Feature-based Summarizing of Hotel Customer Reviews

Dim En Nyaung, Thin Lai Lai Thein
University of Computer Studies, Yangon
dimennyaung@gmail.com, tllthein@ucsy.edu.mm

Abstract

Due to the rapid increase of Internet, web opinion sources dynamically emerge which is useful for both potential customers and product manufacturers for prediction and decision purposes. These are the user generated contents written in natural languages and are unstructured-free-texts scheme. Therefore, opinion mining techniques become popular to automatically process customer reviews for extracting product features and user opinions expressed over them. Since customer reviews may contain both opinionated and factual sentences, a supervised machine learning technique applies for subjectivity classification to improve the mining performance. In this paper, we dedicate our work to the main subtask of opinion summarization. The task of product feature and opinion extraction is critical to opinion summarization, because its effectiveness significantly affects the identification of semantic relationships. The polarity and numeric score of all the features are determined by Senti-WordNet Lexicon how intense the opinion is for both positive and negative features. The problem of opinion summarization refers how to relate the opinion words with respect to a certain feature. Probabilistic based model of supervised learning will improve the result that is more flexible and effective.

Keyword: Opinion Mining, Feature-based Ranking, SentiWordNet

1. Introduction

With the dramatic growth of web's popularity, the number of freely available online reviews is increasing at a high speed. Merchants selling products on the Web often ask their customers to review the products that they have purchased and the associated services. Similarly, manufacturers want to read the reviews to identify what elements of a product affect sales most and what are the features the customer likes or dislikes so that the manufacturer can target on those areas. As e-commerce is becoming more and more popular, the number of customer reviews that a product receives grows rapidly [3].

Therefore, opinion mining is a growing research area both in natural language processing and information retrieval communities as it aims at finding subjective information, which may be more relevant to users than factual information in many applications. A significant number of websites, blogs and forums allow customers to post reviews for various products or services (e.g., amazon.com, tripadvisor.com). Such reviews are valuable resources to help the potential customers make their purchase decisions. In the past few years, mining the opinions expressed in web reviews attracts extensive researches [2, 8]. Based on a collection of customer reviews, the task of opinion mining is to extract customers' opinions and predict the sentiment orientation. The aim is not to compute the general orientation of a document or a sentence, since a positive sentiment towards an object does not imply a positive sentiment towards all the aspects of this object [9], as in: The picture quality is good, but the battery life is short.

There are many ranking methods based on customer preferences. Our work is based on the weight of the feature and score of opinion word, where features are ranked based on their overall quality for each product. Although an overall ranking is an important measure, different product features are important to different customers based on their satisfaction and requirements.

In this paper, we present ranking features of opinion mining system which uses linguistic and semantic analysis of text to identify the score of the feature from customer reviews. Hotel reviews data sets are used in this paper because tourism domain is also interested among online users. Most of the paper extract the features from simple sentence by using adjacent based and pattern based method. Our proposed method can extract product features from both simple sentence and complex sentence.

2. Related Work

The state-of-the-art opinion retrieval techniques on the Association for Computing Machinery (ACM) portal and Google Scholar are identified in early 2011 [6]. Identified techniques were then classified under text classification approach, lexicon-based approach, probabilistic approach, and other emerging approaches.

Most of the current opinion mining work mostly focuses on mining product review data [1], because of the wide availability of review data and their relatively obvious sentiment orientations such as good, bad and so on. The opinion words are extracted using the resulting frequent features, and semantic orientations of the opinion words are identified with the help of WordNet [7]. WordNet can be interpreted and used as a lexical resource. The orientation of each opinion sentence is identified and a final summary is produced. POS tagging is the part-of-speech tagging [3] from natural language processing, which helps us to find opinion features. Then produce a structured summary that informs about positive or negative statements for product features.

Kunpeng et al [4] proposed product ranking methodology to rank product. It is also considered for both subjective and comparative sentences based feature-specific product graph. Then pRank algorithm, one of page rank algorithm, is used to rank products. Thus it can produce the ranking products not features.

Eivind et al [5] proposed how the results of the sentiment analysis of textual reviews can be visualized using Google Maps, providing possibilities for users to easily detect good hotels and good areas to stay in. They contribute opinions to the travel websites. It can also produce the ranked list of hotels based on the grades given by previous travelers by using recommendation techniques.

The remaining paper is structured as follows. Section 2 presents the proposed rank based opinion mining system. Section 3 presents some of the experiment and results. Finally, section 4 concludes the paper.

3. Proposed Opinion Mining System

Our proposed system needs three basic components: a SentiWordNet (SWN) Lexical resource L of opinion expressions, a domain ontology O where each concept and each property is associated to a set of labels that correspond to their linguistic realizations and a review R. Ontologies have been widely used in a variety of natural language applications. Ontologies describing similar domain information varied significantly in syntax and semantics depending on the nature of the ontology language used. The important for NLP systems is not only to get an accurate opinion in texts but also to go beyond explicit features and to propose a fine-grained analysis of opinions expressed towards each feature. The works using ontology aim at organizing features using a model of representation: ontology. The use of ontology would have several advantages in structure features and extract features in the domain of opinion mining.

Following the idea described in (Asher et al, 2009) [10], a review R is composed of a set of elementary discourse units (EDU).An EDU is a clause containing at least one elementary opinion unit (EOU) or a sequence of clauses that expressing an opinion. An EOU is an explicit opinion expression. We have segmented conjoined NPs or APs into separate clauses. Segmented are then connected to each other using a small subset of “veridical” discourse relations, namely:

- Contrast (a, b), implies that a and b are both true but there is some defeasible implication of one that is contradicted by the other Possible makers can be *although, but*.
- Result (a, b) indicated by makers like so, as a result, indicates that the one of EDU is a consequence or result of another EDU.
- Continuation (a, b) corresponds to a sense of speeches in which there are no time constraints and where segments from part of a larger thematic.
- Elaboration (a, b) describes global information that was stated previously with more specific information.

[*The rooms are typical hotel style rooms*]$_a$, [*and the staff is very prompt.*]$_b$

The system first crawls all the reviews, and put them in the review corpus by given inputs. The output is the ranking features with the summarized reviews. The general process for the ranking features for opinion mining system is as follows:

Step 1: for each sentence, part-of-speech tagging and dependency relations are performed as the preprocessing step.
Step 2: product feature candidate and the weight of these features are extracted. Then unfrequented features are removed according to threshold.
Step 3: opinion words are extracted. Then the sentiment orientation and score of the opinion words are identified with the help of SentiWordNet.
Step 4: the extracted opinion words are related with corresponding features by using dependency relation.
Step 5: ranking the features according to the total weight of these features.

3.1 Preprocessing

In the preprocessing step, each review sentence is parsed using Stanford parser, which provides POS tags to English words based on the context in which they appear. And then the sentence is converted into dependency relations using Stanford Parser. The dependency relations encode the grammatical relations between every pair of words as illustrated in Figure 1.The review is then segmented as EDUs by using the discourse parser. For each EDU, the system extracts features that correspond to the context by the pattern based term extraction using domain ontology.

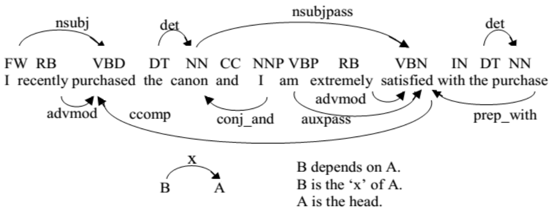

Figure1. Dependency relationship of a sentence

3.2 Extracting Product Feature Candidate

In general, the words those indicating most product features are nouns or noun phrases. Therefore, the next step is to identify a noun phrase as a product feature candidate. A linguistic filtering pattern is used to extract noun phrase. A definite linguistic filtering pattern is a noun phrase as the following patterns:

- NN,
- NN NN, JJ NN,
- NN NNNN, JJ NN NN, JJ JJ NN,
- NN IN DT NN, NN JJ NN NN,
- NN IN DT NN NN

where NN, JJ, DT and IN are the POS tags for noun, adjective, determiner, and preposition respectively. Actually, our system deals with conjunctions (including commas). Figure 1 demonstrates the process to extract all the product feature candidates in reviews. In which domain ontology is used to extract related features with problem domain. The weight of the feature is also calculated by using Apriori Algorithm which is the well know algorithm to mine data in which all of features having minimum support value above a threshold are considered as frequent features. An algorithm for extracting product feature candidates is shown in following:

```
Begin
PS=ϕ
For each tagged sentence s_n Є S
    PC= ϕ
    For k=1 to end of segmented sentence d_n Є D
    For i= Length(c_n) to 0
        j=1;
        T=T_j to T_i+j   /* POS tag of word_j to word_i+j */
        W=word_j to word_i+j
        If T Є P and W Є O then
        j=i+j
        PC=PC ∪ W
        Break
        End
        End
    End
    End
    PS=PS ∪ PC
End
```

The inputs of the algorithm are set of tagged sentences S= $\{s_1, s_2,\ldots,s_n\}$, set of segmented EDU D=$\{ d_1, d_2,\ldots,d_n \}$, set of clause within segmented D: C=$\{c_1, c_2,\ldots,c_n\}$, set of noun phrase patterns P and set of word in domain ontology. The algorithm will output the result as set of product feature candidates for the domain. To extract implicit features, ontology properties are used. For example, the property "good at" links "customer" and "location" concepts.

3.3 Extracting Opinion Word and Score

After the feature words are extracted, adjective words are extracted as opinion word in each EDU. In each EDU, EOU is extracted by using rule-based approach. EOU is the smallest opinion unit within EDU. It is composed of one and only one opinion word. Adjective words are used as opinion words in almost sentences. Therefore, we use adjective words as the attitude for the customer in this paper. The score of the opinion word can get from SentiWordNet(SWN). SWN is the extension of WordNet. The polarity of extracted opinions for each feature is classified by SentiWordNet Lexical resource in which each WordNet synset is associated to three numerical scores: an objectivity score, a positive sentiment score and a negative sentiment score describing how objective, positive, and negative the terms contained in the synsets are. A sample list of opinions and their positive polarity values (shown in parenthesis) obtained through SentiWordNet is beautiful (0.75), clear (0.5), fantastic (0.75), good (0.625) and great (0.75).

3.4 Relating Product Feature and Opinion Word

To relate product feature and opinion word, dependency relations for each pair is considered. We use syntactic information to classify product feature-opinion pair. To reduce the variation of linguistic constructions, we assume that the shortest dependency path tracing from a product feature through the dependency tree to an opinion word gives a concrete syntactic structure expressing a relation between the pair. Our idea is to learn such patterns from the dependency paths for each relationship as shown in Figure1. Furthermore we attempt to capture relating product feature and opinion using dependency relations between them.

3.5 Ranking Features

The overall weight of a feature is calculated by multiplying the polarity value of the opinion word with the number of sentences which contain that opinion.

$$\text{Total Wt} = \sum_{n=1}^{d}(Wt\ of Positive\ features - Wt\ of\ negative\ features) \quad (1)$$

where d is the number of documents which contain this feature along with the review sentences.

The feature after being identified as positive will be considered the top feature if the numeric score of that feature is highest among all positive features extracted and their cumulative weight calculated. If the total weight of a feature is positive then that feature is termed as positive and is thought to be likely by the user. Similarly a negative weight indicates the feature is not liked by the user and hence will be categorized in the negative feature category.

4. Experiment and Results

In this section, we present the experimental details of the proposed opinion mining system. There are three types of experiments: the evaluation of the feature extraction step, the evaluation of the opinion word extraction and ranking.

Evaluation of the feature extraction step:
Since the proposed system use the domain ontology, the precision of this task can be very good because most of the extracted features are relevant. However recall is not as good as a precision because the set of ontology labels cannot totally cover the terms of tourism domain.

Evaluation of the opinion extraction step:
Since most of the reviewers do not follow the grammatical rules while writing reviews the proposed system can miss some opinion words. As a result the errors come from the syntactic parser and dependency link. Implicit opinion expressions and typo can also make not to good the precision value. Therefore some of extraction rules that extract expression of recommendations do not perform very well which imply a loss of precision.

Evaluation of product features ranking:
The weight of the feature is firstly calculated. The final weight of the feature is calculated using equation 1 and has given the values for each feature. Now our last task is to rank the features of a product in the order of importance. Since we have already calculated the polarity value of the features we arrange the features in the descending order of importance. Table 2 and 3 represent the sample finalize ranking features for positive and negative orientation.

According to the equation 1, the score for each feature is calculated. In which the weight for extracted feature and relating opinion word score are used to get the score for this feature. That is the number of users who are writing the reviews and the number of features commented by each user. A sample calculation for generating the weight using equation 1 is as follows:

Wt_{Room}= (1.0x434 + 0.75x18 + 0.65x9) – (0.235x2) = +452.88

$Wt_{Service}$ = (0.25x48 + 0.5x22) – (0.12x32 + 0.125 x12) = +17.66

$Wt_{Cleanliness}$ = - (0.25x56 +0.125x23) = -16.875

According to the total weight mentioned above, the positive and negative features are finalized separately as shown in Table 2 and 3.

Table 2. The finalize ranking of positive features for Central Hotel (Top 5)

Rank	Features	Positive Polarity value
1	Room	452.88
2	Breakfast	65.33
3	Service	17.66
4	Staff	17.58
5	Location	16.52

Table 3. The finalize ranking of negative features for Central Hotel (Top 4)

Rank	Features	Negative Polarity value
1	Cleanliness	16.875
2	view	14.85
3	Internet	12.66
4	Environment	9.3

Figure 2 and 3 gives the graph of feature versus weight value by taking the overall weight of the features both for positive features and negative features.

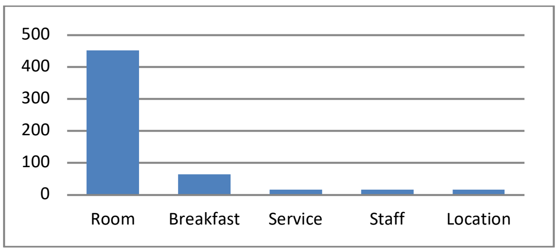

Figure 2.Features versus weight for the positive features

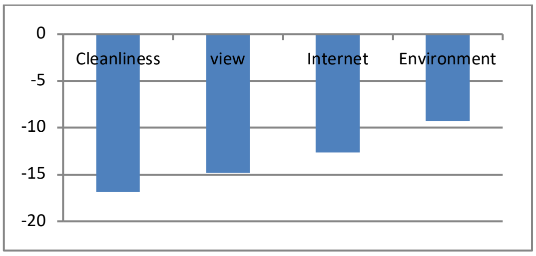

Figure 3. Features versus weight for the negative features

5. Conclusion

In this paper we have proposed a rank based system for features from user generated contents of hotel domain. Firstly we identified the features efficiently. Then we get the weight of frequent features by mentioned above and ranked them on the basis of their score values. As we showed the result as ranking, customers and administrators would know the features which are generally liked and disliked by the customer. So customer can get valuable facts which hotels should stay according to their desire and administrator can know directly the strength and weakness of theirs so that necessary improvement can be done in those areas. Moreover, the ontology is useful thanks to its list of properties between concepts which allows recognizing some opinions expressed about implicit features.

In future work, we can get the accuracy of each evaluation step using standard IR performance measures. We should take into consideration to extract verb, adjective phrase which show the sentiment orientation.

References

[1] Y. Fang, L. Si, N. Somasundaram and Z. Yu, “Mining Contrastive Opinions on Political Texts using Cross-Perspective Topic Model”. WSDM’12, Seattle, Washington, USA, February 8–12, 2012.

[2] Q. Su, X. Xu, H. Guo, Z. Guo, XianWu, X. Zhang, B. Swen and Z. Su, “Hidden Sentiment Association in Chinese WebOpinion Mining”. WWW 2008, Beijing, China, April 21–25, 2008.

[3] M. Hu and B. Liu, “Mining and Summarizing Customer Reviews”.KDD’04, Seattle, Washington, USA, August 22–25, 2004.

[4] K. Zhang and R. Narayanan, “Voice of the Customers: Mining Online Customer Reviews for Product Feature-based Ranking”

[5] E. Bjorkelund, T.H. Burnett and K. Norvag, “A Study of Opinion Ming and Visualization of Hotel Reviews”.iiWAS2012, Bali, Indonesia, December 3-5, 2012.

[6] SYLVESTER O. ORIMAYE, SAADAT M. ALHASHMI and SIEW EU-GENE, “Performance and Trends in Recent Opinion RetrievalTechniques”. The Knowledge Engineering Review, Vol. 00:0, 1-28, Cambridge University Press, 2012.

[7] A. Esuli and F. Sebastiani, “Determining Term Subjectivity and Term Orientation for Opinion Mining”.Padova, Italy.

[8] A. Bakliwal, P. Arora, A. Patil, V. Varma, “Towards Enhanced Opinion Classification using NLP Techniques”. Proceedings of the Workshop on Sentiment Analysis where AI meets Psychology (SAAIP), IJCNLP 2011, Chiang Mai, Thailand, November 13, 2011, pages 101–107.

[9] Alexandru Lucian Gînscă, “Fine-Grained Opinion Mining as a RelationClassification Problem”. Imperial College Computing Student Workshop (ICCSW’12), 2012.

[10] Asher, Nicholas, F.Benamara, and Yvette Y.Mathieu, “Appraisal of Opinion Expressions in Discourse. Lingvisticæ Investigationes”. John BenjaminsPublishing Company, Amsterdam, Vol. 32:2, 2009.