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Analysis of Orientation of Product Reviews Using Sentiment Analysis

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Abstract - In recent years people widely expressing their sentiments on products they purchase from online shopping websites. Large numbers of product reviews are posted by the online buyers. These product reviews has either positive or negative sentiment about the products. Buyers also express sentiments about product features, how good or bad this particular product feature is. In this paper we first build the Web Crawler to extract product reviews from Online Shopping Websites. Using the parts-of-speech tagger identify product features and extract the opinion phrases. Next, Semantic Orientation (SO) of the opinion phrases is calculated using the PMI-IR method. SO is the mutual information between opinion phrases and set of positive and negative word set. Summary is presented based on average SO. Summary describe the classification of sentiments of product features.

Keywords: Sentiment analysis, online product reviews, Semantic Orientation, Summarization, PMI-IR.

I. INTRODUCTION

With the increasing use of internet online shopping websites gaining more trust. Consumers possibly buy everything that online shopping websites sell online. Online Buyers also express opinions about products by posting reviews of products. These reviews contain positive or negative sentiments about products. Reviews also discuss about the characteristics of products i.e. features of products. Some popular products may have hundreds or thousands of reviews. Many reviews are long and take time for reading, some of them are useless. It becomes difficult for people to find generalized opinion about the product. Products are rated based on 5-star ratings; it is overall rating of products that is unable to describe sentiments about product features.

Many researchers of natural language processing are working on sentiment classification. It is also known as opinion mining or polarity mining. Sentiment classification classifies reviews sentences as positive or negative. It is also possible to determine the orientation of product features using featured based sentiment classification.

Two approaches of sentiment classification used to determine orientation of reviews. One is machine learning based methods [9, 10] and second is semantic oriented methods.

Turney [1] presented a semantic oriented based mining method which uses point-wise mutual information and information retrieval (PMI-IR) method for sentiment classification which uses mutual information and statistical data collected by IR.

The first step of Turney's algorithm is to use of parts-of-speech tagger to extract the two word phrases of adjectives and adverbs from the input text. Second step is to calculate semantic orientation of each phrase using PMI-IR algorithm. A numerical value is assigned to each phrase which shows the association with positive reference word (*'excellent'*) and negative reference word (*'poor'*). The association or co-occurrence of phrases with 'excellent' and 'poor' is positive (e.g. "amazing pictures") or negative (e.g. "high price"). The third step determines the average semantic orientation that decides the reviews recommended or not recommended. If the average is positive then review will be considered as useful for product otherwise it will consider as not useful. The magnitude of average semantic orientation also describes the strength of positivity and negativity of the review. The semantic orientation of phrase is calculated using PMI and IR. Mutual information is calculated between each phrase and positive word *'excellent'* and is subtracted from the mutual information of each phrase and negative word *'poor'*. Mutual information is amount of information of the presence of two word phrases when we observe *'excellent* and *'poor'*. When talking about positivity and negativity, frequent occurrence of sentiment phrases is mutual information. So phrases co-occur with *'excellent'* are more likely positive and terms that tend to co-occur with *'poor'* are more likely negative. Turney's algorithm uses 410 reviews from shopping site Epinions collected from four different domains: reviews for travel destinations, banks, automobiles and movies, these are not expert reviews but posted by consumers of Epinoins.

II. SENTIMENT CLASSIFICATION

Following steps shows sentiment classification performed by PMI-IR method.

Step 1. Download the reviews using the web crawler.
Step 2. Using parts-of-speech tagger parse the reviews documents and assigns tags to each word.
Step 3. Based on certain pattern extract two word phrases.
Step 4. Calculate the Semantic Orientation of each phrase,

PMI-IR algorithm takes '*excellent*' and '*poor*' as reference word.

So Semantic Orientation of phrase is calculated as,

$$SO\ (phrase) = PMI\ (phrase, excellent) - PMI\ (phrase, poor) \qquad (1)$$

Here point-wise mutual information between word1 and word2 is defined as,

$$PMI(word1, word2) = \log_2 \left[\frac{p(word1\ \&\ word2)}{p(word1)\ .\ p(word2)} \right] \qquad (2)$$

PMI value is calculated by passing queries to search engine and noting the number of hits (number of matching documents). Here p (*word1 & word2) is* the probability that *word1* and *word2* co-occur. If the words are statistically independent, the probability that they co-occur is given by the product of p (*word1*) and p (*word2*). The ratio between p (*word1 & word2)* and p (*word1*) p (*word2*) is a measure of the degree of statistical dependence between the words. The log of ratio corresponds to a form of correlation, which is positive when words tend to co-occur and negative when the presence of one word makes is likely that the other word is absent.

For example hit (*query*) is the number of hits (matching documents) returned from the online search engine, for the given query SO (*phrase)* is calculated from the equations (1) and (2) as follows:

$$SO(phrase) = \log_2 \left[\frac{\text{hits}(phrase\ \text{NEAR "excellent"})\ \text{hits}(\text{"poor"})}{\text{hits}(phrase\ \text{NEAR "poor"})\ \text{hits}(\text{"excellent"})} \right] \qquad (3)$$

The NEAR operator constraints search to documents that contains *phrase* and *excellent (or poor)* within a given window size.

The semantic orientation of reviews is calculated by averaging the SO of all extracted two-word phrases. If average semantic orientation is greater than threshold value, review has positive opinion otherwise negative opinion.

Table 1 .Patterns of tags for two-word phrase extraction

S. No.	First Word	Second Word
1.	JJ	NN or NNS
2.	RB,RBR or RBS	JJ
3.	JJ	JJ
4.	NN or NNS	JJ
5.	RB,RBR or RBS	VB,VBD,VBN, or VBG

In English language each word is categorized in tags or syntax using parts-of-speech tagger [14]. Few patterns are described in TABLE 1. Following these patterns, two-word phrases extracted from review sentences that contains features of products. These two-word phrases contain adverbs, adjectives, nouns and verbs that show subjectivity and characteristics of products. The patterns that extract two-word phrases are adopted from Turney's study.

The SO of each phrase determines number of positive and negative phrases. If SO is greater than threshold value phrase consider as positive phrase otherwise phrase is negative. Similarly average SO is positive if it is greater than threshold value otherwise average SO is negative. Threshold value in turney's study is zero.

III. PREVIOUS WORK

In 1997 Hatzivassiloglou and McKeown [2] proposed a supervised algorithm that predicts the semantic orientation of adjectives but it is designed only for isolated adjectives rather than two-word phrases that contains of patterns of adjectives, adverbs and nouns. Turney's [2001] first work that uses statistical data acquired by querying online search engine identify synonyms [6] of words. It is a simple unsupervised algorithm called PMI-IR that measure similarity of pair of words. Using PMI-IR algorithm Turney classify online product reviews by extracting the two-word phrases and estimating the semantic orientation of phrases. Product reviews extracted from internet were sampled from four different domains automobiles, banks, movies and travel destinations. Of these 410 reviews 170 are *not recommended* and remaining 240 are *recommended*. The average accuracy of classification algorithm is 74%, ranging from 84% for automobile reviews to 66% for movie reviews.

YE Qiang, LI Yijun, ZHANG Yiwen [3] worked on Chinese product reviews .Their study based on book and cell phone reviews written in Chinese language. They extract two-word phrases from Chinese reviews and calculate the semantic orientation. The orientation of reviews is decided by threshold value. Similar work has been done by ZHANG Zi-qiong, LI YI-jun, YE Qiang and LAW Rob [4] in 2008. They use an unsupervised PMI-IR method for sentiment classification of Chinese product reviews. Instead of using number of hits of query they use snippets returned from Google. For example, to calculate PMI value of a phrase issue a query and crawl returned snippets. Sentiment classification of blog contents is determined by calculating semantic orientation. Depending on context blogs have different sentiments like joy, angry etc. Xuiting Duan, Tingtin HE, Le SONG [5] study blog content and classify contents as joy, angry, fear, sad using semantic orientation method. M. Hu and B. Liu [7] and Won Young Kim, Joon Suk Ryu, Kyu II Kim, Ung Mo Kim [13] study the customer reviews for mining opinions and generate the summary of opinions. X. Ding, B. Liu and PS. Yu [8] suggests a holistic lexicon based approach of feature-based sentiment classification that identify different features of products and detects opinions about features. Qingliang Miao, Qiudan Li, Ruwei Dai [14] study strategy for mining product features and opinions.

All these methods applied on individual reviews and predict the sentiments from reviews and present overall summary. In our study, instead of estimating opinions of individual reviews we calculate the semantic orientation of all reviews of products and extract overall opinion about features of products and show the amount of positivity and negativity about feature of products. In this paper, we study the sentiment classification of most common features of product that expressed in reviews by consumers. Experiments results show that the method is most feasible.

IV. PRAPOSED METHODOLOGY

First of all, we build a web crawler to extract the reviews of five different products of mobiles, tablets and laptops and stored in Inverted Index format in repository called indexing files. Contents are stored and arranged in memory so they can be searched by terms present in files.

After storing reviews common features identified by using parts-of-speech tagger. Features of products are nouns like *camera, battery, price and processor*. These four features are most frequent features of mobiles, tablets and laptops that people talk in reviews. Our study focuses only on explicit feature. Explicit features are directly mentioned in reviews. Next, we find those review sentences where these features mentioned using sentence tokenization. For example *"Camera of this mobile takes amazing pictures"*. From these reviews sentences we extract two-word phrases using parts-of-speech tagger.

In our study, we use 18 positive and negative reference words. These two set contain 18 positive and negative words instead of *'excellent'* and *'poor'*. It improves the efficiency of algorithm by adding more positivity and negativity with phrases.

Pos. ref. word set =

{'excellent', 'good', 'fantastic', 'best', 'super', etc.}

Neg. ref. word set =

{'poor', 'bad', 'worst', 'wrong', 'problem', 'defective', etc.}

To calculate the PMI value of phrase from equation (2) we do not use any web search engine, instead we develop a reviews search engine that contains more than 20,000 online product reviews. By querying reviews search engine, number of hits estimated for phrases (i.e. *'phrase' AND pos/neg.ref word*). The reason for using separate search engine because it contains product reviews which talks about only products and its features nothing else, this improves the reliability.

Using equation (1) semantic Orientation of each phrase is calculated by subtracting PMI values of phrase with pos ref word set and PMI values of phrase with neg. ref word set. SO is positive if it is greater than threshold value otherwise it is negative. It is believed that positivity is always greater than negativity. According to Maite Taboada's SO-CAL program [11] positivity in reviews sentences is 1.5 times greater than negativity. In our study we set threshold value as 2. Semantic orientation of all phrases determine number of positive phrases and negative phrases, this shows the amount of positivity and negativity about features of products. Averaging the semantic orientation of all phrases shows the strength of opinion of features of products. The orientation of average SO is positive if it is higher than threshold value and if average SO is lower than threshold value. Bigger the average SO depicts higher amount of positivity, similarly smaller average SO depicts higher amount of negativity.

At the end, summarization is presented which covers summary of opinions of all four features *camera, battery, price* and *processor* and strength of positivity and negativity of all features of products.

Fig. 1 shows architecture of overall system.

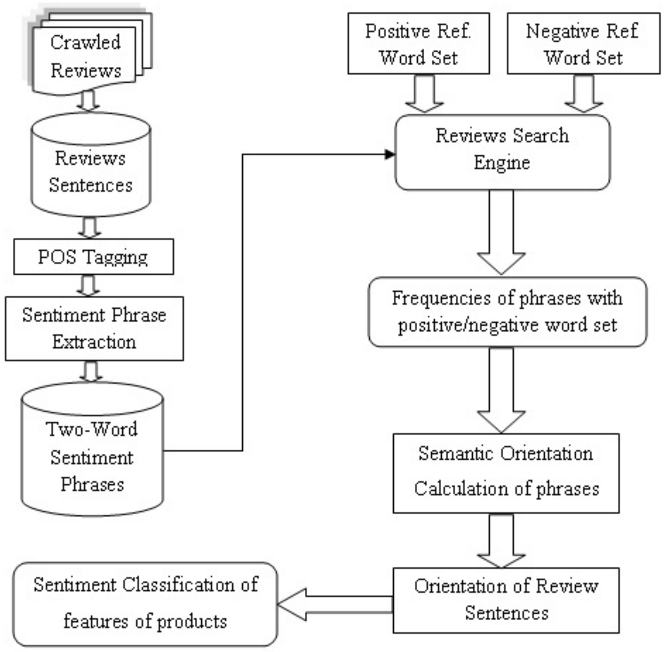

Fig. 1.1 Architectural Overview of Semantic Orientation System

V. EXPERIMENTAL RESULTS

In order to classify the polarity of features of products, we first download 60 reviews of 15 products categorized in mobiles, tablets and laptops. Each category has five products, this makes total of 900 product reviews. All these reviews are downloaded from online shopping website www.flipkart.com using web crawler. In the process of phrase pattern extraction total of 3059 phrases are extracted among them 820 phrases are of feature *camera*, 978 of *battery*, 305 of *processor* and 956 of *price.*

Table 2.Opinion Summary of Features of Mobiles

Apple iPhone 6:			
Camera	**Battery**	**Price**	**Processor**
Positivity 61.62%	Positivity 57.89%	Positivity 78.79%	Positivity 0.0%
Negativity 38.46%	Negativity 42.11%	Negativity 21.21%	Negativity 0.0%
Strength 5.6261	Strength 6.4440	Strength 9.6493	Strength 0
HTC One M8			
Camera	**Battery**	**Price**	**Processor**
Positivity 50.41%	Positivity 53.71%	Positivity 48.38%	Positivity 53.12%
Negativity 49.59%	Negativity 46.42%	Negativity 51.62%	Negativity 46.88%
Strength 1.2763	Strength 3.8621	Strength 0.6408	Strength 0.6737
Lava Pixel			
Camera	**Battery**	**Price**	**Processor**
Positivity 69.35%	Positivity 65.08%	Positivity 81.48%	Positivity 58.82%
Negativity 30.65%	Negativity 34.48%	Negativity 18.52%	Negativity 41.18%
Strength 5.6201	Strength 4.6523	Strength 8.5820	Strength 2.4267
Micromax Canvas Nitro			
Camera	**Battery**	**Price**	**Processor**
Positivity 71.17%	Positivity 68.48%	Positivity 72.00%	Positivity 66.67%
Negativity 28.83%	Negativity 31.52%	Negativity 28.00%	Negativity 33.33%
Strength 7.4362	Strength 6.7715	Strength 6.4304	Strength 6.8845
Samsung Galaxy S6			
Camera	**Battery**	**Price**	**Processor**
Positivity 55.61%	Positivity 62.42%	Positivity 56.86%	Positivity 68.63%
Negativity 44.38%	Negativity 37.58%	Negativity 43.14%	Negativity 31.37%
Strength 5.5556	Strength 6.4846	Strength 4.6918	Strength 7.9760

Table 3.Opinion Summary of Features of Tablets

Apple iPad Air 2:			
Camera	**Battery**	**Price**	**Processor**
Positivity 38.89%	Positivity 61.76%	Positivity 72.73%	Positivity 44.44%
Negativity 61.11%	Negativity 38.24%	Negativity 27.27%	Negativity 55.56%
Strength 1.028	Strength 4.9986	Strength 7.9287	Strength 2.5900
Datawind Tablet			
Camera	**Battery**	**Price**	**Processor**
Positivity 68.75%	Positivity 66.67%	Positivity 60.53%	Positivity 61.54%
Negativity 31.25%	Negativity 33.33%	Negativity 39.47%	Negativity 38.46%
Strength 6.0426	Strength 4.9697	Strength 4.4554	Strength 2.4095
Micromax Tablet			
Camera	**Battery**	**Price**	**Processor**
Positivity 76.19%	Positivity 53.06%	Positivity 80.00%	Positivity 100.0%
Negativity 23.81%	Negativity 46.94%	Negativity 20.00%	Negativity 0.0%
Strength 6.3316	Strength 1.2625	Strength 8.6114	Strength 14.48
Lenovo A7-30			
Camera	**Battery**	**Price**	**Processor**
Positivity 57.14%	Positivity 69.57%	Positivity 100.00%	Positivity 0.0%
Negativity 42.86%	Negativity 30.43%	Negativity 20.00%	Negativity 0.0%
Strength 2.9288	Strength 7.0970	Strength 10.1616	Strength 0
Lenovo Yoga 2			
Camera	**Battery**	**Price**	**Processor**
Positivity 57.38%	Positivity 62.50%	Positivity 54.44%	Positivity 50.0%
Negativity 47.62%	Negativity 37.50%	Negativity 45.56%	Negativity 50.0%
Strength 4.2213	Strength 5.1869	Strength 3.1207	Strength 6.6907

Table 4.Opinion Summary of Features of Laptops

Apple MacBook Pro:							
Camera		**Battery**		**Price**		**Processor**	
Positivity	62.50%	Positivity	41.18%	Positivity	46.81%	Positivity	38.89%
Negativity	37.50%	Negativity	58.82%	Negativity	53.19%	Negativity	61.11%
Strength	1.7682	Strength	0.3151	Strength	1.6112	Strength	0.1756
Dell Inspiron 3542							
Camera		**Battery**		**Price**		**Processor**	
Positivity	0.0%	Positivity	66.67%	Positivity	60.71%	Positivity	62.50%
Negativity	0.0%	Negativity	33.33%	Negativity	39.29 %	Negativity	37.50%
Strength	0	Strength	4.9697	Strength	2.8308	Strength	4.6854
HP Compaq							
Camera		**Battery**		**Price**		**Processor**	
Positivity	0.0%	Positivity	65.63%	Positivity	70.75%	Positivity	56.52%
Negativity	0.0%	Negativity	34.38%	Negativity	29.25%	Negativity	43.48%
Strength	0	Strength	7.8793	Strength	7.6516	Strength	6.1159
Lenovo G50-70							
Camera		**Battery**		**Price**		**Processor**	
Positivity	0.0%	Positivity	47.36%	Positivity	62.79%	Positivity	34.78%
Negativity	0.0%	Negativity	52.63%	Negativity	37.21%	Negativity	65.21%
Strength	0	Strength	3.4938	Strength	6.5374	Strength	-1.2929
Samsung Laptops							
Camera		**Battery**		**Price**		**Processor**	
Positivity	46.43%	Positivity	43.00%	Positivity	50.00%	Positivity	48.97%
Negativity	53.57%	Negativity	57.00%	Negativity	45.00%	Negativity	51.03%
Strength	-0.8329	Strength	-0.7357	Strength	3.2421	Strength	-0.5252

Semantic Orientation of all phrases calculated for each feature and based on SO of positive and negative phrases, percentages calculate for each feature.

Results are shown in TABLE 2, 3 and 4 of each category. It shows classification of each feature based on the amount of positivity and negativity that expressed in the reviews of products. In our experiment we show overall positivity and negativity about each feature. Results also show how strong the orientation of sentiments is expressed in reviews. The strength of average semantic orientation of sentiment is strong when amount of positivity is higher than amount of negativity. Percentages of positivity and negativity are the number of positive and negative phases. Note also that there are possibility of many other implicit features, sentiments about these implicit features is beyond the scope of this paper.

VI. CONCLUSION

This paper uses the PMI-IR method for the classification of features of online selling products. The online product reviews are downloaded from shopping website using the web crawler. From these reviews, sentences are identified in which features of product are mentioned. Two-word opinion phrases are extracted from these review sentences using POS tagging which one of natural language technique by following patterns. The most important step is calculation of semantic orientation of all phrases using the reviews search engine which we developed and used in our experiment. We also extend the positive and negative reference word set to 18 words; this improves the efficiency by adding more positivity and negativity. Sentiment classification of features of products is useful for shopping websites where it is possible to give more detailed information about the product from consumer's point of view. Showing opinions about special features of products is great beneficiary to both online retailer and online buyer of products.

VII. FUTURE SCOPES

For further improvement, we can increase the database of our reviews search engine; bigger the search database will increase the reliability of the system. Threshold value could raise the performance issue; it needs to take proper attention to set the threshold value. Semantic orientation has wide verity of applications in information systems; it is possible to classifying reviews, finding synonyms and antonyms, improving the capabilities of search engine, social media analysis. Also extracting the sentiments about implicit features is a challenge of future work.

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