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An Enhanced Sentiment Analysis Model Using Co-Occurrence For Implicit Aspects Extraction

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Abstract: *Opinion mining is the computational study of opinions or emotions towards product aspects or things. One of the major steps for opinion mining is to extract product features. An aspect-based opinion mining approach helps in analyzing opinions about product aspects and attributes. This paper is based on extracting aspects and related customer sentiments from the product reviews. First, the proposed system performs some pre-processing steps to remove the stop words and special characters in the review sentences. Second, it performs the review analysis by using POS tagging and trigrams and then extract the attributes and opinion word pairs. Third, it forms the co-occurrence matrix to show the relationship between the product attributes and opinion words. Next, the proposed work extracts the implicit aspects by using k means clustering algorithm . Finally, it computes the overall sentiment score and rating of the reviews.*

Keywords: Opinion mining, Implicit aspects ,k-means clustering, co-occurrence, POS tagging ,sentiment score

1.INTRODUCTION

Opinion mining encompasses a set of technologies for extracting and summarizing opinions expressed in web-based user-generated contents. An aspect-based Opinion mining considers relations between the aspects of the object of the opinion and the document polarity (positive or negative feeling expressed in the opinion). For aspect-level sentiment analysis, the first important step is to identify the aspects and their associated entities present in customer reviews. In general, the aspect-level opinion mining consists of three main tasks. They are :(1) Extract product aspects from the review document, *i.e.*, identify the expression purpose of user's opinion. (2) Identify corresponding opinions with product aspects, *i.e.*, mine the opinions related with each product aspect; (3) Determine the sentiment polarity (positive or negative) of the corresponding opinions with product aspects, and this task is similar to sentiment classification task.

In product reviews, users are mostly concerned about the comments on a certain aspect of the product, so opinion mining on product aspects is the current research focus. Most of the researches in this field focused primarily on explicit aspects but neglected implicit aspects.

However, the implicit aspects that are expressed indirectly by a few words or phrases are equally important which can express the user's opinions and help us better to understand the user's comments. The identification of implicit aspects in product reviews is a very challenging task and it is also a significant subtask for opinion mining. When compared to the explicit aspect identification, identifying implicit aspects is much difficult. The problem is that there may be possibilities to associate an aspect with multiple entities.

Figure1.1: Opinion Mining Framework

2.LITERATURE REVIEW

Ekin Ekinci and Sevinç İlhan Omurca [1] used Latent Dirichlet Allocation (LDA) for extraction of implicit aspects. LDA is completely unsupervised and is based on bag-of words assumption. The basic intuition behind LDA is that, documents exhibit multiple topics and topic has a probability distribution over words. Distribution over words and topic proportions are obtained with Dirichlet distribution. Dirichlet distribution is the conjugate prior for the parameters of the multinomial distribution. Reviews concerning 320 different restaurants from 4 different cities (Atlanta, Chicago, Los Angeles and New York City) are obtained from a web site. After the dataset is obtained ,the preprocessing step is performed. From the reviews, 2640 different multiword aspects are obtained. The product aspects are extracted from the restaurants reviews. Three criteria are considered in the evaluation of these aspects: i) The aspects under the same topic should

be compatible with each other, ii) aspects can capture details in the reviews and iii) the most frequently discussed aspects in comments can be captured. For semantic similarity of review concepts, which are obtained by using Babelfy, those things will be extracted and these concepts will be represented in high dimensional space.

El Hannach Hajar and Benkhalifa Mohammed [2] proposed an approach that combines a corpus based and WordNet(WN) dictionary based models for Implicit Aspect Terms (IAT) extraction. This method is motivated by considering all WN related words which do not necessarily co-occur with their adjectives in many corpus sentences to be associated reliably. The proposed approach operates in three phases:(1) Implicit Aspect Representation, (2) Learning Model Enhancement (3) Implicit Aspect Identification. In phase 1, the list of all corpus adjectives are extracted and generates each adjective ai with Word Net frequency vector of all its Word Net related words. Then, computes each aspect Aj training data frequency (fti)vector of all adjectives of that aspect and the global frequency vector for each adjective ai and all its Word Net related words are computed. Finally augment the adjective frequency matrix Ma with Word Net related words frequency matrix Mr to form the term frequency Mt (Na+Nr,NA) matrix. In phase 2, apply a discriminatory factor to Mr (WN related words) of the matrix Mt (learnt model). The objective is to remove noisy WN words. Finally obtain a final term frequency (Final_Mt) matrix. In phase 3, use Final_Mt to test NB classification of all terms (corpus adjectives + reliable WN related words) with respect to different aspects. NB assigns to each pair term/aspect a probability Pij that indicates how reliable the term i is for aspect j identification. In this paper ,they only focus adjective as aspect indicators whereas adverbs and verbs are not considered as aspect indicators .

Hajar El Hannach and Mohammed Benkhalifa [3] addresses the aspect identification task involving implicit aspect implied by adjectives and verbs for crime tweets. The proposed hybrid model is based on WordNet semantic relations and Term-Weighting scheme, to enhance training data for Crime Implicit Aspect sentences detection (IASD) and Crime Implicit Aspect Identification (IAI). The performance is evaluated using three classifiers Multinomial Naïve Bayes, Support Vector Machine and Random Forest on three Twitter crime datasets. Implicit Aspect based Sentiment Analysis (IASA) performed in three steps: 1) implicit aspect sentences detection (IASD), (2) implicit aspect identification (IAI) and (3) sentiment classification. The IASD phase, consists of preprocessing and sentence relevancy classification process.The first step of the preprocessing is the removal of noisy data. Sentence Relevancy Classification, which encompasses two sub-steps, focuses on classifying relevant/irrelevant tweets in order to create an implicit aspect crime corpus from each dataset. In Crime implicit aspect identification phase, the task aims at extracting crime implicit aspects from corpora prepared in phase 1. In sentiment classification phase, three supervised classifiers are used to validate the proposed approach: Multinomial Naïve Bayes (MNB), Support Vector Machine (SVM) and Random Forest (RF). The proposed approach is not suitable for crime detection from variant resources of data such as weather data which significantly influence crime rates and criminal behavior .

Huan-Yuan Chen and Hsin-Hsi Chen [4] aimed at identifying aspects and polarities of opinionated statements not consisting of opinion words and aspect terms. They construct an implicit opinions corpus annotated with aspect class labels and polarity automatically. Aspect and polarity classifiers trained by using this corpus is used to recognize aspect and polarity of implicit opinions. Here the work begins with collecting a Chinese hotel review dataset from booking.com. Here only Chinese reviews are kept and Stanford NLP tool is used to segment, POS tag, and parse all the reviews. At first, construct an opinion dictionary from this dataset. Words of POS tags VA, VV, AD, and JJ are candidates of opinion words. They adopt Chi square test and point-wise mutual information to filter out less confident words from the candidate set, respectively. SVM with linear kernel (BOW) is robust in implicit polarity recognition. It is also challenging when either opinion word or aspect term is absent from the cue segment.

3. IMLPEMENTATION

3.1 System Architecture

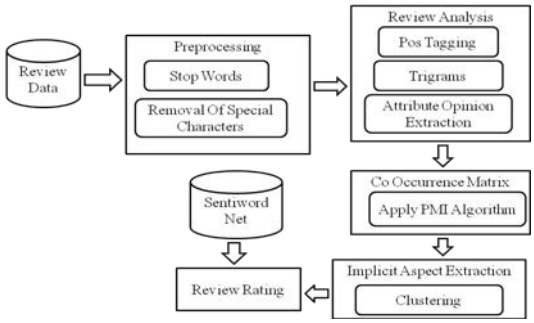

Figure 3.1.1 Overall System Architecture

3.2 Modules

3.2.1 Data Preprocessing

The product reviews are collected from the online websites like Amazon. Preprocessing is performed to remove the stopwords and special characters. After the POS tagging is performed to tag each of the words, trigram is used to form all the three possible combination of words. Then extract the product attributes –opinion word pairs.

3.2.2 Co Occurrence Matrix Formation

After the extraction of attributes and opinion words, the co -occurrence matrix is formed. This matrix contains the co-occurrence values of words, PMI scores, semantic

orientation scores and the positive ,negative scores. Here the PMI score is calculated by using following formula:

$$PMI(X,Y)=\log_2\left(\frac{P(x,y)}{P(x)*P(y)}\right) \text{ and}$$

Semantic orientation score is calculated by using following formula:

SO= PMI Score * 0.25 - PMI Score * 4

The positive(1) and negative(-1) score is calculated by using following formula:

PMIscore=(-0.5)*math.log(P(x,y)/P(x)*P(Y))/math.log(10)

3.2.3 Implicit Aspect Extraction

After the formation of co-occurrence matrix, implicit aspects are extracted by using k-means clustering algorithm. The way k-means algorithm works is as follows:

1. Select the number of clusters(K) and obtain the data points
2. Place the centroids c_1, c_2, ... c_k randomly
3. Repeat steps 4 and 5 until convergence or until the end of a fixed number of iterations
4. for each data point x_i:
   - find the nearest centroid(c_1, c_2 .. c_k)
   - assign the point to that cluster
5. for each cluster j = 1..k
   - new centroid = mean of all points assigned to that cluster
6. End

3.2.4 Review Rating

After the extraction of implicit aspects ,sentiment score is calculated by using the Sentiword Net. Sentiword Net is a dictionary which contains the score of all the opinion words. Using this dictionary,sentiment score is calculated using the following formula:

Review Score=Overall Review Sense/Count

4 .RESULTS AND DISCUSSION

Implicit aspect extraction is the most challenging task in aspect level opinion mining. First, the product attributes and opinion words are extracted to build the co-occurrence matrix which shows the relationship between opinion words and product attributes. Second, implicit aspects are identified by the opinion words and the product features in the implicit features' context by using clustering. From the clustered attributes, the words that are most similar to the preceeding and following words extracted as implicit aspects.

Implicit Aspect Extraction

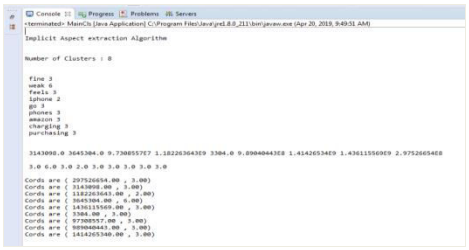

Figure 4.1 Clustering aspects

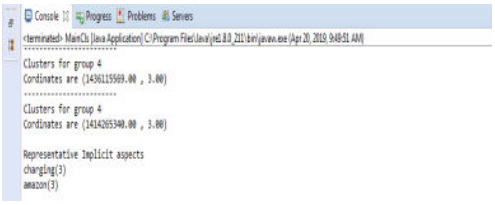

Figure 4.2 Extracted implicit aspects

5. CONCLUSION AND FUTURE ENHANCEMENT

At present, Sentiment analysis is mainly done through the establishment of sentiment corpus, and then according to the text corresponding to the sentiment corpus, sentiment words are extracted. The method is convenient and practical. The proposed system extracts implicit aspects and the related customer sentiments on product domain. This system tries to retrieve implicit sentiments of customer. Co-occurrence between opinion word and other words in the sentence is used to identify an aspect that is implied in an opinion word.

For future work, it would be interesting to extend the proposed work dynamically to improve the model, as new entities and aspects are found. Furthermore, this work can be extended to other domains as well by identifying relationships between aspects specific to a domain and modeling them as a hierarchy.

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