Opinion Mining of Customer Feedback Data on the Web

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ABSTRACT
As people leave on the Web their opinions on products and services they have used, it has become important to develop methods of (semi-)automatically classifying and gauging them. The task of analyzing such data, collectively called customer feedback data, is known as opinion mining. Opinion mining consists of several steps, and multiple techniques have been proposed for each step. In this paper, we survey and analyze various techniques that have been developed for the key tasks of opinion mining. On the basis of our survey and analysis of the techniques, we provide an overall picture of what is involved in developing a software system for opinion mining.

Categories and Subject Descriptors
H.3.1 [Content Analysis and Indexing]: Linguistic processing; H.3.5 [Online Information Services]: Web-based services

General Terms
Documentation

Keywords
Opinion mining, customer feedback, sentiment classification, linguistic resource, opinion summarization

1 INTRODUCTION
The World Wide Web is growing at an alarming rate not only in size but also in the types of services and contents provided. Individual users are participating more actively and are generating vast amount of new data. These new Web contents include customer reviews and blogs that express opinions on products and services – which are collectively referred to as customer feedback data on the Web. As customer feedback on the Web influences other customer's decisions, these feedbacks have become an important source of information for businesses to take into account when developing marketing and product development plans.

Let us consider an example of customer feedback.

> "*This camera is my first digital one and was super easy to learn to use. The picture looks great and it's simple to get the correct exposure. The memory card that comes with the camera has a very small capacity though, (it holds about 4 photos) so a separate memory card is a necessity. I'm not very happy with the memory card.*"

In this example, we can extract several phrases such as 'super easy to learn to use', 'the picture looks great', 'simple to get the correct exposure', 'very small capacity', and 'not very happy with the memory card', which convey customer's opinion rather than facts. In particular, subjective words such as 'super easy', 'looks great', 'simple', 'very small', and 'not very happy' are used to express customer's positive/negative sentiment regarding the product features, which are referred by 'learn to use', 'picture', 'exposure', 'capacity', and 'photo'. Although information gathered from multiple reviews are more reliable compared to information from only one review, manually sorting through large amounts of review one by one requires a lot of time and cost for both businesses and customers. Therefore it is more efficient to automatically process the various reviews and provide the necessary information in a summarized form.

Because of the importance of automatically extracting actionable knowledge from customer feedback data on the Web, "opinion mining (OM)" has become a significant subject of research in the field of data mining. The ultimate goal of OM is to extract customer opinions (feedback) on products and present the information in the most effective way that serves the chosen objectives. This means that the necessary steps and techniques used for OM can be different depending on how the summarized information is presented. For example, if we were to get the number of negative and positive reviews about a given product, classifying each review as positive or negative would be the most important task. On the other hand, if we want to show customer feedback on each of the different features of a product, it is necessary to extract product features and analyze the overall sentiment of each feature.

The methods that are needed for feature extraction, sentiment classification, and opinion summarization have already been targets of research in other areas such as document classification and text summarization. These can be modified and applied to OM. However, the focus of opinion mining is on the sentiment that the customer is expressing and this is where the methods are applied differently. As can be seen from the prior example, making the linguistic distinction between objective words that express facts and subjective words that express opinions is important. In this paper, we examine the two tasks that are specific to opinion mining: development of linguistic resources and sentiment classification. In addition, we present opinion summarization by looking into the existing opinion mining systems which extract opinion expression from large reviews and show how each system applies the methods in order to effectively summarize and present the opinions.

The remainder of the paper is organized as follows. Section 2 introduces the tasks for opinion mining and section 3 presents the methods for defining and developing linguistic resources to be used for OM. Section 4 explains about sentiment classification methods and in section 5, we introduce opinion summarization by examining several opinion mining systems that have been developed. Section 6 concludes the paper.

2 TASKS FOR OPINION MINING

As mentioned in Section 1, opinion mining can be roughly divided into three major tasks of development of linguistic resources, sentiment classification, and opinion summarization. We graphically present these tasks and the areas of research to which they are related in figure 1.

Appraisal theory [14,1] developed by Martin J.R., a computational linguistics researcher, concisely defines the sentiment properties of the linguistic resources that can be used for opinion mining. The techniques used for text classification and text summarization can also be applied to OM, along with linguistic resources. Although sentiment classification and opinion summarization share several steps or techniques, sentiment classification focuses on classifying each review while opinion summarization is about how to effectively extract opinion expressions and summarize them from a large number of reviews of a given product.

3 DEVELOPMENT OF LINGUISTIC RESOURCE

Sentiment related properties are well defined in appraisal theory [14] which is a framework of linguistic resources for describing how writers and speakers express inter-subjective and ideological positions. However, most researches for developing linguistic resources have focused on determining three properties: subjectivity, orientation, and strength of term attitude. For example, 'good', 'excellent', and 'best' are positive terms while 'bad', 'wrong', and 'worst' are negative terms. 'Vertical', 'yellow', and 'liquid' are objective terms. 'Best' and 'worst' are more intense than 'good' and 'bad'.

There are four major approaches in developing linguistic resources for OM: the conjunction method, the pointwise mutual information (PMI) method, the WordNet exploring method, and the gloss classification method.

3.1 Conjunction Method

The work presented in [7] is the first attempt to automatically develop linguistic resources for opinion mining. The approach relies on an analysis of textual corpora that correlates linguistic features or indicators with semantic orientation. The authors demonstrated that conjunctions between adjectives provide indirect information about orientation, based on the hypothesis that "*The conjoined adjectives and conjunctions usually have similar orientation, though 'but' is used with opposite orientation.*"

Their system identifies and uses this indirect information in the following steps: First, all conjunctions of adjectives are extracted from the corpus along with relevant morphological relations. And then, a log-linear regression model combines information from different conjunctions to determine if each of the two conjoined adjectives is of the same or different orientation. The result is a graph with hypothesized same- or different-orientation links between adjectives. Here, clustering algorithm that separates the adjectives into two subjects of different orientation is applied. It places as many words of the same orientation as possible into the same subset. Finally, the average frequencies in each group are compared and the group with the higher frequency is labeled as positive.

Through this approach, decisions on individual words are aggregated to provide decisions on how to group words into a class and whether to label the class as positive or negative. Thus the overall result can be much more accurate than the individual indicators.

3.2 PMI Method

PMI is a measure of association used in information theory and statistics. This can be defined as the following equation 1 which

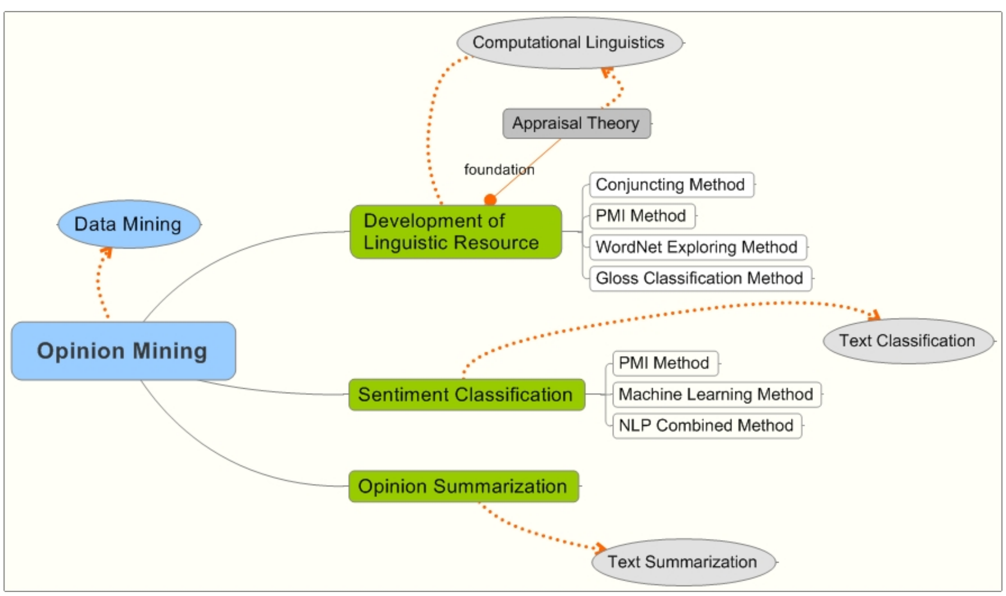

Figure 1. Tasks for opinion mining and its relationship with related areas.

shows the co-occurrence probability of each term x, y. The log of this ratio is the amount of information that we acquire about the presence of one of the words when we observe the other.

$$PMI(x,y) = \log_2 N \frac{p(x,y)}{p(x)p(y)} \tag{1}$$

There are several works that tries to develop sentiment related properties of words by means of PMI.

Turney and Littman [21] tried to develop the term orientation of words by using PMI. Their approach is based on the hypothesis that t*erms with similar orientation tend to co-occur in documents*. The Semantic Orientation (SO) of a term is estimated by combining a PMI measure of the term against some paradigmatic terms.

In their attempt, modified PMI was measured using the number of results returned by the AltaVista search engine with NEAR operator.

$$PMI(t,t_i) = \log_2 N \frac{hits(t\ NEAR\ t_i)}{\#(t)\#(t_i)} \tag{2}$$

, where t is the target term and t_i is a paradigmatic term.

Using the modified PMI, semantic orientation of the target term was estimated to the score *SO(t)* as shown in equation 3,

$$SO(t) = \sum_{t_i \in Pos} PMI(t,t_i) - \sum_{t_i \in Neg} PMI(t,t_i) \tag{3}$$

A term t is classified as having a positive semantic orientation when $SO(t)$ is positive and a negative orientation when $SO(t)$ is negative. The absolute value of $SO(t)$ can be considered the strength of the semantic orientation.

Their experiments show that conjunction method makes more efficient use of corpora than PMI method, but the advantage of PMI is that it can easily be scaled up to very large corpora, where it can achieve significantly higher accuracy.

3.3 WordNet Exploring Method

Hu et al.[9] utilized the adjective synonym set and antonym set in WordNet[15] to predict the semantic orientation of adjectives. In WordNet, adjectives are organized into bipolar clusters and share the same orientation of their synonyms and opposite orientation of their antonyms. To assign orientation of an adjective, the synset of the given adjective and the antonym set are searched. If a synonym/antonym has known orientation, then the orientation of the given adjective could be set correspondingly. As the synset of an adjective always contains a sense that links it to the head synset, the search range is rather large. Given enough seed adjectives with known orientations, the orientations of all the adjective words can be predicted.

3.4 Gloss Classification Method

Esuli and Sebastiani [4, 5] tried to develop linguistic resources by classifying term glosses. They assume that *terms with similar orientation have similar glosses and terms without orientation have non-oriented glosses*.

They use semi-supervised learning methods. By using the manually assigned initial seed sets and expanding them by using the synonyms and antonyms defined in the thesaurus, they formed a final training set which was used for processing the learning step for binary text classifiers such as Naïve Bayes Classifier, Support Vector Machine (SVM), and PrTFIDF [12]. This was then used to find the sentiment related properties of the words in the rest of the test set.

They have developed a publicly available linguistic resource, SentiWordNet, in which each synset of WordNet is associated to three numerical scores Obj(s), Pos(s) and Neg(s), describing how objective, positive, or negative the terms contained in the synset are [2, 6]. The assumption that underlies their switch from terms to synsets is that different senses of the same term may have different opinion-related properties. Each of the three scores ranges from 0.0 to 1.0, and their sum is 1.0 for each synset. Given that the sum of the opinion-related scores assigned to a synset is always 1.0, it is possible to display these values in a triangle whose vertices are the maximum possible values for the three dimensions observed.

4 SENTIMENT CLASSIFICATION

Sentiment classification is the process of identifying the sentiment - or polarity - of a piece of text or a document. In this section, we present three methods only for classifying reviews as positive or negative.

4.1 PMI Method

Turney et al.[20] had tried to classify the sentiment of reviews using PMI. In their process, phrases containing adjectives or adverbs are extracted and the semantic orientation of each phrases are estimated using PMI method. 'Excellent' and 'poor' were used as the base terms calculating the PMI. Reviews are then classified based on the average semantic orientation of the phrase. PMI method requires too much time for sending queries to Web search engines.

4.2 Machine Learning Methods

The machine learning method is the most commonly used method for topic-based text classification and it has been applied for sentiment classification as well. Document-level polarity classification can be considered to be a special case of text categorization with sentiment-based, rather than topic-based, categories. Pang, Lee, and Vaithyanathan [17] applies standard machine learning classification techniques for classifying the sentiment of a document. They refer to such classification techniques as default polarity classification. Classification techniques they use include Naïve Bayes, Maximum Entropy, and SVM. Also, standard bag-of-features framework is used to implement these machine learning algorithms on sentimental elements.

Pang and Lee further improves sentiment classification by removing objective sentences [16]. They developed a subjectivity detector that determines whether each sentence is subjective or not, and then discards the objective ones so that it would be applicable to a default polarity classifier.

Whitelaw et al. [22] applies the appraisal theory to the machine learning approaches of Pang and Lee. In order to express an appraisal, they define a structure that encompasses the appraisal. An appraisal is composed of four elements: attitude, graduation, orientation and polarity. By constructing appraisal resources manually, they were able to improve the classification accuracy.

Machine learning method characteristically uses bag of features along with the pos tagging method. There is no need for prior polarity dictionary though a learning phase is needed.

4.3 NLP Combined Method

With the PMI or machine learning method, it is not easy to get appropriate contextual polarity from texts. So, some natural language processing (NLP) techniques have been applied. Wilson et al. [23], in particular, tries to recognize contextual polarity at the phrase level. Unlike the other two methods, the NLP combined method requires a lexicon where lemmas are labeled with prior polarity. Contextual polarity classification is done as a two-step process that employs machine learning on a variety of features. The first step classifies each of the phrases containing a clue as neutral or polar. The second step takes all phrases marked in step one as polar and disambiguates their contextual polarity (positive, negative, both, or neutral). Currently, accurate sentiment classification that takes into account contextual meaning is being developed by combining the NLP techniques.

5 OPINION SUMMARIZATION

Unlike traditional text summarization that tries to construct short text which efficiently expresses the subject of the original long text, opinion summarization aims to give the overall sentiment of a large amount of reviews or other forms of opinion resources at various granularities. It is relatively trivial that sentiment classification may be one sub-task of opinion summarization. For instance, generally each review is classified and then the ratio of the positives and negatives is suggested as the overall favorableness on the product. Nevertheless we concentrate on how the overall sentiment of each feature of a product is summarized. We do this by looking into several opinion mining systems.

In the systems we have examined, product features are extracted and then sentiment of each feature is assigned. Then these are summarized and presented in various forms. Most of the current systems extract product features largely based on the statistical approach. On the contrary, various methods are used for assigning sentiment to the extracted features: PMI method, unsupervised classification method, and syntactic analysis. Some of the OM systems use linguistic resources which contain sentiment lexicons and others use star ratings or thumbs up/down icons instead.

Systems that do not use linguistic resources will be introduced first: *ReviewSeer* which uses thumbs up/down icons and *RedOpal* which uses star ratings. Next, systems that use linguistic resources will be introduced: *Opinion Observer*, *WebFountain*, Kanayama's System, and *OPINE*.

ReviewSeer [3] uses statistical models for extracting feature terms. Various methods such as metadata and statistical substitutions, linguistic substitutions, language based modifications, n-grams, proximity, and substrings were applied to improve the feature extraction performance. In addition, the authors used Naïve Bayes classifier with positive and negative review sets for assigning a score to the extracted feature terms. The results were shown as simple opinion sentences.

Red Opal is a system for scoring product features from customer reviews [19]. It uses frequent nouns and noun phrases for feature extraction, and assigns sentiment based on star ratings. Each result is shown with a Web-based interface by descending order for each feature and the confidence of the score.

Opinion Observer, developed by Hu et al. [15, 10, 13], is a sentiment analysis system for analyzing and comparing opinions on the Web. Product features are extracted from nouns or noun phrases by the association miner, CBA. They use only adjectives as opinion words and assign prior polarity of these by *WordNet exploring* method. The polarity of an opinion expression, which is a sentence that contains one or more feature term and one or more opinion words, is assigned as a dominant orientation. Extracted opinions are stored in a database in the form of (feature, # of positive expression, # of negative expression). This system shows the results in a graph format, showing the opinions on a product feature by feature.

WebFountain, developed by Yi et al [24], uses bBNP (Beginning definite Base Noun Phrases) heuristic for extracting product features. It extracts definite base noun phrases at the beginning of sentences followed by a verb phrases. To assign sentiments to the features, reviews are parsed and traversed with two linguistic resources. Sentiment lexicon defines the polarity of terms and sentiment pattern database contains the sentiment assignment patterns of predicates. This way, it is possible to develop a simple Web interface that can list the sentiment bearing sentences for a given product.

Kanayama et al. [8] proposes a high-precision sentiment analysis system at a low-cost by using a transfer-based machine translation engine. Sentiment units are extracted from product reviews by using the full parsing and top down tree matching using a syntactic parser with matching patterns and polarity lexicons. Extracted sentiments can be easily summarized and visualized in various formats.

OPINE is built on top of KnowItAll, a Web-based, domain-independent information extraction system [18]. There are four tasks in the review analysis: product feature identification, identification of opinions regarding product features, determination of the opinion polarity, and opinion ranking based on their strength. It extracts explicit product features using the PMI. It uses explicit features to identify potential opinion phrases based on the intuition that an opinion phrase associated with a product feature will occur in its vicinity on syntactic parse tree. After the extraction of the opinion expression, relaxation labeling [11], which is an unsupervised classification technique, is used to disambiguate the semantic orientation of opinion words. As a result, set of (*feature, ranked opinion list*) tuples are extracted.

Table 1 shows the characteristics of the six systems in various aspects. It summarizes the opinion extraction methods and presentation methods of each system. Systems are characterized by the sentiment resource they use and their syntactic analysis technique. Although it is hard to compare the performance of these systems due to the lack of standard test data and methods, systems that adopt syntactic analysis technique tend to show higher precision and lower recall on extracting opinion expressions.

6 DISCUSSION

We provided an overall picture of the tasks and techniques involved in developing an automated system for mining opinions that are found in customer feedback data on the Web. More specifically, we were able to develop this overall picture by conducting a survey and analysis of the techniques involved in each of the key steps of opinion mining. We focused on surveying and analyzing the methods for development of linguistic resources, sentiment classification, and opinion summarization.

Table 1. Characteristics of the six systems for opinion summarization.

System	Sentiment Resource	Syntactic Analysis	Extracting Opinion Expression		Presentation
			Feature Extraction	Sentiment Assignment	
Review Seer(2003)	Thumbs up/down	No	Probabilistic model Naïve Bayes Classifier		List sentences contain the feature term
Red Opal (2007)	Star rating		Frequent noun and noun phrase	Average star rating	Order products by score of each feature
Opinion Observer (2004)	Linguistic Resource		CBA miner Infrequent feature selection	WordNet exploring Dominant polarity of each phrase	Bar graph
Kanayama's System (2004)		Yes	Sentiment unit Modifying the machine translation framework		N/A
WebFountain (2005)			bBNP heuristic	Sentiment lexicon Sentiment pattern database	List sentences which bear sentiment of a product
OPINE (2005)			Web PMI	Relaxation labeling	N/A

We have observed the four major methods for linguistic resource development and compared three methods of sentiment classification as well as looking into the characteristics and technical elements of the six notable systems that utilize these methods in opinion summarization.

With regards to the section on the development of linguistic resources, it was noted that conjunction methods are used by a number of works in constructing lexicons of adjectives to define positive or negative semantic orientations. Here, PMI was used to determine an unknown adjective's semantic orientation by using given seed terms whose semantic orientation has already been defined. In addition, there were two approaches to using a thesaurus, such as WordNet. One approach relies on bipolar clusters in which the adjectives in a cluster are connected according to "similar" relationship and clusters in turn are connected by "antonym" relationship. The other approach uses terms' glosses of a thesaurus and is based on the hypothesis that terms with a similar orientation have similar glosses. Gloss classification method showed the best accuracy among these approaches.

For sentiment classification, PMI was also used for classifying documents according to their polarity. Various machine learning methods, such as Naïve Bayes, MaxEnt, and SVM were used for sentiment classification. In one experiment, only the subjective portion of a document was extracted and used to improve the classification performance. Appraisal theory was combined with the basic machine learning methods and this also improved the performance. These research efforts have laid the foundation for sentiment classification. More recently, feature-level sentiment classification has been the major focus of research in this area.

Finally, opinion summarization methods were examined which include feature extraction, sentiment assignment, and visualization. Feature extraction and sentiment assignment are subtasks of feature-level sentiment classification while visualization is about the effective presentation of the summarized opinion. A total of six systems were introduced. Although each system demonstrated the performance of its inherent feature extraction and sentiment assignment, these cannot be compared to each other due to the lack of a standard measure and common test data set. However, the NLP-combining systems seems to show slightly higher precision of sentiment assignment.

Even now, on the Web, vast amounts of user generated contents are being created on merchant sites and internet forums. These contents have been recognized as measurable resources and various opinion mining methods have been developed to analyze the contents. Furthermore, opinion mining has become important for all types of organizations, including for-profit corporations, government agencies, educational institutions, non-profit organizations, and the military in gauging the opinions, likes and dislikes, and the intensity of the likes and dislikes, of the products, services, and policies they offer and plan to offer. As such, we believe that an understanding of the overall picture of the tasks and techniques involved in opinion mining is of significant importance.

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