Research on Fine-Grained Sentiment Analysis

You Jun[1], Xiong Jun[2]

[1]School of Economics and Management, Chongqing University of Posts and Telecommunications, Chongqing 400065, China;

[2]School of Economics and Management, Chongqing University of Posts and Telecommunications, Chongqing 400065, China;

[a]youjun@cqupt.edu.cn, [b]751376296@qq.com

Abstract

Using the literature research method to understand the current research of online product comments mining, which extends from coarse-grained opinion mining to fine-grained opinion mining. This paper mainly summarizes three main tasks of fine-grained sentiment analysis, including evaluation feature extraction, identification of subjective comment sentences with features opinion and sentiment analysis of the subjective comment sentence. On the basis of clarifying its main tasks, introduces relevant technologies and research progress , points out their advantages and disadvantages about them. This study is helpful to understand the key problems and methods of fine-grained sentiment analysis.

Keywords

Sentiment analysis; fine-grained; opinion mining.

1. Sentiment Analysis

With the explosive growth of social media (such as post bars, forums, microblogs, and posts on social networking sites) on the web, individuals and organizations are increasingly using the content of these media to make decisions. Now, if consumers want to buy a product, they are no longer subject to comments from family and friends because there are a lot of user comments and discussions on the product online. For an organization, polls may no longer be needed to collect public opinion because there is a large amount of such public information. However, finding and monitoring comments online and extracting the information contained remains a different task. Manual identification and analysis of a large number of opinion texts is inefficient, so opinion mining techniques have received more attention in recent years.

The so-called opinion mining, also called sentiment analysis, is a process of effectively extracting, analyzing, and generalizing reasoning that includes people's subjective comments on opinions, attitudes, and emotions of entities such as product services, organizations, and events. Opinion mining involves related technologies such as natural language processing, machine learning, deep learning, sentiment classification, and emotional element extraction. The objects of opinion mining cover a large number of product reviews in e-commerce websites, forum posts, and microblogs.

2. Coarse-Grained Sentiment Analysis

According to the different granularity of the comment text analysis, the sentiment analysis level can be divided into document level, sentence level, and aspect level sentiment analysis, and according to the granularity of sentiment analysis, the sentiment analysis can also be divided into coarse grained sentiment analysis and fine-grained sentiment analysis . In general, coarse grained sentiment analysis covers document level sentiment analysis and sentence-level sentiment analysis. Document level sentiment analysis is the shallowest analysis of all types of sentiment analysis. The document level sentiment analysis treats the entire document as a basic unit of information. The main task is to determine the overall sentiment of the comment text, that is, to determine whether the article (such as the entire online comment) conveys an overall positive or negative opinion. document level sentiment analysis mainly adopts unsupervised methods and machine learning methods. Turney (2002) uses a relatively simple unsupervised learning model to classify textual comments into positive and negative. Firstly, the phrases of adjectives and adverbs are selected and the sentiment dictionary is expanded according to the corresponding calculation formula. The average sentiment tendency of all sentiment words in the article is calculated according to the sentiment dictionary, and the average value is used as the emotional tendency of the whole article[1]. Sentence level sentiment analysis uses a single sentence as the basic unit of analysis and determines whether each sentence expresses positive or negative opinions. H.Yu and V.Hatzivassiloglou (2003) proposed an unsupervised subjective classification method. They took the subjective adjectives of WordNet as the seed words and adopted Simfinder kit to measure the semantic similarity of each word, thus screening out subjective sentences. Commentary sentences; Unigram, Bigram, and Trigram are used as sentiment classification features respectively, and naive Bayesian algorithm is used to make emotional judgments on subjective sentences[2]. In many cases, sentiment analysis at the document level or sentence level is useful. However, It is not sufficient for valuable decisions (for example, whether to purchase products), and there are still several shortcomings in practical applications: First, the integrity of the emotion classification analysis have already can't satisfy people's needs, especially for businesses and consumers, they begin to pursue more detailed and accurate sentiment analysis. Second, although a sentence may have an overall positive or negative emotional tendency, the components in the sentence may express opposite views. A positive review of the product does not mean that the reviewers like all the features or attributes of the product. Negative comments don't mean that reviewers don't like everything. For example, the sentence "The plot of the movie is cliched, but the actors perform well, and overall is not bad" evaluates the two characteristics of the film (entity), namely the plot and the actors. The emotional attitude towards the movie plot is negative, but the actor is good, and the overall evaluation is positive. In fact, comments at the document level and sentence level do not provide detailed information about the specific characteristics or attributes of the evaluation object.

3. Fine-Grained Sentiment Analysis

For the increasingly sophisticated data analysis needs and complex and diverse commentary environment, fine-grained sentiment analysis is the focus of current scholars. B. Liu (2016) believes that subjective sentences can be divided into five parts: the evaluation object, the attributes or characteristics of the evaluation object, the emotional words corresponding to the evaluation object attributes, the publisher of the evaluation, and the evaluation release time[3]. Fine-grained sentiment analysis goes deeper into the product feature level, which is mainly to obtain more specific elements such as evaluation subject, evaluation feature and evaluation feature corresponding opinion words from the review text. Therefore, the main tasks of fine-grained sentiment analysis can be summarized into three aspects: First, evaluation feature extraction. Second, identification of subjective comment sentences with features opinion. Third, sentiment analysis of the subjective comment sentence.

3.1 Evaluation feature extraction

Feature extraction, which can also be seen as an information extraction task. In the context of sentiment analysis, opinion words mostly have their target objects for evaluation. Target objects are usually features or topics extracted from sentences. Therefore, it is important to identify each opinion expression and its target object from a sentence. Here, we will focus on the extraction of explicit features. There are three main methods for feature extraction: (1) Feature extraction based on frequent nouns and noun phrases. (2) Feature extraction based on supervised learning. (3) Feature extraction based on topic model.

3.1.1 Feature extraction based on frequent nouns and noun phrases

After a preliminary analysis of a large number of comment texts, it can be seen that the evaluation feature words are mostly nouns or noun phrases. Starting from a large amount of corpus in a certain field, Hu and Liu (2004) used the data mining Apriori algorithm to automatically extract nouns and noun phrases in the comment text and calculate the corresponding occurrence frequency. Only nominal words whose frequency is higher than a certain threshold can be retained to form the feature word database. The frequency threshold can be determined through experiments[4]. Simple as this method is, it actually works. The reason is that when people comment on a feature or attribute, the words they use are usually limited, and those often mentioned are higher-accuracy evaluation features. Those less common nouns may not be features or less important features. Some commercial companies have made some changes to improve the accuracy of this method. Popescu et al.(2009) further improved the accuracy of feature extraction by screening the candidate nominal phrases. Specifically, the point mutual information (PMI) score between the candidate nominal phrases and the actual product feature words was calculated to filter out those noun phrases that might not be characteristics of the product. The experimental results showed that the accuracy of this method was 22% higher than that of Hu.

The feature recognition method based on frequent items is relatively simple, but the accuracy of this method is not high, and it is easy to mistake high-frequency non-product feature words into feature words, and it is easy to mistake low-frequency feature words.

3.1.2 Feature extraction based on supervised learning

Feature extraction can be regarded as a special case in the field of information extraction. Therefore, the supervised learning-based information extraction method can be applied to feature extraction tasks. Jin and Ho(2009) constructed a lexicalized hidden markov model for machine learning, which integrates language features naturally and can efficiently identify complex product entity features and opinion[5]. Kobayashi et al.(2007) first used dependency trees to find candidate features and pairs of opinion words, and the above below clues and co-occurrence frequency were classified features, then used hierarchical classification method to train candidate pairs and classify them. The experimental results show that adding contextual cues and co-occurrence frequency features improves the classification effect of the model and has good portability[6]. Manevitz and Yousef (2001) used single-class SVM (one-class SVM) algorithm in supervised learning field to extract the vocabulary of evaluation objects. The main advantage of single-class SVM is that for the binary classification problem, only one category of the training data set needs to be annotated. At the same time, clustering is carried out according to the semantic similarity of evaluation features, and ranking is conducted according to the occurrence frequency of evaluation features, so as to obtain the most important evaluation features[7].

Although supervised learning method is effective in the condition of complete training corpus, it has not been widely used. In the current situation of increasing Internet information, previously marked corpus is being eliminated at a faster and faster speed, and the new manual marking of comment information takes time and energy.

3.1.3 Feature extraction based on topic model

In recent years, topic model has become a mainstream method to extract topics from a large number of text documents. The topic model, which belongs to the unsupervised learning domain, assumes that each document contains several topics which are subject to a probability distribution. The topic model is basically a document generation model, which specifies the probability process of generating each document. There are two main thematic models: Probabilistic Latent Semantic Model (PLSA) and Potential Dirichlet Distribution Model (LDA). Mei et al.(2007) proposed a theme-emotion hybrid (TSM) model to extract both theme and emotional polarity. The TSM model made an in-depth analysis of blog articles, revealed the main themes of the articles, connected each theme with the polarity of emotions, and built a dynamic model for each theme and its corresponding emotions. The results show that the TSM model is effective for thematic sentiment analysis[8]. After that, other studies mostly used LDA model to extract evaluation features. Brody and Elhadad(2010) introduced a local topic model that works at the sentence level and uses a small number of topics to automatically infer evaluation features[9]. At the same time, an unsupervised method for automatically extracting the seed sets of positive and negative adjectives is proposed, which replaces the manual construction method commonly used in literature. Zhao et al.(2010) proposed a new theme modeling method, which combined the maximum entropy (max-ent) component and standard generation component to automatically separate feature words and opinion words. The results show that the model can effectively identify feature words and opinion words with small training data[10]. Weijun She et al.(2016) applied the SA-LDA model combining LDA and syntactic analysis to product feature extraction. First, features in corpus were extracted and clustering was used to construct feature sets. Use the improved SA-LDA model to learn the features of each comment topic in the test set[11].

In practical research, some shortcomings of thematic model limit its expansion in sentiment analysis task. The main disadvantage of this model is that it needs a large number of training sets and several parameter adjustments to obtain more accurate results. Secondly, the subject model is suitable for extracting frequently appeared subjects or evaluation features in the context of massive texts, but the effect of extracting frequently featured words in the context of a small number of comment data sets is poor.

3.2 Subjective commentary recognition with feature-opinion pairs

Sentences are usually divided into objective comment sentences and subjective comment sentences. Objective comment sentences state factual information and subjective comment sentences express subjective views and opinions. Fine-grained sentiment analysis task focuses on how to extract the subjective comment sentences with feature-opinion pairs from the comment text. Currently, the existing extraction methods are divided into two categories: natural language processing and semantic analysis.

Opinion words are usually closely integrated with evaluation features. Therefore, natural language processing often uses window-wide methods to extract feature-opinion pairs, specifically focusing on features or opinions to find and identify matches in specific windows. For each sentence in corpus, Hu and Liu(2004) use known opinion words as the central object to find out the evaluation features nearby, so as to screen out subjective comment sentences. This method has a good classification effect for sentences that do not contain candidate frequent feature items[4]. Based on the same method, domestic scholar liu Chen(2017) used PMI-IR method to filter the collection of evaluation features words in the field of hotel, and then mined the opinion words corresponding to the features based on the position relationship between the evaluation features and opinion words, thus forming the feature-opinion pairs[12].

The natural language processing method is based on the fixed position acquisition relationship of words. However, these methods are ineffective in many cases, especially for some sentences with complex sentence expressions or special sentences, and it is difficult to guarantee the precision of feature-opinion extraction. The semantic-based method mainly extracts the feature-opinion pairs based on the semantic dependence between sentence components. This method can further improve the accuracy of the extraction results. In foreign studies, Wu et al. (2009) introduced the concept of phrase dependency analysis, divided the input sentences into phrases, and expressed the relationship between phrases with directed arcs, and simulated phrase dependency tree through kernel function. The research results show that this method can identify the dependencies of phrases wel[13]l. On the basis of previous studies, Lakkaraju et al. (2011) constructed a series of combinatorial probability models that take into account both word sequences and word bags. The machine learning model HMM-LDA was used to realize the extraction of feature-opinion pairs by combining syntactic structure and semantic dependence[14]. Feng et al. (2010) constructed the feature words database and opinions database based on the manual annotation method, and then formulated feature-opinion extraction rules according to the results of syntactic analysis[15]. In domestic research, GuoChong and Wang Zhenyu (2013) combined the advantages of statistical methods and rule methods to propose a priori knowledge matching algorithm, using a custom emotional ontology tree to identify subjective commentary sentences containing feature-opinion pairs[16]. HuZheng et al. (2018) used the two-level fine-grained structure of entity and feature to represent the evaluation features. They identified emotional units by combing the syntactic components of phrases and constructing the syntactic path library, considering the syntactic features of Chinese complex sentence which reduces the difficulty of matching[17].

3.3 Research on sentiment analysis

Online reviews are often accompanied by the subjective evaluation of the reviewers, and the positive or negative polarity classification of the subjective evaluation is called sentiment analysis. Sentiment analysis, also known as sentiment classification, can be divided into two categories. One is based on emotion lexicon, the other is based on machine learning.

3.3.1 Sentiment classification method based on emotion lexicon

In this method, the sentiment score of all sentiment words in the comments is determined according to the sentiment lexicon and the specified computing rules so as to calculate the overall sentiment score of the comments. The sentiment classification method based on sentiment lexicon does not need to manually label the training set, which belongs to the unsupervised learning category. Based on the artificial sentiment lexicon, Yao Tianfang et al. (2006) calculated the sentiment score of the automobile comments and divided comments into positive and negative according to the sentiment score[18]. The key to the classification effect of this method is how to construct such a comprehensive emotion lexicon and it is the first to carry out in foreign research. The most widely used lexicon is the Word Net lexicon, which uses the semantic network to gather words with the same or similar emotional tendency and then gives them corresponding emotional polarity (positive or negative). In China, How Net dictionaries and NTUSD dictionaries compiled by national Taiwan university are most widely used. Turney (2002), on the basis of How Net basic emotion lexicon, calculates the emotional polarity of sentiment words by using the point mutual information method, and realizes the expansion of basic emotion lexicon. Finally, the expanded emotion lexicon is used to judge the emotional polarity of text, with an accuracy rate of 74%[1]. Shen et al. (2009) first constructed various types of lexicons, including sentiment lexicon, negative word lexicon, degree adverbs lexicon, punctuation lexicon, and artificially assigned weight values to various dictionaries. The sentiment score of microblog comments were calculated and classified based on the above lexicons. However, this study ignores the role of double negation in Chinese emotion expression[19].

The lexicon-based sentiment classification method can easily and quickly determine the emotional polarity of the comments without manually labeling the data set, saving human and financial resources. However, this method has certain limitations. The emotion words in different fields vary greatly, so it is impossible to construct an emotion lexicon containing all the emotion words in different fields. Therefore, the applicability and scalability of the lexicographical classification of emotions are poor.

3.3.2 Sentiment classification based on machine learning

At present, the application of sentiment classification based on machine learning is more common. This method is actually a classification problem of supervised learning, which is generally divided into two processes of training and classification. First ,the training process refers to learning the known annotation data set , constructing and training the classifier. The classification process uses this classifier to determine the emotional polarity of unlabeled comments. Pang et al. (2002) first applied machine learning models such as support vector machine, maximum entropy and naive Bayesian to emotion classification tasks in the film field, and selected Bigram and word frequency as classification features. The results show that the classification effect of maximum entropy and naive Bayesian model is unstable and is susceptible to selected features. In contrast, the support vector machine model characterized by Unigram has the best classification effect[20]. Two key problems of emotion classification based on machine learning are text feature selection and model optimization. Zhiming Liu and liu lu (2012) used information gain, Chi statistics and word frequency statistics algorithms to extract features respectively, and the empirical results showed that TF-IDF as the feature weight had the best emotional classification effect[21]. Kang et al. (2012) used supervised learning algorithm to divide comment documents into positive comments and negative comments. The classification accuracy of positive comments was about 10% higher than that of negative comments, resulting in low overall average accuracy. To alleviate this problem, Kang proposed an improved naive Bayesian algorithm. The experimental results show that when unigrams and bigrams are used as features in the algorithm, the recall rate can be improved by up to 10.2%[22]. Wang and Manning (2012) found that although Naive Bayes (NB) and Support Vector Machine (SVM) are often used for sentiment classification, their performance varies widely among different model variables, features, and data sets. For short text sentiment classification tasks, NB is actually better than SVM, while SVM is more advantageous for long text. Therefore, a combination of the two NBSVM models is proposed, which is superior to most existing sentiment classification models[23].

The sentiment classification method based on emotion lexicon is fast, but it relies heavily on the quality of emotion lexicon and calculation rules, and usually the classification accuracy is not high. Traditional machine learning method requires complex preprocessing operations and superb feature extraction techniques. To get higher accuracy. The rise of deep learning technology can make up for the above-mentioned shortcomings. In recent years, it has received extensive attention from researchers and has performed well in the fields of sound, image, and natural language processing.

4. Conclusion

This paper introduces the research on emotion analysis from the granularity level, discusses the evolution process of emotion analysis from coarse granularity to fine granularity, and focuses on the key problems and methods of fine-grained sentiment analysis. Fine-grained sentiment analysis has been unable to meet people's needs, especially for enterprises and consumers, who began to pursue more detailed and accurate feature-based sentiment analysis. In addition, online comments often take the form of mixed emotions, affirming certain aspects while disagreeing with others. Only by going deep into the level of product features, and extracting the specific features and their opinions involved in text comments for fine-grained sentiment analysis, can enterprises and consumers make better product improvement and shopping decision, which is currently worth further research.

Acknowledgements

This paper is one of the research results of the “Research of Online Negative Comments” (No.: 16SKGH059) of Chongqing Project. Project leader: Liang Wei

References

[1] Turney P D. Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews[C]. Proceedings of the 40th Annual Meeting on Association for Computational Linguistics, 2002: 417-424.

[2] Yu H, Hatzivassiloglou V. Towards answering opinion questions: separating facts from opinions and identifying the polarity of opinion sentences[C]. Conference on Empirical Methods in Natural Language Processing, 2003: 129-136.

[3] Liu B. Sentiment Analysis and Opinion Mining[J]. Synthesis Lectures on Human Language Technologies, 2016, 30(1): 167.

[4] Hu M, Liu B. Mining and summarizing customer reviews[C]. Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Seattle, Washington, Usa, August, 2004: 168-177.

[5] Wei J, Ho H H. A novel lexicalized HMM-based learning framework for web opinion miningNOTE FROM ACM: A Joint ACM Conference Committee has determined that the authors of this article violated ACM's publication policy on simultaneous submissions. Therefore ACM has shut off[C]. International Conference on Machine Learning, 2009: 465-472.

[6] Kobayashi N, Inui K, Matsumoto Y. Extracting Aspect-Evaluation and Aspect-Of Relations in Opinion Mining[C]. Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, 2007: 521-574.

[7] Manevitz L M, Yousef M. One-class svms for document classification[J]. Journal of Machine Learning Research, 2001, 2(1): 139-154.

[8] Mei Q, Ling X, Wondra M, et al. Topic sentiment mixture:modeling facets and opinions in weblogs[C]. International Conference on World Wide Web, 2007: 171-180.

[9] Brody S, Elhadad N. An Unsupervised Aspect-Sentiment Model for Online Reviews[C]. Human Language Technologies: Conference of the North American Chapter of the Association of Computational Linguistics, Proceedings, June 2-4, 2010, Los Angeles, California, USA, 2010: 804-812.

[10] Zhao W X, Jiang J, Yan H, et al. Jointly modeling aspects and opinions with a MaxEnt-LDA hybrid[C]. Conference on Empirical Methods in Natural Language Processing, 2010: 56-65.

[11] She W J, Liu Z P, Yang W F. Product feature extraction based on improved LDA subject model [J]. Computer & modernization, 2016, (11): 1-6.

[12] Liu C, Han L, Li D D, et al. Research on extraction and emotion analysis based on features of Chinese block products -- viewpoints [J]. Computer application research, 2017, 34(10): 2942-2945.

[13] Wu Y, Zhang Q, Huang X, et al. Phrase dependency parsing for opinion mining[C]. Conference on Empirical Methods in Natural Language Processing: Volume, 2009: 1533-1541.

[14] Lakkaraju H, Bhattacharyya C, Bhattacharya I, et al. Exploiting Coherence for the Simultaneous Discovery of Latent Facets and associated Sentiments[C]. Eleventh Siam International Conference on Data Mining, SDM 2011, April 28-30, 2011, Mesa, Arizona, Usa, 2011: 498-509.

[15] Feng S, Zhang M, Zhang Y, et al. Recommended or Not Recommended? Review Classification through Opinion Extraction[C]. Web Conference, 2010: 350-352.

[16] Guo C, Wang Z Y. Emotion ontology tree and its automatic construction for fine-grained opinion mining [J]. Chinese journal of information technology, 2013, 27(5): 75-84.

[17] Hu Z, Chen E X, Zeng X H, et al. Fine-grained affective analysis of Chinese comments based on syntactic path [J]. Information technology, 2018, (09): 116-120.

[18] Yao T F, Nie Q Y, Li J C, et al. An opinion mining system for Chinese auto comments [C]. The 25th anniversary academic conference of Chinese information society, 2006.

[19] Shen Y, Li S, Zheng L, et al. Emotion mining research on micro-blog[C]. Web Society, 2009. Sws '09. IEEE Symposium on, 2009: 71-75.

[20] Pang B, Lee L, Vaithyanathan S. Thumbs up?: sentiment classification using machine learning techniques[C]. Proceedings of the ACL-02 conference on Empirical methods in natural language processing - Volume 10, 2002: 79-86.

[21] Liu Z M, Liu L. An empirical study on Chinese microblog emotion classification based on machine learning [J]. Computer engineering and application, 2012, 48(1): 1-4.

[22] Kang H, Yoo S J, Han D. Senti-lexicon and improved Naive Bayes algorithms for sentiment analysis of restaurant reviews[J]. Expert Systems with Applications, 2012, 39(5): 6000-6010.

[23] Wang S, Manning C D. Baselines and bigrams: simple, good sentiment and topic classification[C]. Meeting of the Association for Computational Linguistics: Short Papers, 2012: 90-94.