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Mining opinion components from unstructured reviews: A review

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Abstract Opinion mining is an interesting area of research because of its applications in various fields. Collecting opinions of people about products and about social and political events and problems through the Web is becoming increasingly popular every day. The opinions of users are helpful for the public and for stakeholders when making certain decisions. Opinion mining is a way to retrieve information through search engines, Web blogs and social networks. Because of the huge number of reviews in the form of unstructured text, it is impossible to summarize the information manually. Accordingly, efficient computational methods are needed for mining and summarizing the reviews from corpuses and Web documents. This study presents a systematic literature survey regarding the computational techniques, models and algorithms for mining opinion components from unstructured reviews.

Contents

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1. Introduction

This study presents a systematic literature survey that contains a comprehensive overview of recent research trends, advances, and challenges. The aim of this study is to provide researchers and students access to the latest works in opinion mining as they frame new ideas and further develop the practice.

There has been an increase in research in this area as evidenced by the recent publication of several research survey papers in the past few years (Khan et al., 2009; Pang and Lee, 2008; Tang et al., 2009, Tsytsarau and Palpanas, 2011). Pang and Lee (2008), for example, present an extensive review of opinion mining (OM) concepts and techniques. Khan et al. (2009) provide a short overview of the published works regarding the various issues in the domain of opinion mining. Tang et al. (2009) review the techniques regarding sentiment analysis and polarity classification. Tsytsarau and Palpanas (2011) focus on summarizing opinions and analyzing contradictions. They also present a comparative analysis of machine learning algorithms for sentiment classification. This paper reviews the various advancements in OM research since 2008. Thus, the proposed work presents a review of opinion mining based on opinion component analysis of unstructured text, and accordingly, this paper differs from existing papers in several ways. In this work, we discuss citations published after 2008 that are related to the opinion component of unstructured reviews. We have divided the papers according to the sub-tasks related to opinion mining. These include subjectivity and polarity classification, opinion target extraction, opinion source identification and opinion summarization. Each section presents a comprehensive literature review about the related sub-task. Some new directions have been explored, e.g., features grouping, opinion target identification and semantic-based relevance scoring through lexical resources and concept-based analysis.

This paper is organized as follows. Section 2 presents a general overview of the opinion mining problems, its applications, and related areas. Section 3 explains technical perspectives of opinion mining based on opinion components. Section 4 presents opinion summaries, Section 5 provides an overview of challenges and issues, and Section 6 concludes the paper.

2. Opinion mining

An opinion is the private state of an individual, and as such, it represents the individual's ideas, beliefs, assessments, judgments and evaluations about a specific subject/topic/item. Liu et al. (2012) conclude that others' opinions have a great impact on and provide guidance for individuals, governments, organizations and social communities during the decision-making process. During this process, human beings require fast, accurate and concise information so they can make quick and accurate decisions. Through opinions, humans can integrate the diverse approaches, experiences, wisdom and knowledge of many people when making decisions. It is quite natural for people to participate in discussions and express their points of view. People often ask their friends, family members, and field experts for information during the decision-making process, and their opinions and perspectives are based on experiences, observations, concepts, and beliefs. One's perspective about a subject can either be positive or negative, which is referred to as the polarity of the opinion.

Opinions can be expressed in different ways. The following are examples of opinion statements.

Shahid Afridi is a good player.
She is not a good actress.
The breakfast was quite good.
The hotel was expensive.
Terrorists deserve no mercy!
Hotel A is more expensive than Hotel B.
Coffee is expensive, but tea is cheap.
This player is not worth any price, and I recommend that you not purchase it.

An opinion has three main components, i.e., the opinion holder or source of the opinion, the object about which the opinion is expressed and the evaluation, view or appraisal, that is, the opinion. For opinion identification, all of these components are important.

While opinions can be collected from different sources, e.g., individual interactions, newspapers, television, Internet etc., the Internet has become the richest source of opinion collection. Before the World Wide Web (www), people collected opinions manually. If an individual was to make a decision, he/she typically asked for opinions from friends and family members. To acquire public opinion, organizations often conducted surveys through focused groups. This type of survey, however, was expensive and laborious. Now, the Internet provides this information with a single click and at very little cost.

With the advent of Web 2.0, the Internet allows Web users to generate Web content online and post their information independently. This aspect of the Internet allows Web users to participate in collaborative global environments. Hence, the Internet has become a rich source for social networks, customer feedback, online shopping etc. According to a survey, more than 45,000 new blogs are created daily along with 1.2 million new posts each day (Pang and Lee, 2008). The information collected through these services is used for various types of decision making. For example, social networks can be used for political, religious, and security issues as well as for policy making, while customer feedback can be used for product sales, purchases, and manufacturing. Not only is the trend of online shopping increasing daily, but vendors collect customer feedback for future trend predictions and product improvement through these portals. The key element that has provided the inspiration for this work is…opinion.

Though the Internet is a rich source of opinions with millions of blogs, forums and social websites offering a large volume of updated information, the Web data, unfortunately, are typically unstructured text that cannot be directly used for knowledge representation. Moreover, such a huge volume of data cannot be processed manually. Hence, efficient tools and potential techniques are needed to extract and summarize the opinions contained therein. Research communities are searching for an efficient way to transform this Web information into knowledge requisition and then present the knowledge to the user in a concise and comprehensible manner. While the emergence of Web 2.0 has made the task of posting and collecting opinions via the Web much easier, the quality control, processing, compilation, and summarization of these opinions have become potential research problems.

The term opinion mining (OM) first appeared in 2003 in a paper (Dave et al., 2003), though some papers had previously addressed the same task (Carbonell, 1979; Pang et al., 2002; Turney, 2002; Wiebe, 1994; Wilks and Bien, 1984). The 2003 paper described OM as the analysis of reviews about entities, and it presented a model for document polarity classification as being either recommended or not recommended. This work opened new avenues for applied research in NLP and text mining, and within a few years, extensive research had been done in this area (Abbasi et al., 2008; Changli et al., 2008; Hsinchun and Zimbra, 2010; Hu and Liu, 2004; Liu, 2010a; Tang et al., 2009; Wei, 2011; Yang et al., 2009; Yi et al., 2003).

OM is a procedure used to extract opinion from text. "OM is a recent discipline at the crossroads of information retrieval, text mining and computational linguistics which tries to detect the opinions expressed in natural language texts" (Pang and Lee, 2008). OM is a field of knowledge discovery and data mining (KDD) that uses NLP and statistical machine learning techniques to differentiate opinionated text from factual text. As such, OM tasks involve opinion identification, opinion classification (positive, negative, and neutral), target identification, source identification and opinion summarization. Hence, OM tasks require techniques from the field of NLP, information retrieval (IR), and text mining. The main concern is how to automatically identify opinion components from unstructured text and summarize the opinion about an entity from a huge volume of unstructured text.

Textual information can be classified as either objective or subjective. Objective statements represent facts, while subjective statements represent perceptions, perspectives or opinions. The NLP research preliminary focused on mining factual information from a text, which is an important area with various applications; however, with the advent of Web 2.0, which allows the user to generate Web content, some new and interesting ideas have been developed for the extraction of knowledge from user-generated discourse. The Web 2.0 facility provides the opportunity to acquire required information from Web users and apply IR and KD techniques for various applications. User feedback on the Web is collected through social networks, blogs, commercial organizations, marketing etc. Millions of reviews and comments are collected through marketing and service websites (Amazon, Trip Advisor etc.), social networks (Facebook, Flicker, YouTube etc.), commercial and social media (Voice of America, BBC, CNN, Yahoo etc.), and many other blogs and forum websites. The mining of these reviews can provide answers to numerous research questions.

Mining knowledge from user-generated discourse is known as subjectivity analysis to which there are two sub-domains, i.e., opinion mining and sentiment analysis. Some authors have used these domains interchangeably (Liu, 2011), while others have considered sentiment analysis to be a subarea of OM (Tang et al., 2009). According to (Tang et al., 2009), OM is slightly different from sentiment analysis in that sentiment analysis is simply the analysis or classification of a text as presenting either a positive or a negative attitude of the opinion holder. OM is related to information retrieval, analysis and the rating of a user's opinion about entities such as products, movies etc., while sentiment analysis is related to the extraction and analysis of emotional and sentimental statements in a text. A recent and interesting development in this area is the development of a cognitive model based on a natural language concept using an artificial neural network organized in a brain-like universe to mine opinions from customer reviews (Cambria et al., 2013).

The area of subjectivity analysis is still in the developmental phase and various related problems are being addressed by the researcher. According to (Pang and Lee, 2008), opinion mining, though an intellectually difficult problem, is extremely useful in practical applications.

2.1. Applications

OM has various applications in different fields. It can be used in search engines, recommendation systems, email filtering, Web ad filtering, questioning/answering systems, etc. OM application in daily life is most interesting as OM can be used to improve human–computer interactions, business intelligence, government intelligence, citation analysis etc. The following sample questions could be helpful in better understanding the applications of OM.

- What do people think about government policies?
- What is the general public opinion toward the new tax policy?
- Who is a strong candidate for the general election body?
- Why has the sale of a product declined?
- Which features of a product are liked or disliked by the general public?
- Why do people prefer one product over another?

Although the goal of opinion mining is to have an integrated online environment that directly answers questions such as those listed above, this goal has been only partially achieved, and thus, current research is focused on this problem. Numerous Websites have been functional for collecting of users' opinions regarding a variety of topics and for supporting the search for answers to these questions. Some authors have specifically worked on applications for customer reviews (Balahur and Montoyo, 2008; Chen et al., 2006; Das et al., 2001; Ganesan et al., 2010; Jin et al., 2009; Liu et al., 2005; Thet et al., 2007), while others have applied OM to the mining of newspapers and websites in an effort to extract public opinion (Liang et al., 2011; Maragoudakis et al., 2011; Stepinski and Mittal, 2007). Simmons et al. (2004) has applied the concept of OM to online auctions to predict the end price of items, while other papers have reported work on public opinion mining for government decision making (Stylios et al., 2010). (Furuse et al., 2007) developed an open domain query-based search engine for extracting statements of opinion. Miao et al. (2009) developed a tool called "AMAZING" for opinion mining that uses data mining and information retrieval technology. The paper described a novel ranking mechanism based on the temporal opinion quality (TOQ) relevant to meeting customers' information needs. The system includes the trend movement of customer reviews and a comparison between positive and negative evaluations with visual summarization. Some specialized websites have been working on collecting opinions from various social media and websites and then ranking the collected opinions.

Appinions is an online influencing exchange framework with an extensive database that includes millions of opinions that have been extracted from blogs, Twitter, Facebook, forums, newspaper and magazine articles, and radio and television transcripts for the purpose of identifying, analyzing, and monitoring personal opinions. Appinions is utilized for various purposes and in a variety of fields, such as education, politics, technology, entertainment, business, health, and travel.[1]

Although OM can be applied to the social and business sectors, researchers are also making an effort to effectively employ it in other important areas, e.g., health, education, travel etc. (Goeuriot et al. (2011) proposed social media sites where people post information about their diseases and treatments for the purpose of mining disease and treatment information. In an interesting application of OM, Swaminathan et al. (2010) extract relationships between bio-entities, such as food and diseases. This paper also presented a model for predicting the polarity and the strength of a relationship.

Xia et al. (2009) applied OM techniques to classify patients' opinions about British National Health Services (NHS), and the data for analysis were collected from the NHS website.[2]

Furthermore, OM is being applied in several commercial areas such as tourism, automobile purchasing, electronic product reviews, movie reviews, and game reviews as well as in various political arenas such as public administration, strategic planning, marketing etc. (Abulaish et al., 2009; Blitzer et al., 2007; Das et al., 2001; Feldman et al., 2007; Kessler et al., 2010; Lin and Chao, 2010; Zhuang et al., 2006).

The aforementioned works represent only a small sample of OM applications. Various surveys have been conducted regarding the existing works and the potential applications of OM in practical life, thus indicating the importance of OM (Pang and Lee, 2008; Tang et al., 2009; Tsytsarau and Palpanas, 2011).

2.2. Opinion representation in text

This section describes the features of the private state or personal opinion as presented in textual form. Research has identified various features and patterns that are commonly used to express private states (Hatzivassiloglou and McKeown, 1997; Liu, 2010a; Wiebe, 1994, 2000). While the primary element that has been widely reported in existing research is the use of adjectives, the use of adverbs, verbs and nouns in context are also used to identify private states and opinions.

The private state is presented in text either explicitly or implicitly. The explicit statements are direct subjective statements, e.g., "The room was very comfortable". In this statement, the adjective 'comfortable' represents the positive attitude of the individual having the experience; hence, it shows an explicit opinion. An implicit opinion, on the other hand, is indirectly expressed, e.g., "The room was very hot". While this statement expresses a negative opinion about the room, the adjective 'hot' does not directly express dissatisfaction. Similarly, in the sentence, "I have a cup of hot coffee", the adjective 'hot' implicitly represents a positive attitude regarding the coffee. The implicit opinion is primarily identified by the co-occurrence patterns in language. For example, if 'hot' is used to describe the temperature of a room, then it may have negative connotations, but if hot is used to describe coffee, then it may have positive connotations. Accordingly, corpus-based machine learning techniques are employed to formulate co-occurrence-based similarities (Dagan et al., 1999; Lemaire and Denhière, 2008; Panicheva et al., 2009). Zhang and Zhu (2013) developed a novel co-occurrence association-based method that extracts implicit features from customer reviews and thereby provides more comprehensive and fine-grained mining results.

Another potential indicator of opinion or one's private state is the comparative statement. In texts, comparative sentences generally represent private statements that indicate a judgment and a comparison of two objects. Therefore, comparative sentences are exploited for opinion extraction from texts (Jindal and Liu, 2006). Comparative sentences typically contain comparative adjectives and adverbs such as more, stronger, happier, best, etc. However, some sentences with these words are not comparative. For example, "I cannot study more". Similarly, some sentences do not contain specific comparative words, but they are still classified as comparative. For example, "I like its color but do not like its size". This type of sentence is called a non-gradable comparative. Jindal and Liu (2006) discussed an effective model based on syntactic patterns for identification of comparative opinions. Their method uses a set of key words and key phrases. The key patterns include comparative adjectives (JJR), comparative adverbs (RBR), superlative adjectives (JJS) and superlative adverbs (RBS). Key words include, but are not limited to the following: same, similar, different, as well as, favor, beat, win, etc., (Liu, 2010a,b).

2.3. Related disciplines

This section describes a brief overview of OM related disciplines, two of which are natural language processing (NLP) and information retrieval (IR) using text mining techniques. The broad scope of OM includes Web mining, as opinions are mainly collected from the Web and Web enabled technologies are employed for OM.

2.3.1. Natural language processing

OM, one of the interesting applications of natural language processing, strongly depends on NLP techniques. NLP is a

[1] http://appinions.com/.
[2] http://www.patientopinion.org.uk.

set of computational techniques for analyzing natural language texts that allows computers to understand human language. As such, NLP plays a vital role in the information retrieval (IR) and knowledge discovery (KD) from plain texts. NLP analyzes texts at different levels of language, i.e., at the morphological, lexical, syntactic, semantic, discourse, and pragmatic levels. "The OM discipline places itself at the crossroads of IR and computational linguistics (CL); these are the two disciplines from which OM gathers and combines many concepts, ideas and methods" (Esuli, 2008). With respect to IR, there are two aspects of OM that are specifically related to NLP, i.e., information extraction (IE) and question–answer (QA) (Wilson, 2008). The QA aims to answer those questions that are written in a natural language. An example would be, "What is the view point of the Muslim world regarding the Afghan War?" In the QA system, the search engines target public opinion to answer the questions related to social events, reputation, influencing agents etc.

The primary unit of NLP is the language term. Each language term has various linguistic features, such as grammatical category, meaning, sense, co-occurrence similarity, and contextual relationships that are employed for term classification and subjectivity analysis. Polanyi and Zaenen (2004), described "The most salient clues about attitude are provided by the lexical choice of the writer, but the organization of the text also contributes information relevant to assessing attitude". Hence, the work of OM begins with term analysis and ends with document analysis.

The NLP tasks require a knowledge base for information extraction and analysis. While some techniques are necessary for building a knowledge base, other techniques use existing knowledge bases to analyze documents. A general overview of the NLP tasks is given in Fig. 1.

The IE and QA both perform subjectivity analyses using various NLP and statistical techniques. Research has presented great contributions in this area and diverse approaches have been employed to accomplish the subjectivity analysis.

2.3.2. Text mining

Text mining, a set of techniques used on text for knowledge discovery and prediction, is deeply rooted in the retrieval of information commonly associated with Web documents such that "text Mining techniques are used in Web search engines to extract the most relevant documents to the search query". The basic concept behind the retrieval of information is the similarity measurement among words, phrases, sentences and documents. A simple example of searching for relevant documents is presented in Fig. 2.

The other perspective of text mining involves predictions for learning and classification. Text mining techniques apply statistical methods and formulations for generating similarity scores among terms, phrases, sentences and documents to predict hidden patterns and then to classify them. OM is a field of

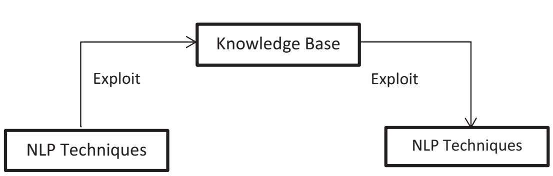

Figure 1 NLP techniques and knowledge base.

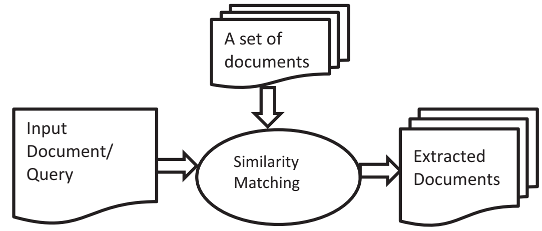

Figure 2 Retrieving matching documents (Weiss et al., 2010).

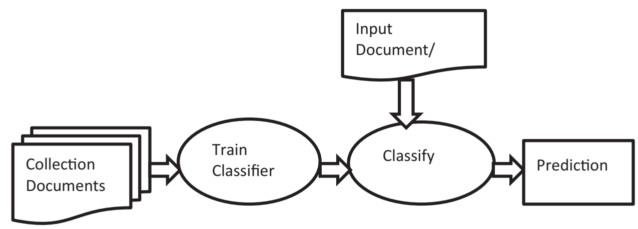

Figure 3 Classification and prediction.

IR that depends on machine learning and classification techniques, which are employed at various levels. For example, at the term level of classification, it is necessary to identify whether the term is opinion and whether it has a positive polarity or a negative polarity. Similar classifications are conducted at the phrase, sentence and document levels. Hence, text mining techniques have had a great influence on OM. A general overview of classification is presented in Fig. 3.

2.3.3. Web mining

One of the rich sources of information for knowledge discovery is the World Wide Web (www). Web mining refers to the implementation of text mining techniques for the purpose of extracting useful knowledge from Web text. OM is typically related to web mining. Mining customer behaviors, public opinions about political issues, social network analyses, and other areas related to opinions based on user feedback acquired through Web content mining, which, in turn, is related to OM. The actual goal of opinion mining is to develop an integrated and efficient system that provides an interface for Web users as the query feedback data on Web articles related to any discipline (Pang and Lee, 2008). Although recent developments in this area have demonstrated considerable growth, it has not yet achieved its goal. Nonetheless, Web content mining has received considerable attention in recent years due to its increase in demand and its potential applications, in general, and, more specifically, to user feedback analysis (Liu, 2011; Tsytsarau and Palpanas, 2011; Wei, 2011).

3. Opinion mining tasks

The OM problem and its sub-problems, each of which has its own relevant importance, are found throughout a variety of topics. The main components of an OM problem are the source of the opinion, the target of the opinion, and the evaluative expressions or comments made by the opinion holder. Liu, 2010a,b defines the OM problem. "Given a set of evaluative text documents D that contain opinions (or

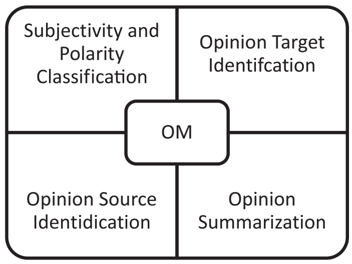

Figure 4 Opinion mining tasks (Liu, 2010).

sentiments) about an object, opinion mining aims to extract attributes and components of the object that have been commented on in each document d ∈ D and to determine whether the comments are positive, negative or neutral''. Generally, an opinion is expressed by a person (opinion holder) who expresses a viewpoint (positive, negative, or neutral) about an entity (target object, e.g., person, item, organization, event, service, etc.). A broad overview of the OM problem and its subcomponents is presented in Fig. 4. Every sub-problem holds considerable importance and has been discussed in various works. The following subsections describe the key tasks and approaches to each sub-problem of opinion mining.

3.1. Subjectivity and polarity classification

The core task of opinion mining is the automatic identification of opinionated text in documents (Montoyo et al., 2012, Cambria et al., 2013). The mined text is then categorized as objective and subjective. Most of the existing research concurs that objective text constitutes factual information while subjective text represents individual perspectives, beliefs, opinions or sentiments. Hence, most opinion mining systems employ the subjective text for opinion hood determination (Ortigosa-Hernández et al., 2012). While various approaches have been adopted for this subtask of OM, the most common include heuristics and discourse structure, coarse- and fine-grained analysis, key word and concept analysis (Cambria and Hussain, 2012).

According to Cook (1989), discourse is ''stretches of language perceived to be meaningful, unified, and purposive while text is a stretch of language interpreted formally, without context''. Opinion mining is greatly concerned with the context of the text, discourse analysis is an important element in the OM process. The current literature has defined several machine-learning approaches of opinion mining through discourse analysis. In this process, sentiment lexicons are created from huge corpuses using unsupervised techniques that are then applied for opinion hood determination. The existing research divides opinion hood determination into two subtasks, i.e., subjectivity classification and opinion polarity classification. Subjectivity classification techniques are used to classify terms, sentences and documents into opinion and non-opinion, while polarity classification techniques are used to classify opinionated terms into positive, e.g., good, and negative, e.g., bad, statements. Some works employ weighting techniques to identify the strength of subjectivity, i.e., weakly positive and strongly positive or weakly negative and strongly negative.

Subjectivity analysis has been performed at various levels Xu et al. (2011). Some systems, for example, consider the whole document as a single unit. Such systems extract all of the opinionated terms and sum up the opinion with polarity. They then conclude whether the document presents a positive or a negative opinion. Other systems rely on sentence-based analysis. In this type of system, each sentence is classified as positive or negative based on the terms and the context events. Accordingly, a sentence can contain positive and negative opinions. For example, the services of this hotel are great, but its rooms are very small. Therefore, as complex sentences may contain multiple opinions, recent works have focused on expression level opinion analysis (Liu, 2010a). The fine-grained level is termed level analysis as it identifies whether the term is positive or negative oriented.

Whitelaw et al. (2005) presented a good taxonomy based on the appraisal theory. The taxonomy of appraisal groups contains a hierarchy of attributes as shown in Fig. 5. Their paper exploited appraisal groups for movie review classification, a method that demonstrated significant results. However, taxonomy development requires manual effort and is typically domain dependent. An example of an analysis of an appraisal group as ''not very happy'' based on the above taxonomy is presented in Table 1.

Earlier studies of subjectivity analysis were conducted in the 1980's. Carbonell (1979) presented a theory of a computer model of a belief system based on subjective understanding. Based on this theory, he implemented a process model in a computer system called ''POLITICS''. The system was used to formulate human ideological reasoning in understanding the natural language text of international political events.

Wilks and Bein (1984) presented a model of beliefs for computer understanding of natural language that is inspired by human mental functioning. This model is based on the belief of the speaker about an entity and on the belief of a speaker about other speakers and vice versa. This paper proposed a knowledge structure of beliefs in multiple environments based on inference rules, an idea that laid the foundation for the extraction of the belief or opinion of a person about an entity and was gradually implemented using various techniques.

Wiebe (1990) presented an algorithm for the identification of subjective characters in sentences of a narrative text. The author's focus in this paper was particularly on the sentences that contained private statements or perspectives of the character. This algorithm, which is designed to identify, in the sentence, the character of the story who has presented his/her point of view depends on text patterns that represent how texts initiate, continue, and resume a character's point of view.

Hearst (1992) described a method for forcing sentence meanings into an abstract model and proposed semantic

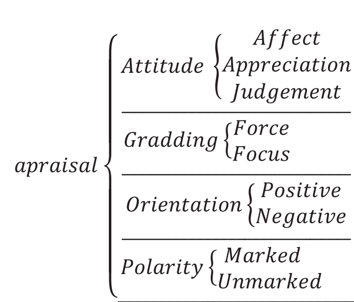

Figure 5 Taxonomy of appraisal (Whitelaw et al., 2005).

Table 1 Example of appraisal group of "not very happy" (Whitelaw et al., 2005).

Feature	Value	Feature	Value	Feature	Value
Attitude	Affect	Attitude	Affect	Attitude	Affect
Orientation	Positive	Orientation	Positive	**Orientation**	**Negative**
Force	Neutral	**Force**	**High**	**Force**	**Low**
Focus	Neutral	Focus	Neutral	**Focus**	**Neutral**
Polarity	Unmarked	Polarity	Unmarked	Polarity	**Marked**
"happy"		"very happy"		"not very happy"	

interpretation to determine the directionality of a sentence for implementation in a hybrid information access system. The intent of this paper was to present a text-based intelligence system that provides a means for answering questions about documents containing a user's perception and beliefs.

Sack (1994) described an idea about the extraction of a point of view from a text in a short extended abstract. Accordingly, the author proposed a system for understanding a realistic story based on the recognition of various perspectives and opinions in the story.

Wiebe (1994) developed an algorithm for understanding a psychological point of view in a text. This approach depends on a naturally occurring narrative and the regularities with respect to the author's point of view in the text. The author implemented the algorithm for an empirical evaluation.

Hatzivassiloglou and McKeown (1997) described a model for predicting the semantic orientation of adjectives. This method automatically retrieves semantic orientation information using indirect information collected from a large corpus and is based on an analysis of textual corpuses that correlates linguistic features or indicators with semantic orientation. Because the method relies on the corpus, it extracts domain-dependent information and automatically adapts to a new domain when the corpus is changed. This method was determined to be highly precise (more than 90%). Thus, the goal of the present work is to use the proposed method in a larger system to automatically identify antonyms and to distinguish near synonyms. The semantic orientation problem is key to subjectivity analysis.

Terveen et al. (1997) developed the system PHOAKS (people helping one another know stuff) system for sharing recommendations on the Web using collaborative filtering that recognizes and reuses recommendations. PHOAKS automatically recognizes, accumulates, and redistributes recommendations of Web resources mined from UseNet news messages.

Some authors have contributed significantly at different levels of the subjectivity analysis (Bruce and Wiebe, 1999; Wiebe, 2000; Wiebe et al., 1999) by presenting a case study to improve inter-coder reliability in discourse tagging based on statistical techniques. They also developed the first gold standard datasets for subjectivity analysis and classification of objective and subjective sentences, and they have worked on the identification of strong subjective clues.

Similarly, Hatzivassiloglou and Wiebe (2000), believing that adjectives are strong predictors of subjectivity, worked on the effects of different types of adjectives for subjectivity classification. This paper proposed a novel machine-learning classifier dependent on statistical methods and demonstrated the performance of the classifier by combining two indicators of the gradable adjectives.

Das et al. (2001) presented a methodology for extracting small investor sentiment from stock message boards. This paper used a hybrid technique that combined different classifier algorithms using a voting scheme. The authors performed an experiment related to time series and included a cross-sectional aggregation of message information. The results showed that this technique improved the quality of the resultant sentiment index, particularly in the presence of slang and ambiguity. The authors argued that these algorithms may be used to assess the impact on investor opinion of management announcements, press releases, third-party news, and regulatory changes.

Turney (2002) presented an unsupervised learning algorithm for classifying reviews as recommended (thumbs up) or as not recommended (thumbs down). The algorithm calculated the pointwise mutual information (PMI) of the candidate word for semantic orientation with two given seed words, i.e., "poor" and "excellent". The algorithm depended on patterns of two consecutive words where one word is an adverb or adjective used for orientation and the other word is used to represent the context. Adjectives and adverbs with different patterns of term categories were used for the semantic orientation, and a review was classified as recommended if the average semantic orientation of its phrases were positive and as not recommended if the average semantic orientation of its phrases were negative.

Pang et al. (2002) conducted a review classification at the document level whereby they determined whether a review is positive or negative. Based on an empirical evaluation, the authors proposed that standard machine-learning techniques outperform human-produced baselines. Thus, this paper employed three machine-learning methods (Naive Bayes, maximum entropy classification, and support vector machines) and determined that the support vector machine performed well. The authors further posited that some form of discourse analysis that uses sophisticated techniques rather than position-based extraction is necessary.

Although different terms, such as subjectivity analysis, sentiment analysis, affect analysis, belief and perception extraction, and point of view extraction, were used somewhat synonymously in numerous papers, the term "opinion mining", appearing in (Dave et al., 2003) for the first time, attracted the attention of researchers. The author proposed an opinion mining system for extracting consumer opinions from customer review data. With gradual improvements in this area, subjectivity analysis and opinion mining became a substantial field of NLP and Text Mining. Hence, over time, more interesting applications and developments in OM were soon introduced. More specifically, after **Dave's (2203) paper, OM research grew rapidly and diverse approaches were introduced to address this rapid growth. That said, OM research has been conducted in a variety of applications and in a variety of fields. (Tang et al., 2009; Tsytsarau and Palpanas, 2011).

Opinion lexical resources play a key role in identifying and evaluating statements of opinion (Esuli, 2008). "Opinion bearing words are instrumental in opinion mining" (Liu, 2011). Opinion lexical resources consist of a set of two types of words, i.e., positive polar words, which provide positive connotations to the text, e.g., good, excellent, nice, etc., and negative polar words. As previously mentioned a positive polar word, while negative polar words, which provide negative connotations to the text, e.g., bad, wicked, corrupt, ugly etc. In the early stages of OM, only the presence of adjective was considered as strong clues for opinion orientation (Hatzivassiloglou and McKeown, 1997; Hatzivassiloglou and Wiebe, 2000). However, its accuracy performance was relatively low.

Hatzivassiloglou and McKeown (1997) explain that conjoined adjectives have the same polarity. This work, which employed a log-linear regression model based on conjunction constraints to predict the polarity of conjoined adjectives, processed a large corpus to extract adjectives that were conjoined with the conjunctions and, or, but, either-or, neither-nor. The results of this study found that if the polarity of one adjective is known then the polarity of conjoined adjectives will be the same. The empirical results indicated that 82% of conjoined adjectives have similar polarity. A similar approach was employed by (Kanayama and Nasukawa, 2006) in a study of Japanese language words. The method is further extended by (Ding and Liu, 2007) in a study that added contextual polarity. All of these studies described pattern-based learning techniques from large corpuses.

Recent works have found that the syntactic pattern-based approaches have been improved. (Qiu et al., 2009) presented a pattern-based approach that exploits dependency relations of features and opinion terms to extract opinion words using a double propagation bootstrapping technique based on a seed list to identify the polarity of opinion words.

Another potential lexical resource for polarity identification is a dictionary. For example, various authors (Hu and Liu, 2004; Kim and Hovy, 2004; Riloff and Wiebe, 2003) have focused on a dictionary-based approach for polarity identification.

As previously mentioned, the other main task of OM is polarity classification. Polarity classification is used to classify opinionated terms, sentences or documents as positive, negative or neutral. Positive polarity means that the opinion holder's statement shows a positive attitude toward the target object/feature, while negative polarity means that the opinion holder's statement shows a negative attitude toward the target object/feature.

During the execution of the opinion mining process, term polarity is identified through an opinion lexicon. An opinion lexicon may consist of a small set of seed words with known polarities or it may comprise a large dictionary with term senses. If the term is similar to or synonymous with a positive polar word, then it is considered as positive. If it is similar to or synonymous with a negative polar word, then it is considered as negative. On the other hand, some opinion words are context dependent, e.g., "The battery life is short". Here, the word "short" has a negative polarity. In the statement, "The processing time of picture printing is short", the word "short" has a positive polarity. However, some opinion words do not depend on context, e.g., bad, good, excellent etc. The polarity of opinion words is changed when used with contextual shifters or negation words (not, never, no, neither, etc.) (Polanyi and Zaenen (2004)). Some authors have also worked on the strength of polarity. In short, considerable attention has been afforded to term polarity, and numerous approaches have been employed to identify such polarity in text.

In a study about two statistical classifiers, i.e., the naive Bayes (NM) and the hidden Markov model (HMM) for polarity identification, Salvetti et al. (2004) described the impact of lexical filtering on the accuracy of machine-learning techniques for polarity classification. Their paper described two types of lexical filters – one based on hyponymy and the other based on the hand-crafted rules according to the part-of-speech (POS) tags.

Baroni and Vegnaduzzo (2004) described a method for ranking a large list of adjectives according to a subjectivity score without any lexical resources or manual annotations. This method relies on a small set of seed words of 35 adjectives with manually tagged features where the subjectivity score is obtained using the PMI scoring technique. Similar approaches have been reported in other papers on lexicon generation whereby they begin with a small list of polar adjectives and expand by adding synonymous words generated by a dictionary search. Turney and Littman (2003) used the following seed list of positive and negative adjectives.

$$\text{Positive} = (\text{good}, \text{nice}, \text{excellent}, \text{positive}, \text{fortunate}, \text{correct}, \text{superior})$$

$$\text{Negative} = (\text{bad}, \text{nasty}, \text{poor}, \text{negative}, \text{unfortunate}, \text{wrong}, \text{inferior})$$

A similar approach is described by (Kamps et al., 2004) in which only two seed words (good, bad) are used. This paper used the following formula for finding the semantic orientation of words from the WordNet dictionary.

$$\text{SO}(\text{w}) = \frac{\text{distance}(\text{w}, \text{bw}, \text{bad}) - \text{distance}(\text{w}, \text{gw}, \text{good})}{\text{distance}(\text{good}, \text{bd}, \text{bad})} \quad (1)$$

In this equation, distance represents the shortest path between the word w and the seed words (good, bad) in the graph of the WordNet hierarchy. The seed word approach, described by (Kim and Hovy, 2004), is conducted by assigning scores for positive and negative words.

Kanayama and Nasukawa (2006) described an unsupervised method for building a domain-based lexical database for use in subjectivity classification in which they used context coherency in a corpus to select candidate polarity based on the overall density and precision of the coherency in the corpus. With respect to density estimation, a statistical technique was exploited for candidate refinement, and a final lexical list without any manual tuning of the threshold values was developed.

For his PhD thesis on automatic generation of lexical resources for OM, (Esuli, 2008) conducted fused gloss classification from WordNet (Stark and Riesenfeld, 1998) and developed a huge database (SENTIWORDNET[3]) of terms with senses (Table 2 represents a set of sample sense terms).

Other lexical resources (SenticNet, General Inquirer, Opinion Finder, VerbNet, ConceptNet, SentiFul, and Turney's

[3] This database is available from the web site http://swn.isti.cnr.it/.

Table 2 Sample of terms sense in SentiWordNet.

#POS	ID	Pos. score	Neg. score	Synset terms
Adj.	1740	0.125	0	Able#1
Noun	1740	0	0	Entity# 1
Verb	1740	0	0	Take_a_breath#1 suspire#2 respire#3
Adv	1837	0	0	Anno_domini#1 ad#1 a.d.#1
Noun	1930	0	0	Physical_entity#1
Adv	1981	0	0	Common_era#1 ce#1 c.e.#1
Adj.	2098	0	0.75	Unable#1
Noun	2137	0	0	Abstraction#6 abstract_entity#1
Adv	2142	0	0	Before_christ#1 bc#1 b.c.#1
Adj.	2312	0	0	Dorsal#2 abaxial#1
Verb	2325	0.125	0	Respire#2

Adjective List) have been developed for subjectivity classification and polarity identification. Poria et al. (2013), for example, presented a methodology for enriching SenticNet concepts with affective information by assigning the concepts an emotion label.

While the problem of polarity classification has been recognized as being of significant importance, considerably more research is needed. In response to this need, most of the recent research is devoted to exploring various dimensions of this sub-problem including topic relevancy and domain-based analysis language dependency and context dependency. (Ge and Houfeng, 2011; Li et al., 2010; Pak and Paroubek, 2011; Wilson, 2008). One of the recent works exploited topic relevancy to define polarity (Wiegand and Klakow, 2009) by examining the usefulness of a joint analysis of topic terms and polar expressions based on syntactic information to classify a document as positive or negative.

3.2. Opinion target identification

The opinion target refers to the person, object, feature, event or topic about which the opinion is expressed. Because opinion target identification is an essential feature of OM, an extensive overview of approaches related to opinion target extraction is necessary. The in-depth analysis of every aspect of a product based on consumer opinion is equally important for the public, the merchants and the manufacturers (Zhang and Liu, 2011). To compare reviews, it is necessary to automatically identify and extract those features that are discussed in the reviews. Hence, feature mining of products is important for opinion mining and summarization especially given that the task of feature mining provides the foundation for opinion summarization (Feldman et al., 2007). However, there are problems related to opinion target extraction. Generally speaking, if a system is capable of identifying target features in a sentence or document, then the system must also be able to identify opinionated terms or evaluative expressions in those sentences. Thus, to identify opinion targets at the sentence or document level, the system should be able to identify evaluative expressions. Moreover, some features are not explicitly presented, but rather, they are predicted from term semantics, also referred to as implicit features. A background study reveals that the process of opinion target extraction involves various natural language processing tasks and techniques such as pre-processing, tokenization, part-of-speech tagging, noise removal, feature selection and classification.

While in most sentences, the opinion targets are explicitly presented, in some sentences, it is implicit and therefore identified either through context dependency or distribution similarity. For explicit feature identification, a noun phrase with syntactic rules is generally employed (Ferreira et al., 2008; Hu and Liu, 2004; Popescu and Etzioni, 2005; Somprasertsri, 2010; Turney, 2002; Yi et al., 2003).

Opinion target extraction is similar to named entity extraction from an unstructured text. However, this is only true if the entity is presented in opinionated text. Hence, named entity recognition is an applicable technique for feature identification, though it requires further processing to identify whether the text containing the entity is opinion oriented or not. An initial study on named entity extraction appeared in a paper (Rau, 1991) wherein t author proposed heuristics and handcrafted rules to extract company names from a text. According to a survey on named entity recognition (Nadeau and Sekine, 2007), the research on this task was relatively slow until 1995, which is evidenced by the fact that only 8 publications were found for the period 1991–1995. However, after a major event, the MUC-6 (Grishman and Sundheim, 1996), research regarding named entity recognition accelerated. Since then, various events have occurred, and hence, a large number of papers have focused on this specific task by exploring different factors, such as the language factor, textual type or domain factor, and entity type factor. The objectives of such early works, however, were aimed primarily at such general purposes as text classification on the basis of topic, etc.

With respect to the automatic identification of opinion targets, several approaches have been employed. These approaches can be broadly divided into two major categories: supervised and unsupervised. Some authors, however, have also used the semi-supervised approach. The supervised learning approaches are based on manually labeled text. In this approach, a machine-learning model is trained on manually labeled data to classify and predict features in the reviews. Although supervised techniques provide good results for feature extraction, it requires manual work for the preparation of the training sets. Accordingly, this process is laborious, skill-oriented, time consuming, and, sometimes, domain dependent. Generally, the most widely used supervised techniques are decision tree, K-nearest neighbor (KNN), support vector machine (SVM), neural network, and naïve Bayesian classifier (Weiss et al., 2010). In contrast, unsupervised techniques do not require labeled data, and they automatically predict product features based on syntactic patterns and semantic relatedness an area in which extensive research has been conducted (Carenini et al., 2005; Gamgarn and Pattarachai, 2008; Hu and Liu, 2004; Nasukawa and Yi, 2003; Popescu and Etzioni, 2005; Somprasertsri, 2010; Toprak et al., 2010; Wei et al., 2010; Zhuang et al., 2006).

Kobayashi et al. (2004) used the unsupervised approach for the extraction of target features and opinion pairs and proposed a semi-automatic process for the extraction of evaluative expressions regarding target features and objects. This method extracts candidate evaluative expressions using text-mining techniques to accelerate the manual annotation process. The authors proposed this method to create an exhaustive list of evaluative pairs for many domains that could be used as training sets for the machine-learning process of feature level opinion mining.

Popescu and Etzioni (2005) used the unsupervised technique to extract product features and opinions from unstructured reviews. Their paper introduced the OPINE system, a system that is based on the unsupervised information extraction approach to mine product features from reviews. OPINE uses syntactic patterns for the semantic orientation of words to identify opinion phrases and their polarity.

Introducing an improved unsupervised method for feature extraction that uses the taxonomy of the product features, Carenini et al. (2005) developed a model based on user-defined knowledge to create a taxonomy of product features. However, while the results of the combined approach are greater than those of the existing unsupervised technique, the pre-knowledge base mechanism makes the approach domain dependent.

Holzinger et al. (2006) used domain ontologies based on tabular data from web content to bootstrap a knowledge acquisition process for extraction of product features. This method creates a wrapper for data extraction from web tables and ontology building. The model uses logical rules and data integration to reason about product specific properties and the higher-order knowledge of product features.

Zhuang et al. (2006), who specifically focused on domain movie reviews for opinion mining, proposed a multi-knowledge based approach that integrates the WordNet, a statistical analysis and a movie knowledge base. The experimental results show the effectiveness of the proposed approach in movie review mining and summarizing and exploits grammatical rules and the keyword list for the identification of feature-opinion pairs in reviews. The authors used a dependency graph to extract pairs of opinion targets.

Believing that appraisal expression is a fundamental task in sentiment analysis, Bloom et al. (2007) described an unsupervised technique for feature and appraisal extraction. The appraisal expression is a textual unit that expresses an evaluative attitude toward some targets. In their paper, the researchers proposed evaluative expressions to extract opinion targets and determined that the system effectively exploited the adjectival appraisal expressions for target identification.

Ben-David et al. (2007) proposed a structural correspondence learning (SCL) algorithm for domain classification, an idea that is dependent on perception to obtain a prediction of new domain features based on training domain features. The authors described the conditions under which a classifier trained on the source domain can be adapted for use in the target domain. This model was inspired by feature-based domain classification, and Blitzer et al. (2007) extended the structural SCL algorithm for opinion target identification.

Lu and Zhai (2008) proposed the automatic integration of opinions expressed in a well-written expert review with opinions scattered in various sources such as blogs and forums. Their paper proposed a semi-supervised topic model that addresses the problem in a principled way, and accordingly, they conducted experiments by integrating opinions about two different topics, i.e., a product and a political review. The intent of their study was to develop a generalized model that could effectively extract opinion targets in multiple domains.

Ferreira et al. (2008) presented an extended pattern-based feature extraction method using a modified log likelihood ratio test (LRT), which was initially employed by (Yi et al., 2003) for target identification. In their paper, they also presented an extended annotated scheme, which was initially presented by (Hu and Liu, 2004), for product features and a comparative analysis between feature extraction by incorporating association mining and LRT techniques. While the association rule mining for target extraction was initially implemented by (Hu and Liu, 2004) for target extraction, it was extended by Chen et al. (2010) to use semantic-based patterns for the refinement of frequent features and the identification of infrequent features.

Kessler et al. (2010) presented an annotated corpus containing mentions, co-references, meronymy, sentiment expressions, and modifiers of sentiment expressions and including neutralizers, negators, and intensifiers. The corpus of their paper addresses automotive domains, and accordingly, it facilitates the quantifying of sentiment phenomena and target features in automotive domains.

Lin and Chao (2010) studied feature-based opinion mining with a specific emphasis on hotel reviews. His model depends on a manually annotated corpus for tourism-related opinions that are collected from blogs. The proposed model used a supervised machine-learning approach to train classifiers for tourism-related opinion mining.

One of the latest works on feature level analysis of opinions was reported by (Zhai et al., 2011). In their study, they described a semi-supervised technique for feature grouping as this technique is an important task in the summarization of opinions. As the same features can be expressed by different synonyms, words or phrases, to produce a useful summary, these words and phrases were grouped. With respect to feature grouping, the process generated an initial list to bootstrap the process using lexical characteristics of terms. This method has empirically demonstrated good results.

Goujon (2011) presented a text mining approach based on linguistic knowledge to automatically detect opinion targets in relation to topic elements. Exploiting linguistic patterns for target identification, the paper focused on the identification of opinion targets related to the specific topic.

Most of the machine-learning techniques employed linguistic features for opinion target identification (Liu, 2010a, Pang et al., 2002, Zhuang et al., 2006) as sentiment or opinion words and other semantic features of language are important for supervised machine-learning approaches (Jin et al., 2009; Wong and Lam, 2008). As a consequence, existing research has explored many types of linguistic features for evaluative expressions and opinion target identification. Some of the more widely reported features are identified herein.

The bag-of-words is used in several approaches for document classification and named entity extraction. This feature incorporates the use and frequency of individual words or phrases, and it disregards contextual and syntactic relations of words in sentences or documents. Term frequency inverse document frequency (TF-IDF) models have exploited the bag-of-words representation for document classification. The bag-of-words feature has also been effectively employed for opinion target and sentiment extraction (Nigam and Hurst, 2004; Qu et al., 2010).

Two of the valuable contributions of NLP research are text parsing and word categorization. Parsing techniques categorize words into their parts of speech (adjectives, adverbs, verbs, nouns, etc.) The adjectives and adverbs have been especially exploited for sentiment classification. Similarly, nouns occurring with sentiment words have been used to identify opinion targets and opinion sources through both supervised and unsupervised approaches (Hatzivassiloglou and Wiebe, 2000; Liu et al., 2005; Popescu and Etzioni, 2005; Turney, 2002; Yi et al., 2003).

Some common opinion words are used to identify strictly sentiment expressions. Such words include good, bad, like, dislike, ugly, pretty, wonderful, amazing, excellent etc. Machine-learning techniques use these words as seed lists to generate opinion lexicon. Hu and Liu (2004) have provided an extensive list of approximately 6800 opinion words along with their polarities. The opinion words are used to extract opinion targets based on the nearest noun phrases. These practices have been reportedly used in both supervised and unsupervised learning techniques (Changli et al., 2008; Esuli, 2008; Pang and Lee, 2008; Somprasertsri, 2010; Wilson, 2008).

Another interesting language feature is the contextual valance shifter, which is used to flip sentiment expressions from positive to negative and negative to positive. An extensive study regarding this feature is that of (Polanyi and Zaenen, 2006). Similarly, (Kennedy and Inkpen, 2006) formulated the effect of valence shifters on classifying movie reviews, while Longton and Adam (2008) described an empirical analysis of lexical polarity and contextual valence shifters for opinion classification.

In another attempt at opinion extraction, some authors have employed comparative and superlative sentences. In these works, the authors exploited the language terms for comparative opinion identification and classification (Carenini et al., 2005; Feldman et al., 2007; Jindal and Liu, 2006; Xu et al., 2011).

It is common and natural to understand a text through its use of words, phrases and sentences. Hence, it is not uncommon to understand extracted opinions from a text using opinion words, phrases or sentences. Furthermore, every language is based on grammar rules, which provide a sequence to words in sentences according to grammatical categories. Accordingly, the syntactic patterns with sequences of word categories, grammar dependencies, and contextual and semantic relationships provide the best clues when using machine-learning techniques to classify and identify opinions and targets of opinion (Di Caro and Grella (2013)). A number of unsupervised learning approaches depend on syntactic and contextual patterns (Ferreira et al., 2008; Hu and Liu, 2004; Kobayashi et al., 2004; Lu et al., 2011; Toprak et al., 2010; Wei et al., 2010; Yi et al., 2003; Zhai et al., 2011). In addition, the base noun phrase (BNP) is often used to represent an entity. The base noun phrase refers to the sequence of nouns (NN) or of adjectives (JJ) and nouns. For example, NN, NN NN, JJ NN, NN NN NN, JJ NN NN, JJ JJ NN, etc., Position-based patterns have been used to identify the relations between opinion words and target features (Fei et al., 2006; Nakagawa et al., 2010; Zhongchao et al., 2004). A recently published work describes opinion word expansion and target identification through dependency relations (Qiu et al., 2011).

3.3. Opinion source identification

An opinion holder or the source of an opinion is the person or medium who presents the opinion. The opinion holder or opinion source is important when authenticating the opinion as well as the strength, application and classification of the opinion, as the quality and reliability of an opinion is greatly dependent on the source of that opinion. For example, a statement may be reliable if the holder or source that produces it is authentic. An expert opinion has greater strength than does the opinion of an ordinary person. Opinions can also be classified based on the opinion holder. For example, a doctor's opinion when making decisions related to health and medical treatment while public opinion is important for a politician. Thus, it is important to identify the source or the holder of the opinion. Identifying the opinion holder is a natural language processing problem that has been the subject of numerous studies over the years.

Various authors and researchers have reported certain problems related to the identification of opinion sources. Opinion sources can be expressed directly or indirectly from other sources in a sentence (Choi et al., 2005). For example, in the sentence, "Prime Minister Yousuf Raza Gilani said regional peace cannot be guaranteed until the core Kashmir issue with India is resolved". In this statement, Prime Minister Yousuf Raza Gilani is the direct opinion holder of the statement regarding regional peace. However, in the sentence, "Ordinary Pakistan citizens do not believe Osama bin Laden is dead and want proof, according to this report", the indirect source of the opinion is the report, while the direct source is the ordinary Pakistani citizens. Thus, a sentence can consist of multiple sources of opinions. Therefore, to identify the opinion holder, the category of the terms of a language must be known. Each opinion document has a set of sentences related to an opinion. As a complete sentence represents a relation between all of the components of the opinion, some sentences may have an opinion holder while others may not. Therefore, researchers are attempting to identify the text span related to the opinion holder or opinion source and the relationship between the terms. Accordingly, a number of approaches have been designed to identify the opinion holder.

Kim and Hovy (2005), when addressing question and answer techniques related to opinion texts, considered the problem of identifying the opinion holder. In fact, their paper focused on the importance of the opinion holder, explaining that the opinion holder's identification can be used independently to answer several opinion questions. This system used the maximum entropy (ME) model trained on manually annotated data to learn the syntactic features used when identifying opinion holders.

Kim and Hovy (2006) presented a method for sentence-based identification of opinion with its holder and topic from online text. Their approach used the semantic structure of a sentence based on opinion bearing a verb and an adjective, and they adopted a mechanism of semantic role labeling based on FrameNet data for opinion holder and topic identification. They also employed a clustering technique to predict the most probable frame for a word that is not defined in FrameNet.

Bethard et al. (2006) proposed an extension of semantic parsing techniques combined with additional lexical and syntactic features to extract propositional opinions and opinion holders. This approach used semantic roles to identify propositional opinions predicated from semantic frames using FrameNet.

Choi and Cardie (2005) presented a model for the identification of sources of opinions, emotions, and sentiments. Their model incorporated a hybrid approach that combined conditional random fields (Lafferty et al., 2001) and a variation of auto slog (Riloff (1996)). The hybrid approach successfully improved results over previous approaches.

Youngho et al. (2007) presented the anaphora resolution-based model for opinion holder identification, a method that exploited lexical and syntactic information for opinion source identification. Their study used online news documents and achieved 72.22% and 69.89% accuracy for the classification of non-anaphoric opinion holder resolution and the anaphoric opinion holder identification, respectively.

Josef Ruppenhofer et al. (2008) described a mechanism for opinion holders and target extraction from online blogs and argued that while automatic semantic role labeling systems (ASRL) provide an important contribution in mining the opinion components, such as opinion holder and opinion targets, such systems cannot solve all of the problems. In this work, the authors performed a manual annotation of opinions, sources, and targets from various genres through human experts. Based on their observations, which was a manual process, they presented a linguistic phenomenon for discourse analysis to identify sources and targets.

Ku et al. (2009) presented a two-phase model for opinion and opinion holder identification, adopting the SVM for opinion recognition and conditional random field (CRF) for opinion holder labeling. This method achieved a higher F-score than did other methods.

Lu (2010) proposed a dependency parser for Chinese news texts that would identify opinion holders by means of reporting verbs and would identify opinion targets by considering both opinion holders and opinion-bearing words. The results of this approach were significantly higher than the other approaches presented in the NTCIR-7 MOAT for the same data sets of Chinese language.

Some recent studies on opinion holder identification in different languages are noteworthy. For example, Das and Bandyopadhyay (2011) have worked on extracting the opinion holder from Bengali language blogs. Their study employed syntactic dependency to extract opinion expressions from Bengali language text using phrase-based similarity. Similarly (Mukund et al., 2011) have studied automatic extraction of opinion holders and targets from the Urdu newswire. In their paper, candidate patterns of word sequences related to opinion are extracted using a linear kernel. A rule-based algorithm is then employed to distinguish between opinion holder and opinion targets. The algorithm results achieve a 58.06% F-Score using sequence kernels and a 61.55% F-Score using a combination of sequence and linear kernels.

Chen et al. (2011) have exploited various structural and semantic features to extract opinion statements from the English text. They built tagging models based on the conditional random field (CRF) techniques and on the combinations of linguistic factors, i.e., morphology, orthography, predicate-argument structure, syntax and simple semantics. The authors determined that the CRF models with MPQA corpus for training and testing performed best in opinion holder identifications.

Wiegand and Klakow (2011) have exploited the contexts of prototypical opinion holders to automatically extract opinion holders. The prototypical opinion holders are described as a group of experts or analysts whose professions or occupations are to form and express opinions toward specific items. This required the use of a supervised learning algorithm where prototypical contexts were considered as labeled training data and rule-based classification, which uses predicates that frequently co-occur with mentions of the prototypical opinion holders.

From the above works, it is concluded that the opinion source identification problem has attracted a great deal of attention in recent years and that while most of the issues have been addressed, there remain some problems, such as context aware sources, semantic annotations, and anaphora resolution, that require further study.

4. Opinion summarization

The analysis of existing opinion-related dimensions can be performed at various levels of granularity. Some applications consider the whole document as a single entity for opinion analysis, while other applications focus on sentence level and still other applications focus on the expression or phrase level and term level. The finest-grain level is the term level analysis.

Document level opinion summarization is a broad level of opinion mining, which is sometimes referred to as topic level opinion mining. This level summarizes the opinion about a given topic. Topic-based opinion summarization sums up the overall positive and negative opinions expressed in documents. Hence, the system of opinion mining visualizes the opinion scores according the positive and the negative scores. While various approaches have been employed for document level opinion mining (Dave et al., 2003; Kim and Zhai, 2009; Pang et al., 2002; Turney, 2002), the following steps are normally followed (an overview of the overall process is presented in Fig. 6).

1. Extract all opinion terms after pre-processing the document.
2. Classify the opinion terms as positive/negative.
3. If the number of positive opinion terms exceeds the number of negative opinion terms, the document is considered to express a positive opinion; if the reverse holds, the document is considered to express a negative opinion.

Turney (2002) discussed an interesting model for review ranking called "thumbs up or thumbs down" whereby an unsupervised model for document polarity identification based on lexical resources is presented. Turney (2002) posits that for any input document d having terms T where each term t belongs to T, if the polarity is (1, 0, −1) where 1 represents positive polarity, 0 represents neutral polarity and −1 represents negative polarity, then if the sum of the polarities of all terms is greater than 0, the document is considered positive; if the sum of the polarities of all terms is less than 0, then

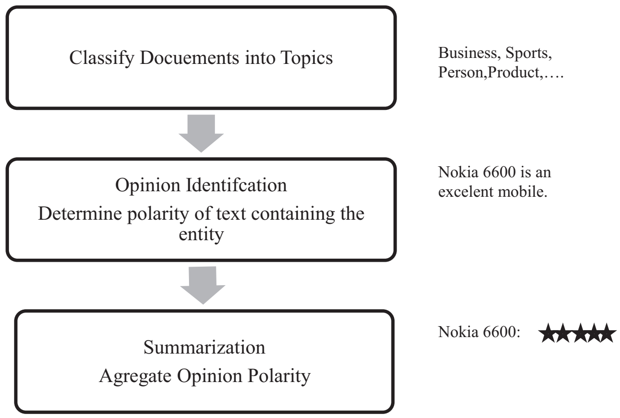

Figure 6 Overview of topic based opinion summarization (Kim and Zhai, 2009).

the document is negative; and if the sum is equal to 0, then the document is considered to be neutral. The model is defined as given below.

$$Polarity(d) = \begin{cases} Positive & \sum_{t \in T(d)} o(t) > 0 \\ Negative & \sum_{t \in T(d)} o(t) < 0 \\ Neutral & \sum_{t \in T(d)} o(t) = 0 \end{cases} \quad (2)$$

Concentrating on the corpus free approach for review classification, Pang et al. (2002) employed three machine-learning algorithms (naïve Bayesian, maximum entropy, and support vector machine) to rank the documents. However, as this method requires training regarding interpretation of data collected from rated reviews, the problem of domain dependency and a pre-knowledge base remains unsolved.

Dave et al. (2003) formulated a model for review classification based on features for machine learning and classification. Their approach depends on a manually annotated corpus whereby each of the annotated corpuses is described by features related to positivity and negativity. The test document is classified through an annotated corpus using similarity scores. The classifier depends on information retrieval techniques for feature extraction and scoring. As such, this paper proposed that a group of sentences or a full review can provide a more reliable analysis than an individual sentence as a sentence-based performance analysis is limited due to noise and ambiguity.

Chen et al. (2006) described a model for review classification. Their work is based on a set of research questions regarding opinions or reviews.

- What are the differences between positive and negative reviews?
- What is the origin of a particular opinion?
- How do these opinions change over time?
- To what extent can differentiating features be identified from an unstructured text?
- How accurately can these features predict the category of a review?

This study first analyzed terminology variations in a huge number of reviews based on syntactic, semantic, and statistical associations and used term variation patterns to represent underlying topics. This method uses a log likelihood ratio test algorithm to select the most predictive terms, and thus, they are potentially exploited for classification of conflicting reviews. The proposed algorithm indicates approximately 70% accuracy in the conflicting review classification.

Finn and Kushmerick (2006) described an approach to classify documents as either subjective or objective. This paper proposed an automatic genre analysis, i.e., distinguishing documents according to style. This method investigates the use of machine learning for automatic genre classification. Furthermore, these authors introduced the concept of domain transfer through genre classifiers so the classifier could be used for multiple topics in a single document. This paper used different features when building genre classifiers for multiple-topic domain classification.

Kim and Zhai (2009) described a novel model for the summarization of contradictory opinions. This model requires that two sets of opinion-oriented sentences (positive and negative) be extracted from input documents and then, based on these sets of sentences, the algorithm generates a comparative summary of the opinion. This framework relies on measuring the content similarities and contrast similarities of the sentences.

An additional dimension of the OM problem is feature level opinion summarization. In feature level opinion mining, the opinion is summarized for every feature. Three main steps are involved in feature level opinion summarization, as given in Fig. 7. "Recent solutions for sentiment analysis have relied on feature selection methods ranging from lexicon-based approaches where the set of features are generated by humans, to approaches that use general statistical measures where features are selected solely on empirical evidence" (Duric and Song (2011)).

5. Research issues and challenges

As the Internet and Web technologies continue to grow and expand, the space and scope in the area of information retrieval is also expanding. Hence, researchers take a keen interest in solving the problems associated with OM, which is one of the subareas related to information retrieval and knowledge discovery from the Web. OM is considered an interesting area of research due to its many applications in society. Over the past few years, the ubiquitous dependency on e-marketing, e-business, e-banking, product recommendations, political reviews, and other social activities has attracted research communities worldwide. Special attention has been given to customer mining of reviews as they seek information from the Web about a product and/or the product's reputation. A number of sub-areas of this topic have been explored and extensive research has been reported on each of the sub-problems (Tsytsarau and Palpanas, 2011; Zhai et al., 2011).

Despite numerous research efforts, the current OM studies and applications still have limitations and margins for improvement. Accordingly, OM suffers from a number of problems, such as accuracy, scalability, quality, standard of data, natural language understanding comprehension, among others.

Some of the major challenges related to natural language processing, such as context dependency, semantic relatedness and ambiguity, have made OM difficult. As practical applications require high accuracy, some of the work must still be

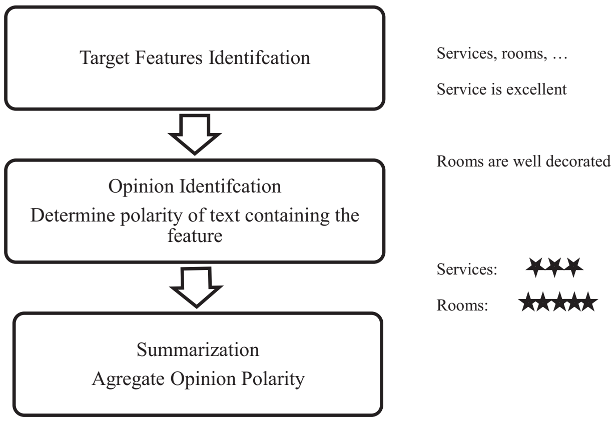

Figure 7 Feature level opinion mining (Tsytsarau and Palpanas, 2011).

performed manually because of the challenging problems with the NLP. For example, the problem of ambiguity, context dependency, and complex and vague sentences require further attention to improve the accuracy of the data analyses. While private blogs are an important source of data for OM, the blog posts are typically written informally and are highly diverse and thus subject to inaccuracies and misinterpretations in analysis.

To execute the OM process, opinions are collected from the World Wide Web. The Web is a huge and diverse source of information that collects and summarizes opinions from a diverse, multi-dimensional, and redundant data source and, as such, it poses a tremendous challenge for a number of reasons. As a result of these issues, opinion collections are currently limited to specific websites, or opinions are collected on a large scale in an ad hoc fashion from different sites and then processed. On-line analytical processing systems are only possible if there is an efficient system to aggregate and summarize the large collection of text (Tsytsarau and Palpanas, 2011).

Most of the existing research regarding opinion mining is domain dependent, which limits the scope of the application as well as the generalization of the information. Machine-learning systems, which are domain dependent, require that data be manually labeled, a difficult task to manage. Hence, generalized domain independent algorithms are needed for the automatic identification and classification of opinion components.

Scalability of the data is another major challenge in the field of OM. The main goal of OM research is to provide a search engine on the Internet that provides fast, accurate, and well-summarized results of queries regarding opinions of people about anything and everything in the world. However, the limited speed, the huge volume of data and the high dimensionality of the data do not allow for a desirable solution. Thus, complex NLP and text processing algorithms as well as scalable solutions are needed to alleviate these overwhelming concerns and to improve efficiency.

Also presenting a huge challenge in the face of OM is the availability and accessibility of a standard dataset. Few data are currently available to facilitate the classification, bench marking and analysis of the derived text. The absence of a standard of measure that evaluates the results of the overall steps of the OM process remains a concern as well because the existing measurement techniques conduct only partial evaluations, such as simple aggregation of data. Performing such aggregations with respect to opinions is not sufficient for a qualitative analysis of opinions as it is also essential to conduct an analysis of conflicting opinions. Tsytsarau and Palpanas (2011) such an analysis of conflicting opinions is termed contradictory analysis (Tsytsarau and Palpanas, 2011), which is a new direction in the field of OM. Thus, to date, little research has been conducted in this area (Choudhury et al., 2008).

Another main challenge in this area is the quality of reviews. Because the Web is openly accessible to everyone, anyone can post a review, a situation that brings into question the quality of a review or opinion. When individuals are making decisions based on the reviews accessed from the Web, it is important that the reviews be credible and of high quality. However, only limited work has been conducted on opinion quality determination. For example, some researchers who have explored this issue have used the profiles of the reviewers as a means to verify the quality of a review (Lu et al., 2010). Because of an increasing trend to use online reviews when determining a product's reputation, stakeholders are including spam reviews on their sites to enhance their products' reputations. Therefore, as it is necessary to identify spam reviews, some studies have focused on spam detection (Chen et al., 2009; Jindal and Liu, 2007; Lim et al., 2010). Even so, this task remains a challenging problem. "An accepted source for information or advice is either an expert on the subject, or a persuasive force to check the quality of opinions that they are believable and trustworthy" (Conrad et al., 2008). Open forums and blogs often suffer from a lack of expertise and the inability to present text in the appropriate way.

Opinions are collected in two formats, i.e., structured questions–answers (Kim and Hovy, 2005) and plain text (Somprasertsri, 2010). Mining opinion from structured data is not the main issue, however. Rather, opinion mining from unstructured text is the problem that invites numerous challenges (Liu, 2010a,b). For example, the identification of the opinion components, context dependency, word sense ambiguity, multilingual effects, and noise in the text, etc. are concerns that are still challenging NLP and affecting opinion mining efficiency.

One of the important problems of OM is the identification of opinion targets from unstructured text. The opinion target is defined as the entity or features of an entity about which an opinion is expressed. The sub-tasks related to opinion target identification include opinion identification, the relevancy of features and features classification, which depends on natural language processing and computation techniques as described in the background study (Somprasertsri, 2010). Another problem is domain dependency, which can be a problem when the target features that are relevant to a specific domain take on different meanings or interpretations when in a different domain. Accordingly, creating a knowledge base for each domain with relevant features and attributes is a difficult but real concern. Hence, generalized procedures are used to identify and disregard the domain dependency of features (Balahur and Montoyo, 2008; Ben-David et al., 2007; Qiu et al., 2009).

6. Conclusion

This work presents an in-depth background study about opinion mining. The subject has attracted considerable attention since the 1990s, specifically with respect to subjectivity analysis and lexical resource generation. Based on web content and the advancements of Web 2.0 technology, this study indicates that considerable attention has been given to opinion mining in the last few years. This study exploits social networks and web blogs, the most popularly employed sources for opinion retrieval, to examine opinion representation, opinion mining models, opinion components, and related problems. A number of computational models and linguistic features related to opinion mining, component analysis and opinion-target identification are thoroughly discussed.

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