposed (graphical) model was called Author Spamicity Model (ASM). Spamicity here means the degree of being spam. The key motivation hinges on the hypothesis that opinion spammers differ from others on behavioral dimensions. This creates a separation margin between population distributions of two naturally occurring clusters: spammers and nonspammers. Inference in ASM results in learning the distributions of the two clusters (or classes) based on a set of behavioral features. Various extensions of ASM are also proposed to exploit different priors.

More specifically, the ASM model belongs to the class of generative models for clustering (Duda et al., 2001). It models spamicity, s_a (degree/tendency of spamming in the range [0, 1]) of an author *a*, and spam/nonspam label, π_r of a review *r* as latent variables. π_r is essentially the *class* variable reflecting the cluster memberships (two clusters in this case, $K = 2$, for spam and nonspam) for every review instance. Each author/reviewer (and respectively each review) has a set of observed features (behavioral clues) emitted according to the corresponding latent prior class distributions. Model inference learns the latent population distributions of the two clusters across various behavioral dimensions, and the cluster assignments of reviews in the unsupervised setting based on the principle of probabilistic model-based clustering (Smyth, 1999). The reviewer/author features include content similarity, maximum number of reviews, reviewing burstiness, and ratio of first reviews. Review features include duplicate/near-duplicate reviews, extreme rating, rating deviation, early time frame, and rating abuse. This method is highly involved. Interested readers should refer to Mukherjee et al. (2013).

A key advantage of employing Bayesian inference is that because the model characterizes various spamming activities using estimated latent variables and the posteriors, it facilitates both detection and analysis in a single framework rendering a deep insight into the opinion spam problem. This is hard to do using other methods.

12.6 Group Spam Detection

Group spamming refers to a group of reviewers writing fake reviews together to promote or to demote some target products (Mukherjee et al., 2012). The reason for multiple fake reviews for a single product or service is that, in many cases, one single fake review is not enough to promote a product or service or change the existing sentiment on the product. Hence, a group writes multiple fake reviews. A spammer group can be highly damaging because it has many people writing fake reviews, and can therefore take total control of the sentiment on a product. It is hard to detect spammer groups using review content features or even indicators for detecting abnormal behaviors of individual spammers because a group has more manpower to post reviews and thus each member may no longer appear to behave abnormally. Here by a group of reviewers, we mean a set of reviewer-ids. The actual reviewers behind the ids could be a single person with multiple ids (sockpuppets), multiple persons, or a combination of both. We do not distinguish them here.

Before proceeding further, let us see a spammer group. Figures 12.2, 12.3, and 12.4 show the reviews of a group of three reviewers.[5] The following suspicious patterns can be noted about this group: (1) the group members all reviewed the same three products, giving all five star ratings; (2) they posted reviews within a small time window of 4 days (two of them posted in the same day); (3) each of them only reviewed the three products (when the Amazon review data was crawled; Jindal and Liu, 2008); (4) they were among the early reviewers for the products (to make a big impact). All these patterns occurring together strongly suggest suspicious activities. Note that none of the reviews themselves are similar to any other (i.e., no duplicates) or appear deceptive. If we only look at the three reviewers individually, they all appear genuine. In fact, five out of nine reviews received 100% helpfulness votes by Amazon users indicating that the reviews are useful. Clearly these three reviewers have taken total control of the sentiment on the set of reviewed products. In fact, there is a fourth reviewer in the group. Owing to space limitations, we omit it here.

1 of 1 people found the following review helpful:
Practically FREE music, December 4, 2004
This review is from: **Audio Xtract (CD-ROM)**
I can't believe for $10 (after rebate) I got a program that gets me free unlimited music. I was hoping it did half what was ....

---

3 of 8 people found the following review helpful:
Yes – it really works, December 4, 2004
This review is from: **Audio Xtract Pro (CD-ROM)**
See my review for Audio Xtract - this PRO is even better. This is the solution I've been looking for. After buying iTunes, ...

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5 of 5 people found the following review helpful:
My kids love it, December 4, 2004
This review is from: **Pond Aquarium 3D Deluxe Edition**
This was a bargain at $20 - better than the other ones that have no above water scenes. My kids get a kick out of the ....

Figure 12.2. Big John's profile.

2 of 2 people found the following review helpful: ☆☆☆☆☆ **Like a tape recorder...**, December 8, 2004 This review is from: **Audio Xtract (CD-ROM)** This software really rocks. I can set the program to record music all day long and just let it go. I come home and my ....
3 of 10 people found the following review helpful: ☆☆☆☆☆ **This is even better than...**, December 8, 2004 This review is from: **Audio Xtract Pro (CD-ROM)** Let me tell you, this has to be one of the coolest products ever on the market. Record 8 internet radio stations at once, ...
5 of 5 people found the following review helpful: ☆☆☆☆☆ **For the price you...**, December 8, 2004 This review is from: **Pond Aquarium 3D Deluxe Edition** This is one of the coolest screensavers I have ever seen, the fish move realistically, the environments look real, and the ....

Figure 12.3. Cletus's profile.

Wow, internet music!
..., December 4, 2004
This review is from: **Audio Xtract (CD-ROM)**
I looked forever for a way to record internet music. My way took a long time and many steps (frustrtaing). Then I found Audio Xtract. With more than 3,000 songs downloaded in ...

2 of 9 people found the following review helpful:
Best music just got ..., December 4, 2004
This review is from: **Audio Xtract Pro (CD-ROM)**
The other day I upgraded to this TOP NOTCH product. Everyone who loves music needs to get it from Internet ....

3 of 3 people found the following review helpful:
Cool, looks great..., December 4, 2004
This review is from: **Pond Aquarium 3D Deluxe Edition**
We have this set up on the PC at home and it looks GREAT. The fish and the scenes are really neat. Friends and family ....

Figure 12.4. Jake's profile.

If a group of reviewers work together only once to promote or to demote a product, it is hard to detect them based on their collective behavior (see also Section 12.7). However, in recent years, opinion spamming has become a business. People get paid to write fake reviews. These people cannot just write a single review as they would not make enough money that way. Instead, they write many reviews about many products. Such collective behaviors of a group can give themselves away. This section focuses on detecting such groups.

Because reviewers in the group write reviews on multiple products, the data mining technique frequent itemset mining (FIM) (Agrawal and Srikant, 1994) can be used to find them. However, the so discovered groups are only group spam candidates because many groups may be coincidental. For example, some reviewers may have happened to review the same set of products due to similar tastes and the popularity of the products (e.g., many people review all three Apple products, iPod, iPhone, and iPad). Thus, our goal is to identify true spammer groups in the candidate set. The algorithm in Mukherjee et al. (2012) works in two steps:

1. *Frequent itemset mining.* The step finds a set of frequent itemsets. Each itemset is a group of reviewers who have all reviewed a set of products. Such a group is regarded as a candidate spam group. FIM (Agrawal and Srikant, 1994) was used to perform the task.

FIM is stated as follow: Let I be a set of items, which is the set of all reviewers in our case. Let T be a transaction set. Each transaction t_i ($t_i \in T$) is a subset of items in I ($t_i \subseteq I$), which are the reviewers who have reviewed a particular product in our case. Each product thus generates a transaction, which is the set of all reviewers who have reviewed the product. By mining frequent itemsets, we discover all frequent itemsets. Each itemset is a set of reviewers who have appeared in the transaction set T at least a minimum number of times (called minimum support count, or minsup_c for short) and at least two reviewers must be in each itemset (group), that is, each group must have at least two reviewers who have worked together on at least minsup_c products. In the paper, the authors used minsup_c = 3.

2. *Rank groups based on a set of group spam features.* The groups discovered in step 1 may not all be true spammer groups. Many of the reviewers are grouped together in pattern mining simply due to chance. This step uses a relational model, called GSRank (Group Spam Rank), to rank the candidate groups based on their likelihood of being a spam group. This relational model captures the relationships among individual group members and the products that they have reviewed. The relational model is defined based on a set of spam indicators or features that aim to capture different types of unusual group and individual member behaviors. In the next two subsections, we define these features. For details on the relational model, please refer to Mukherjee et al. (2012).

This method is unsupervised, as it does not use any manually labeled data for training. A set of labeled spammer groups was, however, used to evaluate the proposed model, which showed promising results. Clearly, with the labeled data, supervised learning can be applied as well. Indeed, in Mukherjee et al. (2012), the authors also experimented with supervised classification, regression, and learning to rank algorithms for the task.

12.6.1 Group Behavior Features

This subsection describes the set of group features, and the next subsection describes the set of individual member features. These features are indicators or clues of spamming activities.

1. *Group time window (GTW).* Members in a spam group are likely to have worked together in posting reviews for the target products during a short time interval. The degree of active involvement of a group is modeled as its GTW:

$$GTW(g) = \max_{p \in P_g}(GTW_P(g, p)) \tag{12.21}$$

$$GTW_P(g, p) = \begin{cases} 0 & \text{if } L(g, p) - F(g, p) > \tau \\ 1 - \frac{L(g,p) - F(g,p)}{\tau} & \text{otherwise} \end{cases}$$

where $L(g, p)$ and $F(g, p)$ are the latest and earliest dates of reviews posted for product $p \in P_g$ by reviewers of group g respectively. P_g is the set of all products reviewed by group g. Thus, $GTW_P(g, p)$ gives the time window information of group g on a single product p. This definition says that a group g of reviewers posting reviews on a product p within a short burst of time is more prone to be spamming (attaining a value close to 1). Groups working over a longer time interval than τ (which is a parameter) get a value of 0 as they are unlikely to have worked together. The group time window $GTW(g)$ considers all products reviewed by the group taking max over p ($\in P_g$) so as to capture the worst behavior of the group. For subsequent behaviors, max is taken for the same reason.

2. *Group deviation (GD).* A highly damaging group spam occurs when the ratings of the group members deviate a great deal from those of other (genuine) reviewers. The larger the deviation, the worse the group is. This behavior is modeled by GD on a 5-star rating scale (with 4 being the maximum possible deviation):

$$GD(g) = \max_{p \in P_g}(D(g, p)) \tag{12.22}$$

$$D(g, p) = \frac{|r_{p,g} - \bar{r}_{p,g}|}{4}$$

where $r_{p,g}$ and $\bar{r}_{p,g}$ are the average ratings for product p given by members of group g and by other reviewers not in g respectively. $D(g, p)$ is the deviation of the group on a single product p. If there are no other reviewers who have reviewed the product p, $\bar{r}_{p,g} = 0$.

3. *Group content similarity (GCS).* Group connivance is also exhibited by content similarity (duplicate or near-duplicate reviews) when spammers copy reviews among themselves. So, the victimized products have many reviews with similar content. GCS models this behavior:

$$GCS(g) = \max_{p \in P_g}(CS_G(g, p)) \tag{12.23}$$

$$CS_G(g, p) = \underset{m_i, m_j \in g, i<j}{avg} (cosine(c(m_i, p), c(m_j, p)))$$

where $c(m_i, p)$ is the content of the review written by group member $m_i \in g$ for product p. For simplicity, it is assumed that each member writes at most one review for a product. $CS_G(g, p)$ thus captures the average pairwise similarity of review contents among group members for a product p by computing the cosine similarity.

4. *Group member content similarity (GMCS).* Another flavor of content similarity is exhibited when the members of a group g do not know one another (and are contracted by a contracting agency). Because writing a new review every time is taxing, a group member may copy or modify her own previous reviews for similar products. If multiple members of the group do this, the group is more likely to be spamming. This behavior can be captured by GMCS as follows:

$$GMCS(g) = \frac{\sum_{m \in g} CS_M(g, m)}{|g|} \tag{12.24}$$

$$CS_M(g, m) = \underset{p_i, p_j \in P_g, i<j}{avg} (cosine(c(m, p_i), c(m, p_j)))$$

The group attains a value ≈1 (indicating spam) on GMCS when all its members entirely copied their own reviews across different products in P_g. $CS_M(g, m)$ models the average pairwise content similarity of the member $m \in g$ over all products in P_g.

5. *Group early time frame (GETF).* Spammers usually review early to make the biggest impact. Similarly, when group members are among the very first people to review a product, they can totally hijack the sentiment on the product. GETF models this behavior:

$$GETF(g) = \max_{p \in P_g}(GTF(g, p)) \tag{12.25}$$

$$GTF(g, p) = \begin{cases} 0 & \text{if } L(g, p) - A(p) > \beta \\ 1 - \frac{L(g,p) - A(p)}{\beta} & \text{otherwise} \end{cases}$$

where $GTF(g, p)$ captures the time frame as how early a group g reviews a product p. $L(g, p)$ and $A(p)$ are the latest date of review posted for product $p \in P_g$ by group g and the date when p was made available for reviewing respectively. β is a threshold where, after β months, GTF attains a value of 0 as reviews posted then are not considered to be early any more.

6. *Group size ratio (GSR).* The ratio of group size to the total number of reviewers for a product can also indicate spamming. At one extreme (worst case), the group members are the only reviewers of the product and are then completely controlling the sentiment on the product. At the other, the total number of reviewers of the product is very large, but the group size is very small. Then the impact of the group is small.

$$GSR(g) = \underset{p \in P_g}{avg}(GSR_P(g, p)) \tag{12.26}$$

$$GSR_P(g, p) = \frac{|g|}{|M_p|}$$

where $GSR_P(g, p)$ is the ratio of group size to M_p (the set of all reviewers of product p) for product p.

7. *Group size (GS).* Group collusion is also exhibited by its size. For large groups, the probability of members happening to be together by chance is very small. Furthermore, the larger the group, the more damaging it is. GS is easy to model. We normalize it to [0, 1]. $\max(|g_i|)$ is the largest group size of all discovered groups.

$$GS(g) = \frac{|g|}{\max(|g_i|)} \tag{12.27}$$

8. *Group support count (GSUP).* The group support count is the total number of products toward which the group has worked together. Groups with high support counts are more likely to be spam groups as the probability that a group of random people happen to have reviewed many products together is small. GSUP is modeled in the following. We normalize it to [0, 1], with $\max(|P_{gi}|)$ being the largest support count of all discovered groups:

$$GSUP(g) = \frac{|P_g|}{\max(|P_{g_i}|)} \tag{12.28}$$

These eight group behaviors were used as group spamming features in modeling or learning.

12.6.2 Individual Member Behavior Features

Although group behaviors are important, they hide a lot of details about its members. Clearly individual members' behaviors also give signals for group spamming. We now describe the behavioral features of individual members used in Mukherjee et al. (2012).

1. *Individual rating deviation (IRD).* Like GD, we can model IRD as

$$IRD(m, p) = \frac{|r_{p,m} - \bar{r}_{p,m}|}{4} \tag{12.29}$$

where $r_{p,m}$ and $\bar{r}_{p,m}$ are the rating for product p given by reviewer m and the average rating for p given by other reviewers respectively.

2. *Individual content similarity (ICS).* Individual spammers may review a product multiple times posting duplicate or near-duplicate reviews to increase the product popularity. Similar to GMCS, ICS of a reviewer m is modeled over all his reviews toward a product p as follows:

$$ICS(m, p) = avg(cosine(c(m, p))) \tag{12.30}$$

The average is taken over all reviews on p posted by m. $cosine(c(m, p))$ represents pairwise similarity comparisons of all reviews from the same reviewer m on the same product p.

3. *Individual early time frame (IETF).* Like GETF, IETF of a group member m for product p is defined as:

$$IETF(m, p) = \begin{cases} 0 & \text{if } L(m, p) - A(p) > \beta \\ 1 - \frac{L(m,p) - A(p)}{\beta} & \text{otherwise} \end{cases} \tag{12.31}$$

where $L(m, p)$ is the latest date of review posted for a product p by member m, $A(p)$ is the date when p was made available for reviewing, and β is a threshold parameter.

4. *Individual member coupling in a group (IMC).* This behavior measures how closely a member works with the other members of the group. If a member m almost posts at the same date as other group members, then m is said to be tightly coupled with the group. However, if m posts at a date that is far away from the posting dates of the other members, m is not tightly coupled with the group. We find the difference between the posting date of member m for product p and the average posting date of the other members of the group for p. To compute the date difference, we use the date when the first review was posted by the group for product p as the baseline. Individual member coupling (IMC) is modeled as:

$$IMC(g, m) = \underset{p \in P_g}{avg} \left(\frac{|(T(m, p) - F(g, p)) - avg(g, m)|}{L(g, p) - F(g, p)} \right) \tag{12.32}$$

$$avg(g, m) = \frac{\sum_{m_i \in G - \{m\}} (T(m_i, p) - F(g, p))}{|g| - 1}$$

where $L(g, p)$ and $F(g, p)$ are the latest and earliest dates of reviews posted for product $p \in$ by group g respectively, and $T(m, p)$ is the actual posting date of reviewer m on product p.

12.7 Identifying Reviewers with Multiple Userids

Another way to detect fake reviewers or spammers is to identify authors with multiple accounts or userids and using them to write reviews. As we mentioned in Section 12.6, in many cases a single review may not be sufficient to establish a desired sentiment or to reverse an existing undesirable sentiment on a product. Multiple spam reviews are often needed. Although a reviewer can write more than one review for a product, writing multiple reviews from a single account for a product is not a good idea because it is easily detected. To avoid detection, a reviewer may register multiple accounts or userids and post one review from each account. This section describes a technique for detecting such multi-id reviewers. The technique was proposed in Qian and Liu (2013). In fact, variations of the technique can also deal with the following two related problems:

- *Same reviewer posting on multiple sites*. When an author/reviewer promotes a product, he may write fake reviews for the product on multiple sites that sell the product. Thus, we want to solve the problem of detecting accounts or userids from multiple sites that may belong to the same author.
- *Author change*. A reviewer with good reputation on a website may sell his account or userid to a spammer, who then uses the account to post fake reviews. There are also cases where a person purposely "raises" a userid (just like raising a child) for sale. That is, the person posts truthful reviews organically for a period of time to establish the reputation for the account and then he sells the account or userid to a spammer. In this case, we need to detect whether there is an author change for the account.

In what follows, we first present the technique in Qian and Liu (2013) for identifying multi-id authors, and then discuss how the preceding two problems can be tackled as well.

12.7.1 Learning in a Similarity Space

Problem definition: Given a set of userids $ID = \{id_1, \ldots, id_n\}$ and each id_i has a set of reviews R_i, we want to identify userids in ID that belong to the same physical authors.

One application scenario is that ID is the set of all userids that have posted reviews for a single product. R_i is the set of all reviews that userid id_i has posted on this and other products.

The task has some similarity to *authorship attribution* (AA). Conventional AA aims to identify authors of some given documents, and is often solved using supervised learning. Let $A = \{a_1, \ldots, a_k\}$ be a set of authors (or classes) and each author $a_i \in A$ has a set of training documents D_i. A classifier is then built using the training documents to be used to predict the author a of each test document d, where a must be one of the authors in A. However, this approach is not suitable for our task because we only have userids, not authors. Because some userids may belong to the same author, we cannot treat each userid as a class because in that case, we will be classifying different userids, which does not solve the problem of identify multi-id authors.

The algorithm proposed in Qian and Liu (2013) still uses supervised learning, but it learns in a similarity space (LSS). In LSS, the data consist of a set of similarity vectors, called *s*-vectors. Each feature is a similarity between two reviews. One of the reviews is called the query review q and the other the sample review d. If q and d are written by the same author, the class label for the *s*-vector is labeled q-positive (or 1) meaning "d is written by the author of q"; otherwise the class label is q-negative (or −1), meaning "d is not written by the author of q."

The LSS formulation thus gives a two-class classification problem. Any supervised learning method can be used to build a classifier. SVM was used in Qian and Liu (2013). The resulting classifier can decide whether two reviews were written by the same author or not. This capability is needed to solve the multi-id problem.

for each author $ar_i \in AR$ **do**

  select a set of query documents $Q_i \subseteq DR_i$

  for each query $q_{ij} \in Q_i$ **do**

    // produce positive training examples

    select a set of documents from author ar_i, $DR_{ij} \subseteq DR_i - \{q_{ij}\}$

    for each document $dr_{ijk} \in DR_{ij}$ **do**

      produce a training example for dr_{ijk}, $(Sim(dr_{ijk}, q_{ij}), 1)$

    // produce negative training examples

    select a set of documents from the rest of authors, $DR_{ij,rest} \subseteq (DR_1 \cup \ldots \cup DR_n) - DR_i$

    for each document $dr_{ijk,rest} \in DR_{ij,rest}$ **do**

      produce a training example for $dr_{ijk,rest}$, $(\mathrm{Sim}(dr_{ijk,rest}, q_{ij}), -1)$

Figure 12.5. Generating training examples in LSS.

12.7.2 Training Data Preparation

For learning, we have the set of training authors $AR = \{ar_1,\ldots, ar_n\}$. Each author ar_i has a set of documents (or reviews) DR_i. Each document in DR_i is first represented with a document vector (or *d*-vector). The algorithm for producing the training set is given in Figure 12.5.

The algorithm first randomly selects a small set of queries Q_i from documents DR_i of each author ar_i (lines 1 and 2). For each query $q_{ij} \in Q_i$ (line 3), it selects a set of documents DR_{ij} also from DR_i (excluding q_{ij}) of the same author (line 4) to be the *q*-positive documents for q_{ij} (written by the author of query q_{ij}) and labeled 1. Then, for each document dr_{ijk} in DR_{ij}, a *q*-positive training example with the label 1 is generated for dr_{ijk} by computing the similarities of q_{ij} and dr_{ijk} using the similarity function *Sim* (lines 5 and 6). In line 7, it selects a set of documents $DR_{ij,rest}$ from other authors to be the *q*-negative documents for q_{ij} (not written by the author of q_{ij}) and labeled −1. For each document $dr_{ijk,rest}$ in $DR_{ij,rest}$ (line 8), a *q*-negative training example with label −1 is generated for dr_{ijk} by computing the similarities of q_{ij} and $dr_{ijk,rest}$ using *Sim* (line 9). How Q_i, DR_{ij} and $DR_{ij,rest}$ (lines 2, 4, and 7) is selected is left open intentionally to give flexibility in implementation.

Let us see an example. Supposing we have two training authors, $\{a_1, a_2\}$. Each author has two documents d_{i1} and d_{i2}. We assume d_{i1} is used as a query and call it q_{i1} for clarity. With two query documents q_{11} and q_{21} and two nonquery documents, d_{12} and d_{22}, we obtain four training examples with their class labels in Figure 12.6, where $Sim(d, q)$ represents *d*'s *s-vector* to *q*.

From these four training examples (*s*-vectors) of two classes, a two-class classifier can be trained, which can be used to determine whether any two documents/reviews are written by the same author. A very important property of LSS is that reviewers/authors used in testing do not have to be used in training because the classifier only takes an *s*-vector generated from two documents and determines whether they are written by the same author. It does not decide whether a test document is written by a training author or not as in AA.

// for d_{12} of author a_1	// for d_{22} of author a_2
$<Sim(d_{12}, q_{11}), 1>$	$<Sim(d_{22}, q_{11}), -1>$
$<Sim(d_{12}, q_{21}), -1>$	$<Sim(d_{22}, q_{21}), 1>$

Figure 12.6. Example training data for LSS.

12.7.3 d-Features and s-Features

d-features. Each feature in the *d*-vector is called a *d-feature* (for *document-feature*). Qian and Liu (2013) used four types of *d*-features about length (Gamon, 2004; Graham et al., 2005), frequency, *tf.idf*, and richness. For frequency and *tf.idf* based *d*-features, the algorithm first extracts word unigrams and syntactic and stylistic tokens from the raw documents and the parsed syntactic trees, and then computes their frequency and *tf.idf* values. Syntactic features are POS n-grams ($1 \le n \le 3$) (Hirst and Feiguina, 2007) and rewrite rules (Halteren et al., 1996). Besides the *common stylistic features* such as punctuations and function words (Argamon and Levitan, 2004), some review-specific stylistic features were also included: *all capital letter word*, *quotation mark*, *bracket*, *exclamatory mark*, *contraction*, *two or more consecutive nonalphanumeric characters*, *modal auxiliary*, and *sentence with the first letter capitalized*. For richness, it applies the richness metrics in Burrows (1992).

s-features. Each feature in an *s-vector* is called an *s-feature* and is computed using a similarity measure between document *d*'s *d*-vector and query *q*'s *d*-vector. Five types of *s*-features were used, Sim4 length, Sim7 retrieval, Sim3 sentence, SimC tfidf, and SimC richness s-features. Sim7 and Sim3 were defined in Metzler et al. (2005) and Cao et al. (2006). The two SimC s-features used the cosine similarity. Sim4 length *s*-features were defined in Qian and Liu (2013). For more details about all these features, please refer to the paper.

Let us see an example. Suppose we have the following *d*-vector of a query *q*:

$$q: \quad 1:1 \;\; 2:1 \;\; 6:2$$

Here *i*:*j* is a *d*-feature representing term/token *i* with frequency count *j* in *q*. *d*-features with the value 0 are omitted. We also have two nonquery documents: d_1 written by the author of *q* and d_2 not written by the author of *q*. Their *d*-vectors are:

$$d_1: \quad 1:2 \;\; 2:1 \;\; 3:1 \qquad d_2: \quad 2:2 \;\; 3:1 \;\; 5:2$$

If we use cosine as one measure of similarity, we can generate one *s*-feature 1:0.50 for d_1 and one *s*-feature 1:0.27 for d_2. With more similarity measures we can generate more *s*-features. Attaching their class labels (1 or -1), we obtain:

$$(q, d_1): \quad 1 \;\; 1:0.50 \ldots \qquad (q, d_2): \quad -1 \;\; 1:0.27 \ldots$$

where *x*:*y* is an *s*-feature representing the *x*th similarity measure and its similarity value *y* between *q* and d_k.

12.7.4 Identifying Userids of the Same Author

We now use the classifier to solve our problem of identifying userids of the same author. To simplify the problem, the algorithm in Qian and Liu (2013) assumes that there were at most two userids belonging to the same author. The algorithm consists of two main steps:

1. *Candidate identification*. For each user id_i, the algorithm first finds the most likely userid id_j ($i \neq j$) that may have the same author as id_i. id_j is called the *candidate* of id_i. This function is called *candid-iden*, that is, id_j = *candid-iden*(id_i).

2. *Candidate confirmation*. In the reverse order, the algorithm applies the function *candid-iden* on id_j, which produces id_k, that is, id_k = *candid-iden*(id_j).

Decision making: If $k = i$, the algorithm concludes that id_i and id_j are from the same author; otherwise, id_i and id_j are not from the same author.

The detailed algorithm is given in Figure 12.7. Lines 1–2 partitions the documents set D_i of each id_i in the given userid set $ID = \{id_1, id_2,\ldots, id_n\}$. How the partition is done is flexible. Line 4 is the step 1 of candidate identification, and line 5 is the step 2 of candidate confirmation. Lines 6–7 performs the decision making of step 2. The key function here is *candid-iden*. Its algorithm is in Figure 12.8.

1. **for** the document set D_i of each $id_i \in ID$ **do**
2.   partition D_i into two subsets:
        (1) query set Q_i and (2) sample set S_i;
3. **for** the document set D_i of each $id_i \in ID$ **do**
4. id_j = candid-iden(id_i, ID), $i < j$;   // step 1: *candidate identification*
5. id_k = candid-iden(id_j, ID), $k \neq j$;   // step 2: *candidate confirmation*
6.   **if** $k = i$ **then** id_i and id_j are from the same author
7.   **else** id_i and id_j are not from the same author

Figure 12.7. Identifying userids from the same authors.

Function candidate-iden(id_i, ID)

for the sample document set S_j of each $id_j \in ID - \{id_i\}$ **do**
    $pcount[id_j], psum[id_j], psqsum[id_j], max[id_j] = 0;$
    for each query $q_i \in Q_i$ **do**
        for each sample $s_{jf} \in S_j$ **do**
            $ss_{jf} = <(id_i, q_i), (Sim(s_{jf}, q_i), ?)>;$
            Classify ss_{jf} using the classifier built earlier;
            if ss_{jf} is classified positive, i.e., 1 **then**
                $pcount[id_j] = pcount[id_j] + 1;$
                $psum[id_j] = psum[id_j] + ss_{jf}.score$
                $psqsum[id_j] = psqsum[id_j] + (ss_{jf}.score)^2$
            if $ss_{if}.score > max[id_j]$ **then**
                $max[id_j] = sr_{jf}.score$

// Four methods to decide which id_j is the candidate for id_i

if for all $id_j \in ID - \{id_i\}$, $pcount[id_i] = 0$ **then**

$$cid = \arg\max_{id_j \in ID - \{id_i\}} (\max[id_j])$$

else

$$cid = \arg\max_{id_j \in ID - \{id_i\}} \left(\frac{pcount[id_j]}{|S_j|}\right) \quad \text{// 1. Voting}$$

$$cid = \arg\max_{id_j \in ID - \{id_i\}} \left(\frac{psum[id_j]}{|S_j|}\right) \quad \text{// 2. ScoreSum}$$

$$cid = \arg\max_{id_j \in ID - \{id_i\}} \left(\frac{(psum[id_j])^2}{|S_j|}\right) \quad \text{// 3. ScoreSqSum}$$

$$cid = \arg\max_{id_j \in ID - \{id_i\}} (\max[id_j]) \quad \text{// 4. ScoreMax}$$

return cid;

Figure 12.8. Identifying the candidate.

The *candid-iden* function takes two arguments: the query userid id_i and the whole set of userids *ID*. It basically classifies each sample ss_{jf} in sample set S_j of $id_j \in ID\text{-}\{id_i\}$ to positive (q_i-positive) or negative (q_i-negative) (lines 4, 5, 6). We then aggregate the classification results to determine which userid is likely to belong to the same author as id_i. Line 2 initializes the variables for recording the aggregated values used in the final decision-making process.

One simple aggregation method is voting. It counts the number of positive classifications of the sample documents of each userid in $ID\text{-}\{id_i\}$. The userid id_j with the highest count is the candidate *cid* that may share the same author as query id_i. *cid* is returned as the candidate.

There are also other methods that may depend on what output value the classifier produces. Four methods, including the voting method, were proposed in Qian and Liu (2013). The other three methods require the classifier to produce a prediction score to reflect the positive and negative certainty. SVM produces the such a score for each classification.

To save space, all four alternative methods are given in Figure 12.8, which are as follows:

1. *Voting*. For each sample from userid id_j, if it is classified as positive, one vote/count is added to *pcount*[id_j] (line 8). The userid with the highest *pcount* is regarded as the candidate userid, *cid* (line 15). Note that the normalization is applied because the sizes of the sample sets S_j can be different for different userids. Lines 13 and 14 mean that if all documents of all userids are classified as negative (*pcount*[id_j] = 0), which also implies *psum*[id_j] = *psqsum*[id_j] = 0), we use method 4).

2. *ScoreSum*. This method works similarly to voting, except that instead of counting positive classifications, this method sums up all scores of positive classifications in *psum*[id_j] for each userid (line 9). The decision is also made in a similar way (line 16).

3. *ScoreSqSum*. This method works in the same way as ScoreSum, except that it sums up the squared scores of positive classifications in *psqsum*[id_j] for each userid (line 10). The decision is also made in a similar way (line 17).

4. *ScoreMax*. This method works similarly to the voting method as well except that it finds the maximum classification score for the documents of each userid (lines 11 and 12). The decision is made in line 18.

The experiments were conducted using a large set of Amazon.com book reviews. The results showed that even with 100 userids, the F_1 score can reach 0.85. When the number of userids is smaller, the results were almost perfect.

We now turn to the two related problems given at the beginning of the section:

- *Same reviewer posting on multiple sites*. The preceding algorithm can be directly applied to solve this problem. There is also another method which solves this problem purely based on the user behaviors (Zafarani and Liu, 2013).
- *Author change*. This problem can be solved in about the same way. Here, we assume that the review hosting site can detect a major change of IP address used by a userid/account, meaning that either the reviewer has moved to a new place or there is an author change. To find out which is the case, we can use the reviews of the userid before the change as queries and the reviews after the change as samples. If the classification results show that most samples are *q*-negative, it is likely to be an author change.

Finally, I would like to point out that identifying authors with multiple userids is to some extent related to the problem of finding spamming groups because an author with multiple userids can be regarded as a group. In Section 12.6, a group is defined as a set of userids that have all posted reviews for a set of more than one product. Because a spamming author with multiple userids usually write reviews for multiple products (especially for paid reviewers), we can use the algorithm in Section 12.6 to find the userid groups. It can also be done by using frequent pattern mining on the transaction data where each transaction represents a single userid containing all products that the userid has reviewed. However, these methods cannot determine whether the userids in a group belong to the same author or multiple authors. Clearly these methods can also be integrated for more accurate detection.

12.8 Exploiting Burstiness in Reviews

This section studies spamming activities manifested as review bursts. A review burst is a sudden increase in the number of reviews in a short period of time for a product (Fei et al., 2013). In a normal situation, reviews for a product arrive randomly. However, there are time periods when the reviews for a product are bursty, meaning that there are concentrations of reviews in these time periods. Incidentally, review bursts also occur at the individual reviewer level, meaning that a reviewer posts a large number of reviews in a short period of time. This has been used as a behavioral feature in several existing detection algorithms. In this section, we focus only on review bursts for each product.

A review burst can be due to either one or both of the following reasons:

- A sudden increase in popularity of the product. For example, a product may suddenly get popular because of a successful TV commercial. If a large number of customers purchase the product, the product is likely to get more reviews. Most reviewers in this kind of bursts are likely to be genuine reviewers. Such bursts can be easily detected by merchant sites such as Amazon.com that sell the product and also host its reviews.
- The product is under a spam attack. A number of spam or fake reviews are posted in a short period of time. As mentioned earlier, posting a single fake review may not be able to change the overall sentiment on the product if the product already has some negative or positive reviews. Even if the product has no review, posting only a single positive review may not be enough either because readers usually do not trust the single positive review. Spam bursts mainly are generated in two main situations:
  - A business promotes its products or services by giving its customers discounts on the condition that they write positive reviews for the products.
  - A spammer group uses several accounts or reviewer-ids to write fake reviews aimed at promoting or demoting some target products in a short period of time.

In Fei et al. (2013), a fake reviewer detection algorithm was proposed based on bursts. The algorithm rests on the hypothesis that reviewers within the same burst usually have similar states (spam or nonspam). That is, if a burst is deemed to be an attack by spammers, then most reviewers in the burst are likely to be spammers; however, if a burst is not a spam attack, reviewers in it are likely to be genuine reviewers. By exploiting several features of reviewers in bursts, the algorithm is able to capture their spammicities (the degrees of being spammers). The algorithm works in two steps:

1. detect review bursts for each product using *kernel density estimation* (KDE)

2. use Markov random fields (MRFs) to model and to detect spammers

Because using KDE to discover bursts is quite standard, we only focus on step 2.

MRF are a class of probabilistic graphical models particularly suited for solving inference problems with uncertainty in observed data. An MRF consists of an undirected graph where each node can be in any of a finite number of states. The state of a node is assumed to be dependent upon each of its neighbors, and independent of any other node in the graph. This assumption yields a pairwise MRF which is a special case of the general MRF. In pairwise MRF, the joint probability of the network can be written as a product of pairwise factors rather than maximal cliques in general MRF.

In the setting of Fei et al. (2013), a node is a reviewer that can be in any of the three states: Spammer (S), Mixed (M), or NonSpammer (NS). The rationale for using “Mixed” as a state is that some reviewers may write fake reviews sometimes (for various reasons), but write genuine reviews some other times as legitimate buyers. Each edge between any two nodes signifies that the corresponding reviewers have appeared in a burst together. Based on the graph, the algorithm infers the maximum likelihood assignment of states to nodes, that is, computing node marginals. Fei et al. (2013) used the loopy belief propagation (LBP) method to perform the inference with the help of a set of spammer features such as *ratio of verified purchase*, *rating deviation*, *burst review ratio*, *review content similarity*, and *reviewer burstiness*, and burst features such as *burst-verified purchase ratio*, *burst sharpness*, *burst content similarity*, and *burst rating deviation*.

Evaluation based on classification. Besides the preceding burst-based spam detection method, the paper also proposed an objective method for evaluating spam detection results. Owing to the difficulty of obtaining ground truth data on spam (or fake) and nonspam (or nonfake) that can be used in model building and model testing, researchers have mainly used human evaluation in previous works. However, human evaluation is subjective as different evaluators often have different tolerance levels even if they are given the same set of behavior indicators and reviews of a reviewer. The proposed method uses supervised classification to evaluate the discovered review spammers, which is complementary to human evaluation, and thus gives us more information about whether the detection algorithm is doing a good job or not. First, it assumes that if a reviewer is labeled as a spammer, all his reviews are considered as spam reviews and if a reviewer is labeled as a nonspammer, all his reviews are considered as nonspam reviews. This gives us a two-class classification problem. A classifier can then be built to separate the two classes of reviews. Fei et al. (2013) used SVM with unigram features and Boolean assignment of feature values. A key point here is that in the detection algorithm, only behavior features were employed, but in the review classification, only linguistic features are applied. If the classification shows good accuracy, we know that the reviews written by reviewers labeled as spammer and nonspammer based on their behaviors are also separable based on their review text. This, to some extent, shows that the spam detection algorithm is effective.

Xie et al. (2012) proposed another burst-based method to detect singleton reviewers who are likely to be involved in review spamming. Singleton reviewers are reviewers who wrote only a single review. The paper used the store review data in Wang et al. (2011). Their technique first detects review bursts for each store. If a burst has many reviews with ratings (e.g., 5 stars) that are very different from other reviews and many of the reviewers are singleton reviewers, the algorithm concludes that these singleton reviewers are likely to be involved in spamming. That is, they probably received some discounts or other benefits from the store in exchange for positive reviews about the store.

The preceding algorithms only anlayzed bursts of reviews for individual products or services. As we mentioned at the beginning of the section, bursts also occur for reviewers, that is, a reviewer writes many reviews in a short period of time. Such a burst may also indicate possible spamming ativities. For example, the reviewer wrote positive reviews for many products of a brand in a short period of time. However, I am not aware of any focused study of this problem in the literature except using some predefined bursts of reviewers as features in some supervised and unsupervised detection algorithms.

12.9 Some Future Research Directions

Although many algorithms have been proposed to detect fake reviews, there is still a long way to go before we can weed out opinion spamming activities. There are also many interesting research directions that have not been or barely been explored. Here, I describe several such directions:

Multiple site comparisons. Spammers who promote or demote some target products may write fake reviews in multiple sites to achieve the maximum effect as many websites may sell the products or host reviews about the products. It will be interesting to compare reviews of the same product across these sites to discover abnormalities, for example, similar reviews (contents or ratings) that are written at about the same time, similar userids, and the same/similar IP address. It is quite unlikely for a genuine reviewer to be bothered to post a positive review for a product in multiple sites considering one often needs to register and sign-in to post a review at a website.

Language inconsistency. To suit different products and stress personal experiences, fake reviewers may write something that is inconsistent or against social norms in different reviews. For example, to promote a woman's watch, a paid reviewer may write "*I bought this watch for my wife and she simply loves it*." Later on, to promote a man's shirt, the same reviewer may write "*I bought this shirt for my husband yesterday.*" To promote a diaper, a reviewer may write "*my baby loves the diaper*." Later on, to promote a wedding gown, she may write "*my girlfriend tried the wedding gown yesterday*." The first and the second sentences indicate gender inconsistency, while the third and the fourth sentences show that the reviewer's behavior is against the social norm. There are many other possible inconsistencies that can be detected, for example, age, with/without children, ethnicity, and so on.

Nature of business. In many cases, the nature of the product or business can help detect fake reviewing activities. For example, if all positive reviews of a hotel come from people living in the nearby area of the hotel (based on their IP addresses), these positive reviews are suspicious because few people would stay in a hotel, if they have homes nearby. However, there are so many types of businesses and manually compile such normal and abnormal behavior patterns is very difficult. The challenge is how we can design an algorithm to automatically discover such abnormal behavioral patterns for each domain.

Web usage abnormality. Web servers record almost everything that a person does at a website, which is valuable for detecting fake reviews. For example, using the IP address information and click behaviors, we may find that all positive reviews for a product are from the same or similar

IP addresses, or many reviewers who have never visited a website suddenly came to a product page directly and wrote some positive reviews. In the first case, all the reviews might have come from the same person, and in the second case, the seller of the product might have paid people to write reviews for the product and also provided a link to the product page. The fake reviewers simply clicked the link and posted fake reviews. The rule mining method described in Section 12.4 can be extended to find many such abnormal patterns automatically. I am aware that several review hosting sites are using such data to detect fake reviews, but there is still no reported academic research using the web usage data of reviewers to detect fake reviews. The main reason is that academics have difficulty to get access to such data for research, partly due to privacy concerns and partly due to the fact that review hosting companies do not want publications of any detection methods that they may use because if fake reviewers know the methods, they will change their behaviors and/or writing styles to avoid detection.

Early detection. Most existing algorithms rely on patterns detected from review contents and reviewers' behaviors. For most types of patterns to form, it takes some time. However, when the patterns show themselves finally, some major damages might have already been done. Thus, it is important to design algorithms that can detect fake reviews as soon as possible, ideally, right after they are posted.

12.10 Summary

As social media is increasingly used for critical decision-making by organizations and individuals, opinion spamming is also becoming more and more sophisticated and widespread. For many businesses, posting fake opinions themselves or employing professional fake review writers to do it for them has become a cheap way of marketing and brand promotion. Fortunately, major online review hosting sites are actively combating fake reviews by detecting them using computer algorithms.

In the past few years, many effective algorithms have been proposed in academia and some of them or their simplifications (the industry usually uses simpler algorithms) have been used in practice. I believe that we already have the main ideas and algorithms that can catch most fake reviews and reviewers. The algorithms just need to be adapted to the real-life application environment. For example, none of the published research papers have used any site private data, which are web usage data (e.g., IP addresses and click behaviors) and reviewer profile data, in their algorithms or in their evaluations. If such private site data are available in an application, existing published algorithms can be augmented with additional features from them. In certain cases, modifications of the published algorithms will be needed. Companies can also apply a large number of web usage mining algorithms in the existing literature to generate effective features (Liu, 2006, 2011). Going forward, I believe that the main technical difficulty is how to spot fake reviews right after they are posted. This is a challenge because most existing algorithms need enough evidences to judge whether a review is suspicious or not (except text classification algorithms), but such evidences may take a while to accumulate. This period of time can be devastating for a small business if it is a nasty negative review.

As detection algorithms are getting smarter in spotting sophisticated fake reviewers, fake reviewers are also becoming more careful and sophisticated in their writing. They also try to guess the strategies that are used by detection algorithms to avoid being detected. This is an arms race between detection algorithms and spammers. I am optimistic that fake reviews will become less and less of an issue in the future due to the joint effort between researchers, practitioners, regulators, and law enforcement agencies. Measures are also being taken by review hosting sites to make it difficult to post fake reviews. For example, some sites do not allow people to write reviews for a product or service unless they have purchased the product or have used the service. However, it will be very hard to completely eradicate fake reviews or deceptive opinions because the incentive is too high.

Finally, I would like to reiterate that opinion spamming occurs not only in reviews, but also in other forms of social media such as blogs, forum discussions, commentaries, and microblogs. Although there is little direct research in these contexts, many algorithms designed for detecting fake reviews are also applicable to detecting opinion spam in these other forms of social media. There are, however, also some additional complexities in these forms of social media. For example, some existing detection algorithms need review ratings, which reflect the sentiments of the reviewers about the products being reviewed. However, none of the posts in the other forms of social media have such a rating. If an algorithm needs this information, it has to perform sentiment analysis first.

5 http://www.amazon.com/gp/pdp/profile/A3URRTIZEE8R7W; http://www.amazon.com/gp/pdp/profile/A254LYRIZUYXZG; http://www.amazon.com/gp/cdp/member-reviews/A1O70AIHNS4EIY.

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Quality of Reviews

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In this chapter, we discuss the quality of reviews. The topic is related to opinion spam detection, but is also very different because low-quality reviews may not be spam or fake reviews, and fake reviews may not be perceived as low-quality reviews by readers because as we discussed in the last chapter, it is very difficult to spot fake reviews simply by reading them. For this reason, fake reviews may also be seen as helpful or high-quality reviews if the imposters write their reviews early and craft them well.

The objective of this task is to determine the quality, helpfulness, usefulness, or utility of each review (Kim et al., 2006; Zhang and Varadarajan, 2006; Ghose and Ipeirotis, 2007; Liu et al., 2007). This is a meaningful task because it is desirable to rank reviews based on quality or helpfulness when showing reviews to the user, with the most helpful reviews first. In fact, many review aggregation or hosting sites have been practicing this for years. They obtain the helpfulness or quality score of each review by asking readers to provide helpfulness feedback to each review. For example, in Amazon.com, the reader can indicate whether she finds a review helpful by responding to the question "*Was the review helpful to you?*" just below each review. The feedback results from all responses are then aggregated and displayed right before each review, for example, "*15 of 16 people found the following review helpful*." Although most review hosting sites already provide the service, automatically determining the quality of each review is still useful because a good number of user feedback may take a long time to accumulate. That is why many reviews have few or no feedback. This is especially true for new reviews.

13.1 Quality Prediction as a Regression Problem

Determining the quality of reviews is usually formulated as a regression problem. The learned model assigns a quality score to each review, which can be used in review ranking or review recommendation. In this area of research, the ground truth data used for both training and testing are usually the user-helpfulness feedback given to each review, which as we discussed earlier is provided for each review at many review hosting sites. So, unlike fake review detection, the training and testing data here is not an issue. Researchers have used many types of features for model building.

In Kim et al. (2006), SVM regression was used to solve the problem. The feature sets include,

Structure features: review length, number of sentences, percentages of question sentences and exclamations, and number of HTML bold tags <b> and line breaks <br>.

Lexical features: unigrams and bigrams with TFIDF weights.

Syntactic features: percentage of parsed tokens that are of open-class (i.e., nouns, verbs, adjectives, and adverbs), percentage of tokens that are nouns, percentage of tokens that are verbs, percentage of tokens that are verbs conjugated in the first person, and percentage of tokens that are adjectives or adverbs.

Semantic features: product aspects, and sentiment words.

Meta-data feature: review rating (number of stars).

In Zhang and Varadarajan (2006), the problem was also formulated as a regression problem. They used similar features, for example, review length, review rating, counts of some specific POS tags, sentiment words, TFIDF weighting scores, wh-words, product aspect mentions, comparison with product specifications, comparison with editorial reviews, and so on.

Unlike the preceding approaches, Liu et al. (2008) considered three main factors, which are reviewers' expertise, the timeliness of reviews, and the style of reviews based on POS tags. A nonlinear regression model was proposed to integrate the factors. This work focused on movie reviews.

In Ghose and Ipeirotis (2007, 2010), three additional sets of features were used, namely, reviewer profile features which are available from the review site, reviewer history features which capture the helpfulness of her reviews in the past, and a set of readability features, that is, spelling errors and readability indices from the readability research. For learning, the authors tried both regression and binary classification.

Lu et al. (2010) looked at the problem from an additional angle. They investigated how the social context of reviewers can help enhance the accuracy of a text-based review quality predictor. They argued that the social context can reveal a great deal of information about the quality of reviewers, which in turn tells the quality of their reviews. Specifically, their approach was based on the following hypotheses:

Author consistency hypothesis. Reviews from the same author are of similar quality.

Trust consistency hypothesis. A link from a reviewer r_1 to a reviewer r_2 is an explicit or implicit statement of trust. Reviewer r_1 trusts reviewer r_2 only if the quality of reviewer r_2 is at least as high as that of reviewer r_1.

Co-citation consistency hypothesis. People are consistent in how they trust other people. So if two reviewers r_1 and r_2 are trusted by the same third reviewer r_3, then their quality should be similar.

Link consistency hypothesis. If two people are connected in the social network (r_1 trusts r_2, or r_2 trusts r_1, or both), then their review quality should be similar.

These hypotheses were enforced as regularizing constraints and added into the text-based linear regression model to solve the review quality prediction problem. For experiments, the authors used the data from Ciao (http://www.ciao.co.uk), which is a community review website. In Ciao, people not only write reviews for products and services, but also rate the reviews written by others. Furthermore, people can add members to their network of trusted members or “Circle of Trust,” if they find these members’ reviews to be consistently interesting and helpful. Clearly this technique will not be applicable to websites which do not have a trust social network in place.

13.2 Other Methods

O'Mahony and Smyth (2009) proposed a classification approach to classifying helpful and nonhelpful reviews. Many features were used:

Reputation features. Mean and standard deviation of review helpfulness over all reviews authored by the reviewer, percentage of reviews authored by the reviewer that have received a minimum of *T* feedback, and so on.

Content features. Review length, ratio of uppercase to lowercase characters in the review text, and so on.

Social features. Number of reviews authored by the reviewer, mean and standard deviation of the number of reviews authored by all reviewers, and so on.

Sentiment features. Rating score of the review, and mean and standard deviation of the sub-scores assigned by the reviewer, and so on. Sub-scores are ratings assigned to aspects.

In Liu et al. (2007), the problem was also formulated as a two-class classification problem. However, they argued that using the helpfulness votes as the ground truth may not be appropriate because of three biases: (1) vote imbalance (a very large percentage of votes are helpful votes); (2) early bird bias (early reviews tend to get more votes); (3) winner circle bias (if a review gets many votes, it will be ranked high on the review site, which helps it get even more votes). Those lowly ranked reviews get few votes, but they may not be of low quality. The authors then divided reviews into four categories, "best review," "good review," "fair review," and "bad review," based on whether the reviews discuss many aspects of the product and provide convincing opinions. Manual labeling was carried out to produce the gold-standard training and testing data. In classification, they used SVM to perform binary classification. Only the "bad review" category was regarded as the low-quality class and all the other three categories were regarded as belonging to the high-quality class. The features for learning were informativeness, subjectiveness, and readability. Each of them contained a set of individual features.

Tsur and Rappoport (2009) studied the helpfulness of book reviews using an unsupervised approach which is quite different from the preceding supervised methods. The method works in three steps. Given a collection of reviews, it first identifies a set of important words in the reviews. These words together form a vector representing a virtual optimal or core review. Then, each actual review is mapped or converted to this vector representation based on occurrences of the discovered important words in the review. After that, each review is assigned a rank score based on the distance of the review to the virtual review (both are represented as vectors).

Moghaddam et al. (2012) proposed a new problem of personalized review quality prediction for the recommendation of helpful reviews. All of the preceding methods assume that the helpfulness of a review is the same for all users/readers, which, the authors argued, is not true. To solve the new problem, they proposed several factorization models. These models are based on the assumption that the observed review ratings depend on some latent features of reviews, reviewers, raters/users, and products. In essence, the paper treated the problem as a personalized recommendation problem. The proposed technique to solve the problem is quite involved. Some background knowledge about this form of recommendation can be found in Chapter 12 of Liu (2006, 2011).

All the approaches so far rank reviews based on the computed helpfulness or quality scores. However, Tsaparas et al. (2011) argued that these approaches do not consider an important fact that the top few high-quality reviews may be highly redundant and repetitive. In their work, they proposed the problem of selecting a *comprehensive* and yet *small* set of high-quality reviews that cover many different aspects of the reviewed entity and also different viewpoints of the reviews. They formulated the problem as a maximum coverage problem, and presented an algorithm to solve the problem. An earlier work in Lappas and Gunopulos (2010) also studied the problem of finding a small set of reviews that cover *all* product aspects.

13.3 Some New Frontiers

Although the existing research can help identify high-quality reviews to some extent, new problems have also emerged. I had the opportunities to talk to several industrial executives who deal with reviews in their daily work. They told me that the information overload problem is still not solved. On the consumer side, people still find that reviews are too long to read even though good reviews are ranked high. There are some evidences that the brief pros and cons of each review used at some review hosting sites are useful because they give people a quick summary of the review. However, they also have a weakness, that is, they are not detailed enough and some people still want to selectively read the detailed opinions and their reasons in the review about those aspects that they really care about (e.g., why they are good or bad and in what sense). There is no simple way to get there without reading the whole reviews. In other words, pros and cons do not provide links to the details in the review. One way to solve this problem is to mine reasons for opinions and summarize them as we discussed in Section 2.2, and then provide a link from each pro or con item to the text segment in the review that elaborates the opinion. This leads to the next problem, that is, how to effectively present opinions and their reasons to the user in a visual framework so that they can see the opinions and reasons easily. So far, little work has been done on this. I can think of two ways. First, we can extend the summarization framework in Hu and Liu (2004) to include a summary of opinion reasons. That is, when presenting positive or negative sentences for each aspect, the system also summarizes them so that those big issues and benefits can be clustered and put at the top. The advantage of this approach is that it is brief and focused, and thus easy for users to see. The disadvantage is that they are not in the context from where they were extracted. In many cases, understanding the context in which an opinion or reason appears is very important. The second solution is to use links and some color scheme to connect and highlight each pro or con and their detailed reasons in each actual review. The disadvantage and advantage of this approach is just the opposite of the first approach. Perhaps a combination of the two will give the user a better experience. Of course, there could be some other even better solutions.

On the business side, the reasons for opinions are extremely important as we discussed earlier because companies want to know the detailed complaints and issues about their products or services as experienced by their customers. That is also why, in many applications, negative opinions weigh more than positive ones. Hence, mining, summarizing, and highlighting reasons for opinions are critical.

13.4 Summary

In summary, determining review helpfulness is an important research topic. It is especially useful for products and services that have a large of number reviews. To help the reader get to quality opinions quickly, review sites should rank reviews based on their quality or utility. Many review hosting sites are already doing that. However, I would like to add some cautionary notes here. First, as we discussed in the chapter about opinion search and retrieval, the review ranking (rankings) should reflect the natural distribution of positive and negative opinions. It is not a good idea to rank all positive (or all negative) reviews at the top simply because they have high-quality scores. The redundancy issue raised in Tsaparas et al. (2011) is a good one. In my opinion, both quality and distribution (in terms of positive and negative viewpoints) are important. Second, readers tend to determine whether a review is helpful or not based on whether the review expresses opinions on many aspects of the product and appear to be genuine. A spammer can satisfy that requirement by carefully crafting a review that is just like a normal helpful review. So, using the number of helpfulness feedback to define review quality or as the ground truth can be problematic. Furthermore, user feedback can be spammed. Feedback spam is a subproblem of click fraud in search advertising, where a person or robot clicks on some online advertisements to give the impression of real customer clicks. Here, a robot or a human spammer can click on the helpfulness feedback button to increase the helpfulness counts of a review. Finally, in the last section, we discussed the problem where people do not want to read long reviews even if they are ranked. Thus, finding reasons for opinions, issues/problems and benefits, summarizing them, and presenting them in a suitable way are required. However, little research has been done in this direction so far.

14
Conclusions

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This book introduced the field of sentiment analysis or opinion mining. It presented some basic knowledge and mature techniques in detail and surveyed numerous other state-of-the-art algorithms. Owing to numerous challenging research problems and a wide variety of practical applications, sentiment analysis has been a very active research area in several computer science fields, for example, NLP, data mining, web mining, and information retrieval. It has also spread to management science (Hu et al., 2006; Archak et al., 2007; Das and Chen, 2007; Dellarocas et al., 2007; Ghose et al., 2007; Park et al., 2007; Chen and Xie, 2008) and other social science fields such as communications and political science because of its importance to business and society as a whole. With the rapid expansion of social media on the web, the importance of sentiment analysis is also growing by the day.

In the book, I first defined the problem of sentiment analysis (Chapter 2), which provides a common framework to unify different research directions and research problems in the area. It also presents a schema to convert unstructured free text to structured data, which facilitates qualitative and quantitative analysis of opinions. I then discussed the widely studied problem of document-level sentiment classification (Chapter 3), which aims to determine whether an opinion document (e.g., a product review) expresses a positive or a negative sentiment. This was followed by Chapter 4 on sentence-level subjectivity and sentiment classification. These tasks determine whether a sentence is opinionated, and if opinionated, whether it carries a positive or negative opinion. Chapters 5 and 6 focused on aspect-based sentiment analysis, which employs the full problem definition in Chapter 2. They also showed that sentiment analysis is a multifaceted problem with multiple challenging subproblems. The existing techniques for dealing with these problems were also presented. Due to a large amount of information, this topic was covered in two chapters. Chapter 5 was dedicated to the task of aspect-based sentiment classification, and Chapter 6 was devoted to the task of opinion target extraction, which includes the extraction of entities and their aspects. These are the two core tasks of aspect-based sentiment analysis and have been studied extensively in different communities. After that, Chapter 7 studied the problem of sentiment lexicon generation. Two dominant approaches were covered. This was followed by Chapter 8 about mining of comparative and superlative opinions. Comparisons represent a different type of opinions and require different methods for their analysis.

The chapter first defined the problem and then presented some techniques for comparison mining. Chapter 9 studied opinion summarization and search. Opinion summarization is a special form of multidocument summarization but differs from the traditional multidocument summarization in that opinion summarization can be done in a structured manner, which enables both qualitative and quantitative analysis, and the visualization of opinions. The topic of opinion search or retrieval was also introduced in that chapter. Chapter 10 moved to online debates, discussions, and comments, which represent different types of social media content than reviews. They are characterized by dialogues involving user exchanges of opinions and arguments. Such social media forms also introduced another type of sentiment, that is, *agreement* and *disagreement* (or *contention*). The chapter described several novel mining tasks. The analysis of debates and discussions also brings us to the social science research fields of communication and political science as researchers in these fields are very interested in online discussions and debates about social and political issues and the behaviors of people participating in such debates and discussions. Chapter 11 focused on intention mining, which is another important social media mining task that is closely related to but also different from sentiment mining. This topic has not received much attention in academia or the industry so far. However, I believe it has a great potential for commercial applications. For example, commercial intents expressed in social media are clearly useful to advertisers and recommender systems. Chapter 12 discussed opinion spam detection. Opinion spamming by writing fake or deceptive reviews and posting bogus comments are increasingly becoming an important issue as more and more people are relying on the opinions on the web for their decision-making. To ensure the trustworthiness of such opinions, combating opinion spamming is an urgent and critical task. Last but not least, we discussed the quality and/or utility of online reviews in Chapter 13. Studying the quality of reviews enables websites to rank high-quality reviews at the top so as to facilitate users to get needed opinions easily and quickly.

After reading this book, you probably feel that sentiment analysis is highly challenging technically. It is indeed. Although the research community has attempted many subproblems and proposed a large number of approaches to solving the problems, none of the subproblems is solved satisfactorily. There is not even a single standard approach for any subproblem. Our understanding and knowledge about sentiment analysis and its solution are still very limited. The main reason is that it is a NLP task, and NLP has no easy problems. Another reason may be due to our popular ways of doing research, which rely too much on machine learning. Some of the most effective machine learning algorithms, for example, support vector machines (SVMs), naïve Bayes, and conditional random fields (CRFs), produce no human understandable results such that although they may help us achieve improved accuracy, we know little about how and why, apart from some superficial knowledge gained in the manual feature engineering process. To rectify the situation, I covered a great deal of linguistic knowledge in this book, which tells us what expressions people often use to voice their opinions and also how we can recognize these expressions computationally. As explained early on in the book, my presentation of this linguistic information does not follow the linguistic tradition because my objective is computational realization of the linguistic knowledge in a computer program to extract opinions and sentiments from text. I encourage linguists to join this research. After all, sentiment is an important aspect of semantics of the natural language, and it is also of great practical importance. These should provide enough motivations to develop a computational linguistic theory of sentiment and opinion, and their related concepts such as emotion, mood, and affect from a natural language perspective. Although these concepts have been researched extensively by psychologists, neuropsychologists, and sociologists, their focuses are on people's psychological states of mind, not language constructions used in expressing such states of mind or feelings. Beyond the applications of mining consumer opinions about products and services and public opinions about politics, such a theory will also be very useful for analyzing people's states of mind from their posts on social media platforms such as Facebook and Twitter, which can have a profound impact on the society. For example, schools always want to know the mental health of their students. They want to detect any depression and even suicidal intentions of children. Law enforcement authorities want to know potential criminals and people with antisocial behaviors who might cause major damage to the society. For example, in some mass shooting cases in the United States, those shooters had shown many troubling signs in their social network pages.

We are truly in an exciting time. The massive amount of social media data are enabling scientists to reunderstand people and the society. Most past research results in social sciences were derived from small-scale lab experiments. With the big social media data, social scientists can now conduct research on a massive scale, which, on one hand, enables them to have a better understanding of the human nature and the society as a whole, and on the other hand, allows them to understand each and every one of us at the individual level. This has never been possible in the past. It is sometimes said that the virtual society may be a truer society in the sense that people hide behind anonymous userids and speak their true feelings without having to follow any social norms such as being polite in front of people. It is a familiar story that, before knowing that a person has committed a terrible crime, her neighbors believed that she was a very nice person. We now have the capability to analyze everyone's posts on Facebook and Twitter to detect any early warning signs.

On the opinion spam detection front, social scientists who study lies and deceptions can potentially contribute a great deal to the detection of deceptions, lies, and rumors in social media. Such unethical posts are widespread on the web. Detecting them is important to ensure the healthy growth of the social media and to institute social media as a trusted source of information rather than just a place for people to spread lies and rumors. Although we have already studied these topics to some extent in the computer science community, we have only scratched the surface and computer scientists also lack the necessary training and expertise to do a good job.

The past decade of research has made significant progresses in both research and application of sentiment analysis. This is evident from the large number of start-ups and established companies that offer sentiment analysis services. There is a real and huge need in the industry for such services because every business wants to know how consumers perceive their products and services, and those of their competitors. The same is also true about consumers as whenever one wants to buy something, one wants to know the opinions and experiences of existing users. In the past few years, government and private organizations are also showing strong interests in obtaining public opinions about their policies and their images. These practical needs and the technical challenges will keep the field vibrant and lively for years to come.

Building on what has been done so far, I believe that two research directions are particularly promising. First, there are many opportunities to design novel machine learning algorithms to learn from large volumes of text data to mine general as well as domain-specific knowledge that is useful to sentiment analysis. Domain-specific knowledge is very important because every domain has some special desirable and undesirable situations that are different from other domains. I also believe that learning to perform a single task is not very productive. Integrated learning of all related tasks simultaneously by exploiting their interrelations is especially interesting. Learning should also consider prior knowledge, which can guide training to learn much more accurately. Second, along with research, we should build more advanced sentiment analysis systems. Practical system building and applications will enable us to see the full spectrum of the problem and also to gain deeper insights. For system building, I believe that a holistic or integrated approach is more likely to be successful. The system should try to deal with all subproblems at the same time because their interactions can help solve each individual subproblem. I am optimistic that the problem will be solved satisfactorily in the near future for widespread practical applications.

By no means do I claim that a fully automated and accurate solution can be designed and implemented very soon. However, I do believe that it is possible to devise effective semiautomated solutions. The key is to fully understand the whole range of issues and pitfalls, cleverly manage them, and determine which portions can be done automatically and which portions need human assistance. In the continuum between the fully manual solution and the fully automated solution, as time goes by we can push more and more toward automation. I do not see a silver bullet any time soon. A good bet will be to work hard on a large number of diverse application domains, understand each of them, and design general solutions gradually. After all, a human person also needs to take many years of continuous learning and experiencing to understand things around him.

I also believe that interdisciplinary research involving both computer scientists and social scientists can potentially make major contributions to both fields and to the society. Many social scientists have realized the potential of social media analysis and sentiment analysis and are actively working on related projects. However, their ability to handle large volumes of data is limited. Collaboration with computer scientists can enable novel discoveries. My own group is involved in two such collaborations, and it has been an eye-opening and mutually beneficial experience. Several research problems and their solution techniques described in Chapter 10 were resulted from these collaborations.

Finally, I would like to point out that much of the current research on sentiment analysis has been done in English. Although researchers from many countries have conducted research in the field, most of them still use English texts. This book is also mainly based on research done in English and my own experience in building a sentiment analysis system to analyze English opinion text. I am aware of many systems in other languages, but they are mostly based on methods developed for the English language with some customizations and/or additions to handle language-specific issues. I expect that more research in other languages will be reported in the research literature in the future. I also hope that a language-independent platform can be built so that a developer can specify opinion- and sentiment-related knowledge of a language to the system and the system will perform sentiment analysis in that language automatically.

Appendix

Additional categories of sentiment composition rules to those given in Section 5.2.1 are listed here.

11. *Having everything or nothing*: If an entity has everything that one wants, then one is positive about the entity. Conversely, if an entity has nothing that one wants, then one is negative about the entity, for example,

"*This car has everything that my mother really wants*."

"*This plan has nothing that I need*."

"*This car has all the features*."

We thus have the following composition rules:

PO	:: =	HAVE EVERYTHING
NE	:: =	HAVE NOTHING
HAVE	:: =	have | has | …
EVERYTHING	:: =	everything | all | …
NOTHING	:: =	nothing | …

In using these rules, we need to consider some exceptions, which are not difficult to deal with, for example,

"*This car has everything that is bad*."

"*This car has nothing bad*."

"*This program has all the bad features*."

12. *Being exact the way that one wants*: If something is exact the way that one wants, then one is positive about the entity.

"*This phone is designed exactly the way that I wanted*."

"*They polished the car exactly the way that I wanted*."

"*My hair looks exact the way that I want*."

We then have the following PO rule:

PO	:: =	EXACTLY the way ONE WANT
EXACTLY	:: =	exact | exactly | …
ONE	:: =	I | we | you | one | …
WANT	:: =	want | need | …

Composition rules for this category of sentiment expressions can be diverse. The PO rule here covers only a small subset of cases.

13. *Having or using some positive or negative potential items, or having something that one wants*: If an entity has some positive potential items (PPIs) or anything that one wants, then one tends to be positive about the entity. If an entity has some negative potential iterms (NPIs), then one tends to be negative about the entity, for example,

"*Google has the answer*."

"*This vacuum cleaner has/uses bag*."

"*This store has the shoes that I want*."

Here *answer* is a PPI, *bag* is a NPI in the vacuum cleaner domain (as older vacuums use bags to hold dusts which are expensive to buy and troublesome to change) and shoes are neither PPIs nor NPIs. See the definitions of PPI and NPI in Section 5.2.1.

PO	:: =	USE PPI
| HAVE NOUN-PHRASE ONE WANT		
NE	:: =	HAVE NPI
USE	:: =	use | have | has | …
NOUN-PHRASE means any noun phrase.		

14. *Saving or wasting resources*: If an entity saves resources, it is desirable (or positive), but if it wastes resources, it is undesirable (or negative), for example, “*This device can save electricity*.”

“*Buying this car is wasting of money*.”

“*He has wasted a great opportunity.*”

We thus have the following rules ([] means optional):

PO	:: =	SAVE RESOURCE
NE	:: =	WASTE [PO] RESOURCE
SAVE	:: =	save | …
WASTE	:: =	drain | waste | …

15. *Causing or preventing negative or positive effects or situations*: If an entity can cause positive (or negative) effects, it is positive (or negative). If it prevents a negative (or positive) effect from happening, it is positive (or negative), for example,

“*The sensitive brake has prevented a major accident*.”

“*This drug caused my back pain*.”

“*This device keeps you away from danger*.”

“*This tool protects you from virus attack*.”

We have the following composition rules:

PO	:: =	CAUSE PO | PREVENT NE
NE	:: =	CAUSE NE | PREVENT PO
CAUSE	:: =	cause | result in | …
PREVENT	:: =	prevent something from | keep someone away | protect against | protect from | …

16. *Solving problems or making improvements*: These concepts imply positive sentiment.

<table>
<tr><td>PO</td><td>:: =</td><td>SOLVE NE</td></tr>
<tr><td></td><td>|</td><td>MAKE_IMPROVEMENT [NE]</td></tr>
<tr><td>SOLVE</td><td>:: =</td><td>solve | address | clear up | deal with | fight | fix | handle | help with | give a solution | make up for | tackle | offer a solution | resolve | settle | sort out | tame | …</td></tr>
<tr><td>MAKE_IMPROVEMENT</td><td>:: =</td><td>make improvement | improve | make progress | …</td></tr>
</table>

Again, [] means optional. Here are some example sentences:

"*The company has fixed the voice quality problem.*"

"*The noise problem has been addressed.*"

"*The programmer has solved the terrible filtering problem.*"

"*The company has made some major improvement to this phone.*"

17. *Destroying positive or negative items*: If someone kills a positive item, then the sentiment is negative. If someone kills a negative item, the sentiment is positive:

<table>
<tr><td>PO</td><td>:: =</td><td>DESTROY NE</td></tr>
<tr><td>NE</td><td>:: =</td><td>DESTROY PO</td></tr>
<tr><td>KILL</td><td>:: =</td><td>kill | destroy | dash | end | put to death | smash | …</td></tr>
</table>

Some example sentences are:

"*They kill a great idea.*"

“*He dashed my hope*.”

“*They kill the goose that laid the golden eggs*.”

18. *Capable of performing some action*: If an entity is capable of performing a useful or a negative action, it is positive (or negative). We have the following composition rules:

PO	:: =	CAPABLE_OF USEFUL_ACTION
NE	:: =	CAPABLE_OF NE_ACTION
CAPABLE_OF	:: =	can | able to | capable of | have the capability of | …

We do not specify USEFUL_ACTION as they are different in different domains. NE_ACTION is usually indicated by a NE expression. Some example sentences are:

“*This car can climb very steep hills*.”

“*This drug is capable of treating that disease*.”

“*This software can damage your hard drive*.”

19. *Keeping or breaking one’s promise*: Keeping one’s promise is positive but breaking one’s promise is negative.

PO	:: =	keep (promise | words)
NE	:: =	break promise

Here are some examples:

“*Their service people always keep their promises*.”

“*Their service people never keep their words*.”

“*They break their promises all the time*.”

20. *Taking or enduring pain or abuse*: The following examples show this case:

“*This phone has held up to my daily abuse*.”

"He can endure the pain."

"Due to a large cash reserve, the company can take a beating."

The composition rule is as follows:

PO	:: =	ENDURE NE
ENDURE	:: =	endure | take | stand | hold up | withstand | sustain | resist | …

The negative expressions here are usually related to *suffering*, *pain*, *abuse*, *hardship*, and so on.

21. *Throwing away something*: If something desirable (or undesirable) is thrown away, it is negative (or positive). We have the following composition rules:

NE	:: =	THROW_AWAY (PO | PPI)
PO	:: =	THROW_AWAY [NE | NPI]
THROW_AWAY	:: =	do away with | get rid of | sell off | throw way | …

The following are some example sentences:

"The company throws away a great idea."

"I got rid of the phone the second day."

"I want to throw this phone out of the window."

22. *Staying away from, drifting away, or coming back to something*: If we want to stay away from something, that something is usually undesirable. If we like to come back to something, that something is usually desirable. Drifting away from an undesirable state is positive, while drifting away from a desirable state is negative. We thus have the following rules.

NE	:: =	STAY_AWAY_FROM (ENTITY | ASPECT)

	|	DRIFT_AWAY_FROM PO
	|	DRIFT_AWAY_FROM NE
PO	:: =	COME_BACK_TO ENTITY
STAY_AWAY	:: =	avoid | get away from | run away from | stay away from | steer away from | …
DRIFT_AWAY	:: =	(drift | move | slip | slide) away from | …
COME_BACK_TO	:: =	come back to | come to | …
ENTITY	:: =	this ENTITY_TYPE | ENTITY_NAME
ASPECT	:: =	ASPECT_NAME

ENTITY_TYPE is a product/service type, for example, car, phone, and so on. ENTITY_NAME stands for a named entity, for example, *iPhone* and *Motorola*. ASPECT_NAME stands for the name of an aspect of an entity. The following are some example sentences:

"*You should stay away from this car*."

"*I always come back to Dove*."

"*The company has drifted away from a profitable situation*."

The COME_BACK_TO rule needs to be used with care as in many cases, it expresses no opinion, for example, "*I will come back to office at 5 pm*."

23. *Supporting or voting for something*: If an entity E1 supports another entity E2, then E1 has a positive opinion about E2. If E1 supports a negative (or positive) item, then the opinion about E1 is negative (or positive).

PO	:: =	ENTITY SUPPORT

		ENTITY
	|	ENTITY SUPPORT PO
NE	:: =	ENTITY SUPPORT NE
SUPPORT	:: =	support | always there for | cheer for | give the green light to | root for | stand behind | stand by | vote for | …

Note that we are unable to specify opinion targets using this concept level specification language. Section 5.7 presented an expression-level rule representation language that allows us to specify opinion targets. Some example sentences for this set of rules are:

"*I will vote for the Republican Party*."

"*He gave the green light to some criminal activities*."

"*They are always there for you*."

"*They always stand behind their products*."

24. *Associated or friendly with something*: The following example shows this case.

"*He is friendly with the bad guy*."

The sentence is negative about *he* although *friendly* is a positive sentiment word. We have the following rule:

NE	:: =	FRIENDLY_WITH NE
FRIENDLY_WITH	:: =	friendly with | associated with | …

25. *Choosing this or something else*: When making a recommendation or suggestion, people often say "choose this one" (positive) and "choose something else" (negative).

PO	:: =	ENTITY is for you
	|	ENTITY is it

<table>
<tr><td></td><td>|</td><td>ENTITY is the one</td></tr>
<tr><td></td><td>|</td><td>ENTITY is your baby</td></tr>
<tr><td></td><td>|</td><td>go (with | for) ENTITY</td></tr>
<tr><td></td><td>|</td><td>ENTITY is the way to go</td></tr>
<tr><td></td><td>|</td><td>this is it</td></tr>
<tr><td></td><td>|</td><td>(search | look) no more</td></tr>
<tr><td></td><td>|</td><td>CHOOSE ENTITY</td></tr>
<tr><td></td><td>|</td><td>check ENTITY out</td></tr>
<tr><td>NE</td><td>:: =</td><td>forget (this | it | ENTITY)</td></tr>
<tr><td></td><td>|</td><td>keep looking</td></tr>
<tr><td></td><td>|</td><td>look elsewhere</td></tr>
<tr><td></td><td>|</td><td>CHOOSE (another one | something else)</td></tr>
<tr><td>CHOOSE</td><td>:: =</td><td>buy | check | check out | choose | get | grab | pick | purchase | select |…</td></tr>
<tr><td>ENTITY</td><td>:: =</td><td>this | this ENTITY_TYPE | ENTITY_NAME</td></tr>
</table>

These rules are commonly used in conditional sentences when making suggestions or recommendations. They have been discussed in Section 4.4. They are reproduced here for completeness. ENTITY_TYPE and ENTITY_NAME have been defined in rule set 22. Some example sentences are as follows:

> "*If you want a great phone, choose the iPhone*."

> "*If you are in the market for a new phone, choose something else*."

The second sentence indicates that the phone being reviewed or discussed is not good.

26. *Under control or out of control*: *Under control* is a positive phrase and *out of control* is a negative phrase.

PO	:: =	[NE] UNDER_CONTROL
NE	:: =	[NE] OUT_OF_CONTROL
UNDER_CONTROL	:: =	in control | keep a rein on | under control | …
OUT_OF_CONTROL	:: =	beyond control | out of control | …

Some example sentences are:

"*The rescue team got the terrible situation under control*."

"*This vacuum cleaner keeps a rein on dust*."

"*The federal spending is out of control*."

27. *Undercutting or undermining some positive effort*:

NE	:: =	UNDERMINE [PO]
UNDERMINE	:: =	undercut | undermine | …

The following are some example sentences:

"*The company undercuts their own great effort of producing a new phone*."

"*His action is undermining his party's effort to draw more voters*."

28. *Cannot wait to do something to a desirable* (PO) *or undesirable* (NE) *item*:

PO	:: =	cannot wait PO
NE	:: =	cannot wait NE

The following are some example sentences:

“*I cannot wait to get rid of this lousy car*.”

“*I cannot wait to get this beautiful phone*.”

These rules are included because *cannot* here does not mean negation. Also, when *cannot wait* is not followed by a negative or positive item, it is usually positive, for example, “*I cannot wait to get an iPhone*” (see Section 5.4).

29. *Positive or negative* (*potential*) *items return*: When a positive item (PO) or a PPI returns, it is positive. When a negative item (NE) or a NPI returns, it is negative. Take, for example, the following sentences:

“*My pain has returned*.”

“*This drug got my life back*.”

We then have the following rule:

NE	:: =	(NE | NPI) RETURN
PO	:: =	(PO | PPI) RETURN
RETURN	:: =	bring back | come back | get back | is back | return | …

30. *Emerging from undesirable situation*: The following sentences give us some examples. The three sentences are all positive about the company, although the sentences have negative sentiment words.

“*This company has emerged from the poor economy*.”

“*The economy has jumped out of recession*.”

“*The company comes out of the bankruptcy*.”

We then have the following composition rules:

PO	:: =	COME_OUT_FROM (NE | NPI)
COME_OUT_FROM	:: =	back from | come out | emerge from | …

We can also have a rule for ‘*get into an undesirable situation*’, but it is unnecessary because the undesirable situation (NE) can already determines the sentiment.

31. *Positive* (*negative*) *outweighing negative* (*positive*): This concept expresses a comparison of positive and negative sentiments on some entities or aspects.

PO	:: =	PO OUTWEIGH NE
NE	:: =	NE OUTWEIGH PO
OUTWEIGH	:: =	outweigh | make up for | more significant than | …

For example, the following sentences are all positive about the car, although the sentiments are different on different aspects of it.

“*For this car, the pros outweigh the cons*.”

“*The beauty of the car well outweighs its high price*.”

“*The beauty of the car makes up for its high price tag*.”

However, handling these sentences in practice can be tricky, especially for the second and the third sentences, because two aspects are involved and authors are not positive about both. In a practical application, there are a few options, for example, (1) assigning positive to aspect *appearance* and the *car* entity, and negative to aspect *price*, (2) assigning positive to aspect *appearance* and the *car* entity, ignoring the sentiment on *price*, and (3) assigning positive to the *car* entity, ignoring both aspects.

32. *Changing from positive* (or *negative*) *to negative* (or *positive*): The following sentences illustrate this concept:

“*They changed the good policy to a lousy one*.”

“*The company changed the unreliable switch to a highly reliable one*.”

“*The company changed the previous switch to a highly reliable one*.”

We have the following rules:

PO	:: =	CHANGE_FROM [NE] to PO

NE	:: =	CHANGE_FROM [PO] to NE
CHANGE_FROM	:: =	change from | switch from | …

33. *Something that is going to die*: The following sentences give some examples:

“*This company’s days are numbered*.”

“*This great company may die next year*.”

We have the following composition rules:

NE	:: =	[NE] DIE
PO	:: =	PO DIE
DIE	:: =	days are numbered | die | …

34. *Extending one’s ability or making it difficult*: Something that extends one’s ability is positive and something that makes it difficult for one to do something is negative, for example,

“*This tool enables me to do filtering easily*.”

“*This security hole allows a hacker to destroy your computer easily.*”

“*This policy makes it very difficult to cheat.*”

“*This system makes it very hard to take multiple pictures quickly*.”

We have the following composition rules:

PO	:: =	ENABLE (PPI | PO)
	|	MAKE_DIFFICULT (NPI | NE)
NE	:: =	ENABLE (NPI | NE)
	|	MAKE_DIFFICULT (PPI | PO)

ENABLE	:: =	allow | enable | make it easy | …
MAKE_DIFFICULT	:: =	make it (difficult | hard | impossible) | …

35. *Forced to do something*: The following are some example sentences:

"*The doctor forced me to take the medicine*."

"*They made you pay for the lunch.*"

We have the following composition rules:

NE	:: =	FORCE_TO_DO [PO | NE | PPI | NPI]
FORCE_TO_DO	:: =	forced to | make someone do something | pressurized to | …

36. *Comparing with something desirable or undesirable*: The following are some example sentences:

"*This car is similar to or on par with the best car*."

"*This furniture is like a piece of art*."

We have the following composition rules:

NE	:: =	SUB_PAR (PO | NE)
	|	ON_PAR NE
PO	:: =	ON_PAR PO
SUB_PAR	:: =	subpar | worse than | …
ON_PAR	:: =	better than | like | on par | the same as | …

This set of rules is related to comparative opinions, which have been discussed in Chapter 8.

37. *High or low on a ranked list*: There are many ways to express this situation. Most of them are difficult to recognize. The following sentences give some examples:

"*This car is high on my list*."

"*This song is in the top 10 list*."

"*This song is now near the top of the chart*."

We have the following rules:

NE	:: =	AT_BOTTOM_OF_LIST
PO	:: =	ON_TOP_OF_LIST

The concepts of AT_BOTTOM_OF_LIST and ON_TOP_OF_LIST can be expressed in many diverse ways, which are not easy to specify simply.

38. *Doing things automatically*: Doing desirable things automatically is positive but doing undesirable things automatically is negative.

PO	:: =	(PO | PPI) AUTIMATICALLY
NE	:: =	(NE | NPI) AUTIMATICALLY
AUTIMATICALLY	:: =	automatically | by itself | …

The following sentences give some examples:

"*The recorder stops suddenly by itself*."

"*The system automatically avoids obstacles*."

39. *Positive* (*negative*) *initially*, *but become negative* (*positive*) *later*: This type of sentences occur fairly frequently in product reviews, especially for products that are of low quality or do not last. The sentiment in the second part of the sentence usually overwrites the first part. The following sentences give some examples:

"*This car was good in the first two months, and then everything started to fall apart*."

“*This phone worked quite nicely initially, and then the sound became unclear*.”

“*I did not like the car at the beginning, but then it impressed me more and more*.”

“*The car worked very well until yesterday*.”

“*At first this seemed prohibitive to me, but they do give a lot of discount*.”

We have the following composition rules:

NE	:: =	PO INITIAILLY NE LATER
PO	:: =	NE INITIAILLY PO LATER

There are numerous ways to express INITIALLY and LATER. The example sentences give some such expressions. This type of opinion is hard to detect because typically intrasentence discourse analysis is required.

40. *Positive but not positive enough*: This category is similar to rule set 39, but there is no time or sequence expression to help detect this case. In such a sentence, the sentiment of the second part often overwrites the first part. The following are some example sentences:

“*This car is good but not good enough*.”

“*Although they have made a lot of improvement to the car, it is still lousy*.”

We have the following composition rule:

NE	:: =	PO BUT_STILL NE

Sentences covered by this rule usually use *but*, *although*, or other similar words or expressions to indicate BUT_STILL. Many such sentences are also hard to recognize as they too may need the discourse-level analysis.

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