

FEATURE BASED SENTIMENT ANALYSIS ON CUSTOMER FEEDBACK

¹AVANI JADEJA, ²PROF. INDR JEET RAJPUT

^{1,2} Department of computer Engineering, Hasmukh Goswami College of Engineering
Ahmadabad – 382330, India

ABSTRACT: With the rapid development of E-commerce, the number of the customer reviews that a product receives grows rapidly. After using product, consumers usually express their experience or feedback via online reviews on e-commerce sites. For the popular product, there is large number of customer feedback. This makes it is difficult for potential customer to make informed decision on purchasing the product, as well as the manufacturer of the product to keep track and to manage customer opinion. Instead feature based summary can certainly help potential buyer and manufacture. This type of summary generation is divided broadly in main two tasks.1) feature extraction 2) sentiment analysis.

This paper contributes to the field of sentiment analysis which aims to extract emotions, sentiments and opinions from customer feedback. A basic goal is to extract product features and classify customer's sentiment i.e. positive or negative towards it. We have proposed new approach to extract product features from customer feedback. For this, we have first fetched product's features from internet by crawling manufacture or e-commerce sites. Than using WordNet [12], we have extracted synonyms for the product features. In next step, we have collected customer reviews from internet and extracted nouns, adjectives and adverbs from each sentence of reviews. We have than created bucket of related sentences against feature by comparing noun words with feature and its synonyms. This step is required to authenticate noun word as feature. Then with help of Sentiwordnet [16], we have calculated semantic score of related sentences. At last we have generated feature wise summary by summing up semantic scores.

Key Words: Sentiment, Opinion, Semantic, Machine Learning, Sentiment Classification

Introduction

Customer feedbacks contain opinions about product and its features. It is real time feedback mechanism to manufacturers to know what their customer's experience with products.

For example, Apple has developed iMap, a map application to replace Google map for iOS6. But when launched in market, consumers complained about not working correctly via reviews, forums and blogs.

Challenge is customer feedback is unstructured text written in natural language. One has to manually read and summarize it according to his understanding. In recent years, good amount of researchers are introducing new techniques to summarize reviews in quantifiable manner. Summarization includes features extraction and opinion mining.

In case of feature extraction, reviews contain explicit

and implicit features.

For example,

“**Voice recognizer** of this phone is very amazing. It recognizes all my commands so perfectly and makes me feel that it is my personal assistance.”

“You need to carry charger everywhere you go, and feed your phone after every 2 hours.”

In first example, **Voice recognizer** feature is explicitly mentioned while in second one, **Battery life** feature is implicitly mentioned.

Opinion mining refers to identification and classification of the viewpoint or opinion expressed in the text span, using information retrieval and computational linguistics. Opinion mining extracts the subjective information using natural language processing and text analysis from reviews.

Related Works

Our work is closely related to Hu and Liu's work in [1] on mining opinion features in customer reviews.

In [1], they design a system to perform the summarization in two main steps: feature extraction and opinion direction identification. The inputs to the system are a product name and an entry page for all the reviews of the product. The output is the summary of the reviews.

The system performs five tasks: (1) POS tagging [13], which parses each sentence and yields the part-of speech tag of each word (whether the word is a noun, verb, adjective, etc) and identifies simple noun and verb groups (syntactic chunking). (2) Frequent feature generation. Hu and Liu use association rule mining [9] to find all frequent item sets, which is a set of words or a phrase that occurs together. The association rule miner CBA [10] based on the Apriori algorithm in [9], finds all frequent item sets in the transaction set with the user-specified minimum support 1%. (3) Feature Pruning aims to remove those incorrect features. Two types of pruning are presented: (a) Compactness pruning checks features that contain at least two words, which are named feature phrases, and removes those that are likely to be meaningless. (b) Redundancy pruning removes redundant features that contain single words. (4) Opinion words extraction with all the remaining frequent features after pruning. (5) Infrequent feature identification. Hu and Liu suppose people like to use the same opinion word to describe different features. So they can use the opinion words to look for features that cannot be found in (2). If one sentence contains no frequent feature but one or more opinion words, find the nearest noun or noun phrase of the opinion word as an infrequent feature.

Weishu Hu, Zhiguo Gong and Jingzhi Guo's work in [2] to mine product features from online reviews is also related to Hu and Liu's work in [1]. They followed same POS tagging [13] process as Hu and Liu's with only change in linguistic parser. They used probability based algorithm to generate features as follows:

Probability of any candidate feature being correct feature = Number of occurrence of that candidate feature / Number of sentences if appeared in.

Also for semantic orientation calculation, they used SentiWordnet [16] and calculates positive and negative score for each adjective, adverb and verb from Sentiwordnet [16] and calculates average positive or negative score of sentence.

In [3], Popescu and Etzioni introduce an unsupervised information-extraction system (OPINE), which mines reviews in order to build a model of important product features, the evaluation by reviewers and the relative quality across products. OPINE performed four main tasks: (1) Identify product features. (2)

Identify opinions regarding product features. (3) Determine the polarity of opinions. (4) Rank opinions based on their strength. OPINE is built on top of KnowItAll, a Web-based, Domain-independent information extraction system [17], which instantiates relation-specific generic extraction patterns into extraction rules to find candidate facts. KnowItAll's Assessor assigns a form of Point-wise Mutual Information (PMI) between phrases that is estimated from Web search engine hit counts [18]. It computes the PMI between each fact and automatically generated discriminator phrases. Given fact f and discriminator d , the computed PMI Score as (1):

$$\text{PMI}(f, d) = \text{Hits}(d + f) / (\text{Hits}(d) + \text{Hits}(f)) \quad (1)$$

The PMI scores are converted to binary features for a Naive Bayes Classifier, which outputs a probability Associated with each fact [20]. OPINE extracts explicit feature for the given product class from parsed review data. (1) The system recursively identifies both the parts and the properties of the given product class and their parts and properties, in turn, continuing until no candidates are found. (2) The system finds related concepts and extracts their parts and properties. Opine achieves 22% higher precision than Hu's, but has 3% Lower recall.

Akash Bakliwal and Vasudeva Varma's work in [4] on Mining Sentiments from Tweets uses two different datasets which are built using emotions and list of suggestive words respectively as noisy labels. They give a new method of scoring "Popularity Score", which allows determination of the popularity score at the level of individual words of the tweet text.

In [5], authors proposed Domain independent model for product attributes extraction from user reviews using Wikipedia. In [6], authors proposed approach to find sentiments from blogs. They split blogs into sentences and made a bag of sentences (BOS). Then they identifies sentences as subjective or objective by using rule based lexicon method. Further subjective sentence is classed as positive, negative or neutral by identifying its opinion expression with help of SentiWordnet [16].

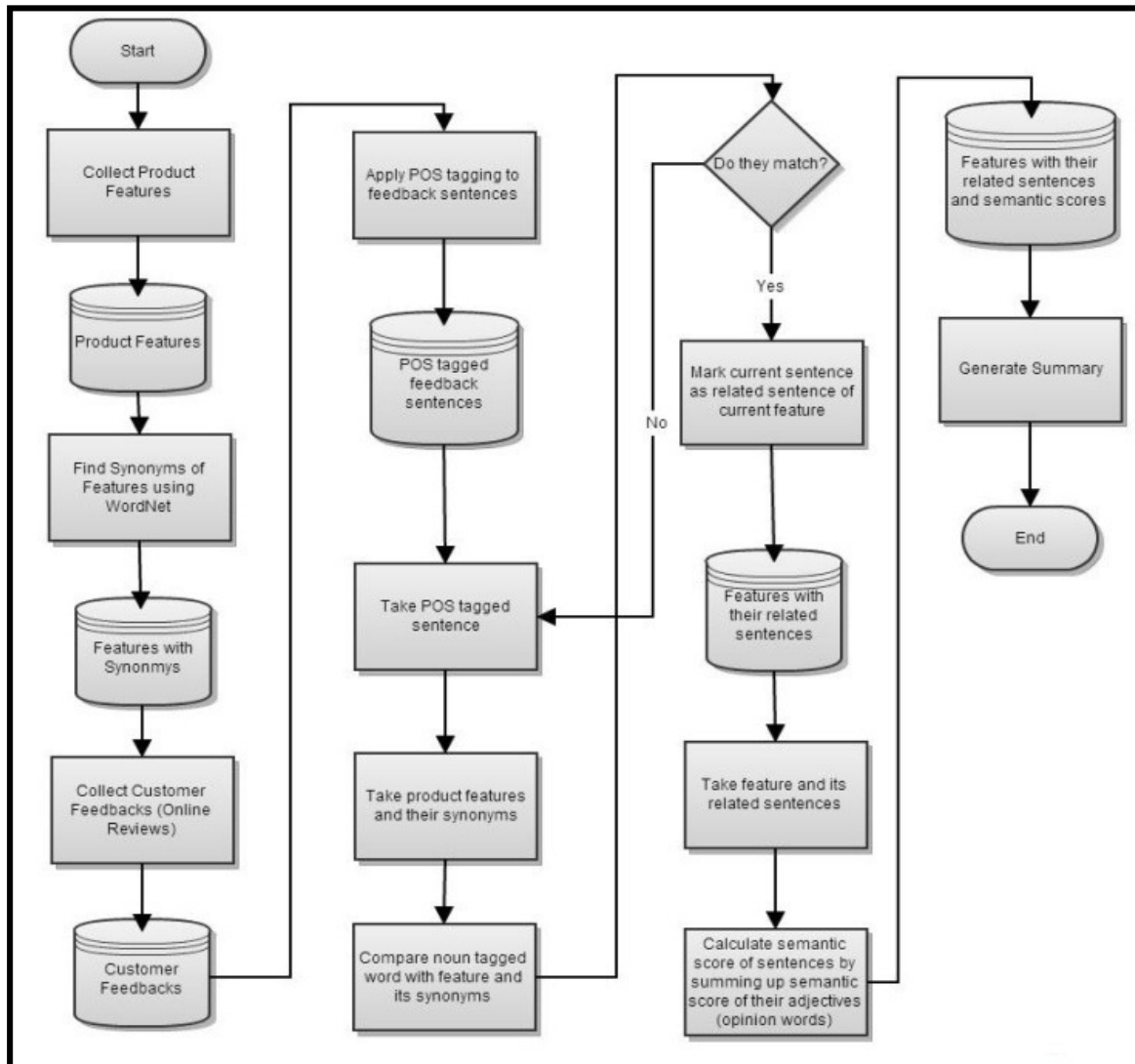
Our Approach

In Hu and Liu's work, main challenge was any noun word with more frequency gets identified as feature. But it can not be true on every case. Also infrequent noun with opinion word got identified as feature. There was no feature authentication process and results get biased. In our approach, we first collect product's features from either manufacture or from internet. Once we have product features, our task becomes easy as we need to find whether customer feedback contains any feature from given list and if

yes, than what is customer's opinion about it. We are performing following operations to complete above task. 1) Similar Word Extraction - We collect synonyms for every collected product feature by using WordNet [12]. This step increases our chances to find product features from customer feedback as he may have used different wording to describe a feature. 2) POS Tagging [13] - Part Of Speech tagging is used to identify every word of feedback as either a noun, adjective or adverb. As per Hu and Liu's work, we take nouns to be identified as product features. This way we can identify explicit features. 3) Feature Related Sentence Identification - We compare product features and their synonyms with nouns of every

sentence. If they match, we identify that sentence as a related sentence of a feature. This way we have a feature-wise bag of related sentences. 4) Semantic Orientation Identification - After finding a bag of related sentences, we use SentiWordnet [16] to identify the semantic orientation of each sentence by finding the semantic score of adjectives and adverbs. The sum of semantic scores defines the semantic orientation of sentences, i.e. if the semantic score is greater than 0, the sentence has a positive semantic orientation and if the semantic score is less than 0, the sentence has a negative semantic orientation.

Following is the flow chart of our approach



Experimental Setup and Result

A system, called FEBASE based on the proposed techniques has been implemented in Java with MySQL as backend to store data. We conducted our experiments using customer reviews of 22 mobile phones of different manufacturers. The reviews were collected from Flipkart.com by creating a java program

to crawl the site. Products in this site have a large number of reviews. Each of the reviews includes a text review, a title, author name and date and time. For each product, we first crawled and downloaded the reviews. Then we have stored them in MySQL database.

We have integrated Wordnet[12] 3.0 library for synonyms[18] identification, Stanford Core NLP library to identify sentences, words and to apply POS tagging and SentiWordnet[16] 3.0 data file to identify semantic score of adjectives and adverbs. For database integration in java, we have used Hibernate. Our system generates feature wise summaries and gives output in csv file. CSV file has metrics like total reviews count, mentioned in reviews count, positive in reviews count, negative in reviews count and neutral in reviews count for every product features. For finding accuracy, we have manually read all the reviews and listed out mentioned features. We have than also find its semantic orientation in that review and compare it with system generated result. System generated results have 84% accuracy in features finding and 77.5% similarities with semantic orientation.

Conclusion

In this paper, we proposed a set of techniques for mining and summarizing product reviews based on data mining and natural language processing. The objective is to provide a feature-based summary of a large number of customer reviews of a product sold online. Summarizing the reviews is very useful to manufactures and potential buyers. Our approach to first take product features list and compare them with customer reviews gives better result in terms of accuracy.

In our future work, we plan to further improve feature related sentence identification process by introducing new method to compare nouns and product features. We also plan to use other sources for synonyms identification like ExtendedWordNet and Relate

References

[1] Hu, Minqing and Bing Liu. 2004. "Mining and summarizing customer reviews." SIGKDD '04, pages 168-177, NY, USA. ACM.

[2] Weishu Hu, Zhiguo Gong and JingzhiGuo, "Mining Product Features from Online Reviews." IEEE 2010.

[3] Ana-Maria Popescu and Oren Etzioni, "Extracting Product Features and Opinion from Reviews", Proceeding of Human Language Technology Conference and Conference on Empirical Methods in Natural Language, ACL, Vancouver, October 2005, pp 339-336.

[4] AkashBakliwal, VasudevaVarma, "Mining Sentiment from Tweets", Association for Computational Linguistics (ACL) 2012.

[5] SudheerKovelamudi, SethuRamalingam, ArpitSood and VasudevaVerma, "Domain Independent Model for Product Attribute Extraction

from User Reviews using Wikipedia", 5th International Joint Conference on Natural Language Processing, page 1408-1412, Thailand, Nov-2011.

[6] Aurangzeb Khan, BaharumBaharudin, "Sentiment Classification Using Sentence-level Semantic Orientation of Opinion Terms from Blogs", IEEE, 2011.

[7] NLPProcessor – Text Analysis Toolkit. 2000. <http://www.infogistics.com/textanalysis.html>

[8] Hu, M., and Liu, B. 2004. "Mining Opinion Features in Customer Reviews." To appear in AAAI'04, 2004.

[9] Aggrawal, R. & Srikant, R. 1994. "Fast algorithm for mining association rules." VLDB'94, 1994.

[10] Liu, B., Hsu, W., Ma, Y. 1998. "Integrating Classification and Association Rule Mining." KDD'98, 1998.

[11] Bruce, R., and Wiebe, J. 2000. "Recognizing Subjectivity : A Case Study of Manual Tagging." Natural Language Engineering

[12] Miller, G., Beckwith, R, Fellbaum, C., Gross, D., and Miller, K. 1990. "Introduction to WordNet: An on-line lexical database." International Journal of Lexicography (special issue), 3(4) : 235-312.

[13] Manning C. and Schutze H., "Foundations of Statistical Natural Language Processing." MIT Press, May 1999.

[14] OpenNLP, open source toolkit for natural language processing <http://opennlp.sourceforge.net/>

[15] Jokinen P., and Ukkonen E., "Two algorithms for approximate string matching in static texts", Mathematical Foundations of Computer Science, 1997.

[16] Andrea Esuli and Fabrizio Sebastiani, "Sentiwordnet: A publicly Available Lexical Resource for Opinion Mining", In Proceedings of LREC-06, 5th Conference on Language Resources and Evaluation, Genova, IT. 2006, pp 417-422.

[17] Etzioni, M. Cafarella, D. Downey, S. Kok, A. Popescu, T. Shaked, S. Soderland, D. Weld, an A. Yates. 2005. "Unsupervised named-entity extraction from the web: An experimental study." Artificial Intelligence, 165(1) : 91-134

[18] D. Turney. 2001. "Mining the Web for Synonyms: PMI-IR versus LSA on TOEFL." In Procs. Of the Twelfth European Conference on Machine Learning (ECML-2001), pages 491-502, Freiburg, Germany.

[19] R.A.Hummel and S.W.Zucker. 1983. "On the foundations of relaxation labeling processes." In PAMI, pages 267-287

[20] O. Etzioni, M. Cafarella et al., "Unsupervised named-entity extraction from the web: An experimental study", Artificial Intelligence, 2005, pp. 91-134.