

Sentiment Analysis

Mining Opinions, Sentiments, and Emotions

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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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 true 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. 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 learning 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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Bing Liu
Chicago, USA
July 10, 2014

Introduction

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 Schütze, 1999; Indurkha 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.

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 $A = \{a_1, a_2, \dots, a_n\}$; e can be expressed in text with any one of a finite set of its entity expressions $\{ee_1, ee_2, \dots, ee_s\}$. Each aspect $a \in A$ of entity e can be expressed with any one of a finite set of its aspect expressions $\{ae_1, ae_2, \dots, ae_m\}$.

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

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.

Digital Camera 1:

Aspect: GENERAL		
Positive:	105	<Individual review sentences>
Negative:	12	<Individual review sentences>
Aspect: Picture quality		
Positive:	75	<Individual review sentences>
Negative:	42	<Individual review sentences>
Aspect: Battery life		
Positive:	50	<Individual review sentences>
Negative:	9	<Individual review sentences>

...

Figure 2.1. An aspect-based opinion summary.

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

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

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.

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 Johnson-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

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.

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

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

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		

emotions that are useful to the application. We also do not need to worry about whether they are primary, second, or tertiary.

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.

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., *sloooooow*), 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-implicit 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.