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Co-Extracting Opinion Targets and Opinion Words From Online Reviews Based on The Partially Supervised Word Alignment Model

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Abstract:

Mining opinion targets and opinion words from online reviews are important tasks for fine-grained opinion mining, the key component of which involves detecting opinion relations among words. A novel approach based on the Partially Supervised Word Alignment model is proposed in a monolingual scenario to mine opinion relations in sentences and estimate the associations between opinion target candidates and potential opinion words by incorporating partial alignment links into the alignment process that is generated by the use of pos tagging, where a potential opinion relation is comprised of an opinion target candidate and its corresponding modified word. Next, an Opinion Relation Graph will be constructed to model all opinion target/word candidates and the opinion relations among them. Where all nouns/noun phrases in sentences are assumed to be an opinion target candidates, and all adjectives/verbs are regarded as potential opinion words, each candidate will be assigned a confidence. Finally, candidates with higher confidence than a threshold will be extracted as the opinion targets or opinion words. Moreover our model captures opinion relations more precisely, especially for long span relations. Our experimental results on the customer review datasets (CRD), which includes English reviews of five different products show that our approach provides better Precision (74.2%), Recall (64.4%) and F-Measure (65.3%). Our Partially Supervised Word Alignment model effectively alleviates the negative effects of parsing errors when dealing with informal online texts. In particular, this model not only inherits the advantages of the traditional methods for opinion relation identification, but it also has a more precise performance because of the use of partial supervision. Thus, it is reasonable to expect that the PSWAM

is likely to yield better results for extracting opinion targets and opinion words.

Keywords: Customer review datasets, Mining opinion, Opinion words, Opinion Relation Graph

Introduction

Today's world is a world of Internet, almost all work can be done with the help of it, from simple mobile phone recharge to biggest business deals can be done with the help of this technology. People spent their most of the times on surfing on the Web; it becomes a new source of entertainment, education, communication, shopping etc. Users not only use these websites but also give their feedback and suggestions that will be useful for other users. In this way a large amount of reviews of users are collected on the Web that needs to be explored, analyze and organized for better decision making. As the social media, blogs, forums, e-commerce web sites, etc. provides a great medium for people to share things. It also provides a great source of unstructured information (especially opinions) that may be useful to others (e.g. companies and other Customers ..) where people's opinions and experience are very valuable information in decision making process, but to get benefits from these opinion and experience, the accumulated content should be extracted and analyzed properly.

These contents are mostly written in natural language. An automatic natural language processing tool is needed to extract and analyze the people sentiments from these unstructured texts. Numerous researches are undergoing in this domain is called Opinion mining and sentiment analysis. Opinion Mining is an extension of data mining that involves building a system to collect and categorize opinions about a product. Automated opinion mining often uses machine learning, a type of artificial intelligence (AI) and/or NLP techniques. More informally, it's about extracting the opinions or sentiments given in a piece of text. It's also referred as Sentiment Analysis, which is a study of human behavior in which user opinions and emotions are extracted from plain text.

The above figure explains how the input is being classified on various steps to summarize the reviews. Opinion Retrieval is the process of collecting review text from review websites. Different review websites contain reviews for products, movies, hotels and news. Information retrieval techniques such as web crawler can be applied to collect the review text data from many sources and store them in database. And Opinion Classification is the primary step in sentiment analysis the approach involves classifying review text into two forms namely positive and negative, Machine learning based approach is more popular. And Opinion Summarization is a major part in opinion mining process. Summary of reviews provided should be based on features or subtopics that are mentioned in reviews. Feature based summarization a type summarization involves finding of frequent terms (features) that are appearing in many reviews. The summary is presented by selecting sentences that contain particular feature information. The architecture of Opinion Mining shows how the input is being classified on various steps to summarize the reviews. Analyzing customer review is very important, it tend to rate the product and provide opinions which is been a challenging problem today.

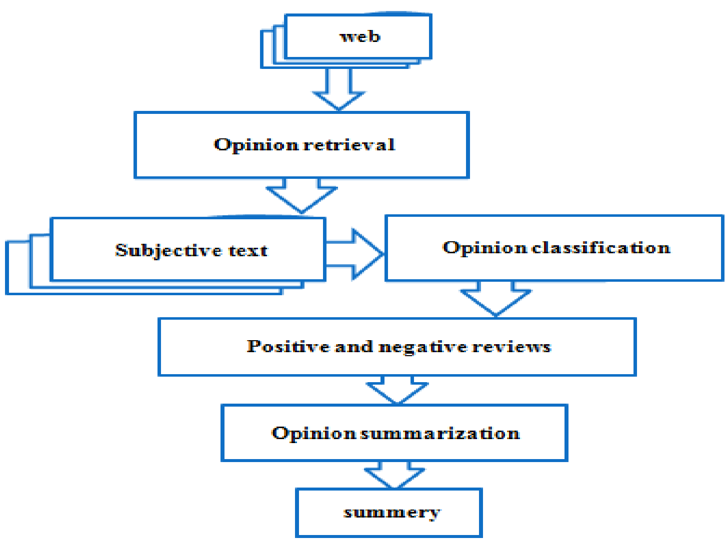

Figure 1.1 Architecture of Opinion Mining

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PSWA Model:

With the rapid development of Web 2.0, a huge number of product reviews are springing up on the Web. From these reviews, customers can obtain first-hand assessments of product information and direct supervision of their purchase actions. Meanwhile, manufacturers can obtain immediate feedback and opportunities to improve the quality of their products in a timely fashion. Thus, mining opinions from online reviews has become an increasingly urgent activity and has attracted a great deal of attention from researchers, to extract and analyze opinions from online reviews; it is unsatisfactory to merely obtain the overall sentiment about a product. In most cases, customers expect to find fine-grained sentiments about an aspect or feature of a product that is reviewed. For example: (This phone has a colorful and big screen, but its LCD resolution is very disappointing), readers expect to know that the reviewer expresses a positive opinion of the phone's screen and a negative opinion of the screen's resolution, not just the reviewer's overall sentiment, To fulfill this aim, both opinion targets and opinion words must be detected. First, however, it is necessary to extract and construct an opinion target list and an opinion word lexicon, both of which can provide prior knowledge that is useful for fine-grained opinion mining.

An opinion target is defined as the object about which users express their opinions, typically as nouns or noun phrases. In the above example, "screen" and "LCD resolution" are two opinion targets. Previous methods have usually generated an opinion target list from online product reviews. As a result, opinion targets usually are product features or attributes. Accordingly this subtask is also called as product feature extraction; In addition opinion words are the words that are used to express users' opinions. In the above Example, "colorful", "big" and "disappointing" are three opinion words. Constructing an opinion words lexicon is also important because the lexicon is beneficial for identifying opinion expressions. For these two subtasks, previous work generally adopted a collective extraction strategy. The intuition represented by this strategy was that in sentences, opinion words usually

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co-occur with opinion targets, and there are strong modification relations and associations among them (which are called opinion relations or opinion associations). Therefore, many methods jointly extracted opinion targets and opinion words in a bootstrapping manner. For example, "colorful" and "big" are usually used to modify "screen" in the cell-phone domain, and there are remarkable opinion relations among them. If "big" is expected to be an opinion word, then "screen" is very likely to be an opinion target in this domain. Next, the extracted opinion target "screen" can be used to deduce that "colorful" is most likely an opinion word. Thus, the extraction is alternatively performed between opinion targets and opinion words until there is no item left to extract.

Problem Statement

- If a customer-One comments on mobile phone, "the voice quality is excellent" and customer-Two comments, "Sound quality of phone is very good". Both are talking about same feature but with different wording. To group the synonym words is also a challenging task.
- Users usually express opinions on some unrelated objects in reviews, such as "good feelings", "wonderful time" and "bad mood". Obviously, "feelings", "time" and "mood" are not real opinion targets. However, because they occur frequently and are modified by real opinion words ("good", "wonderful" and "bad", etc), only employing opinion relations could not filter them out.
- Misleading Opinions due to spam opinion refers to the issue of dishonest opinions/reviews that intend to affect opinion mining about a product or service. Detecting such opinions is important for practical utilization of opinion mining.
- Some reviews could be dominated by high-degree vertices, which are prone to collecting more information from the neighbors and have a significant impact on other vertices, in review texts, these usually represent general words. For example, "good" may

be used to modify multiple objects, such as (good design), (good feeling) and (good things), good is a general word, and its degree in the Opinion Relation Graph is high. If the word (design) has higher confidence to be an opinion target, its confidence will be propagated to (feeling) and (thing) through (good) As a result (feeling) and (thing) most likely have higher confidence as opinion targets, this is unreasonable.

Existing Techniques:

In previous methods, mining the opinion relations between opinion targets and opinion words was the key to collective extraction, the most adopted techniques have been (Nearest Neighbor Rules), (Syntactic Information) and (Word Alignment Model).

1) Nearest Neighbor Rules (NNR) that proposed in regard the nearest adjective/verb to a noun/noun phrase in a limited window as its modifier.

2) Syntactic Information (SI) that proposed in is used to improve the NNR, in which the opinion relations among words are decided according to their dependency relations in the parsing tree, accordingly several heuristic syntactic patterns were designed.

3) Monolingual Word Alignment Model (WAM) that proposed in is used to identify potential opinion relations in sentences and estimate associations between opinion targets and opinion words; this task is formulated as a monolingual word alignment process. It assumes that opinion targets to be nouns or noun phrases, and opinion words may be adjectives or verbs, Every sentence is replicated to generate parallel corpus, and the word alignment algorithm is applied to the monolingual scenario to align a noun/noun phrase (potential opinion targets) with its modifiers (potential opinion words) in sentences, for mining opinion relations in sentences, For example in Figure 1.2, the opinion words "colorful" and "big" are aligned with the target word "screen".

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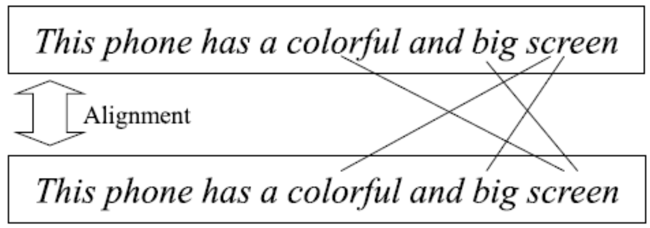

Figure 2 Mining Opinion Relations between Words Using the WAModel

Formally, given a sentence with n words S= {w_1, w_2, …, wn}, the word alignment A= {(i,a_i) | i ϵ [1,n] | a_i ϵ [1,n]} can be obtained as shown in Eq. 1.1:

$$A^* = \underset{A}{argmax}\, P(A \,|\, S),$$

Where (i,a_i) means that a noun/noun phrase at position i is aligned with its modifier at position a_i. There are several word alignment models for usage, such as IBM-1, IBM-2 and IBM-3. IBM-3 model is selected, which has been proven to perform better than other models. As shown in Eq. 1.2:

$$P_{ibm3}(A \,|\, S) \propto \prod_{i=1}^{n} n(\phi_i \,|\, w_i) \prod_{j=1}^{n} t(w_j \,|\, w_{a_j}) d(j \,|\, a_j, n),$$

Where there are three main factors $t(w_j \mid w_{aj})$, $d(j \mid a_j, n)$ and $n(\varphi_i \mid w_i)$ that model different information to indicate the opinion relations among words.

- $t(w_j \mid w_{aj})$ models the co-occurrence information of two words in corpora. If a word frequently modifies a noun (noun phrase), they will have a higher value of $t(w_j \mid w_{aj})$ For example, in reviews of cell phone, “big” often co-occurs with “phone’s size”; therefore, “big” has high association with “phone’s size”.
- $d(j \mid a_j, n)$ models word position information, which describes the probability that a word in position a_j is aligned with a word in position j.
- $n(\varphi_i \mid w_i)$ describes the ability of a word for “one-to-many” relation, which means that a word can modify (or be modified by) several words. φ_i denotes the number of

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words that are aligned with w_i . For example, “Iphone4 has an amazing screen and software”. In this sentence, “amazing” is used to modify two words: “screen” and “software”. Thus, φ equals to 2 for “amazing”.

Notably, if the standard alignment model was directly applied, an opinion target candidate (noun/noun phrase) may align with the irrelevant words rather than potential opinion words (adjectives/verbs), such as prepositions and conjunctions. Thus, some constraints in the alignment model are introduced as follows:

1) Nouns/noun phrases (adjectives/verbs) must be aligned with adjectives/verbs (nouns/noun phrases) or a null word, aligning to a null word means that this word either has no modifier or modifies nothing.
2) Other unrelated words, such as prepositions, conjunctions and adverbs, can only align with themselves. According to these constraints, for the sentence in Figure 1.2, the following alignment results shown in Figure 1.3 will be obtained, where “NULL” means the null word. From this example, the unrelated words, such as “This”, “a” and “and”, are aligned with themselves. There are no opinion words to modify “Phone” and “has” modifies nothing; therefore, these two words may align with “NULL”.
To obtain the optimal alignments in sentences, an EM-based algorithm is adopted to train the model. Specifically, for training the IBM-3 model, the simpler models (IBM-1, IBM-2 and HMM) are sequentially trained as the initial alignments for the subsequent model. Next, the hill-climbing algorithm, a greedy algorithm, is used to find a local optimal alignment.

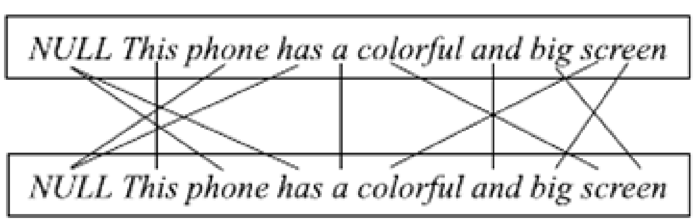

Figure 3 Mining Opinion relations between words using the word alignment model under constrains

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Cross-Domain Co-Extraction of Sentiment and Topic Lexicon

In the past few years, opinion mining and sentiment analysis have attracted much attention in Natural Language Processing (NLP) and Information Retrieval presented. Sentiment lexicon construction and topic lexicon extraction are two fundamental subtasks for opinion mining. A sentiment lexicon is a list of sentiment expressions, which are used to indicate sentiment polarity (e.g., positive or negative). The sentiment lexicon is domain dependent as users may use different sentiment words to express their opinion in different domains (e.g., different products). A topic lexicon is a list of topic expressions, on which the sentiment words are expressed. Extracting the topic lexicon from a specific domain is important because users not only care about the overall sentiment polarity of a review but also care about which aspects are mentioned in review. Note that, similar to sentiment lexicons, different domains may have very different topic lexicons, recently studies showed that supervised learning methods can achieve state-of-the-art results for lexicon extraction. However, the performance of these methods highly relies on manually annotated training data. In most cases, the labeling work may be time consuming and expensive. It is impossible to annotate each domain of interest to build precise domain dependent lexicons. It is more desirable to automatically construct precise lexicons in domains of interest by transferring knowledge from other domains.

The focus will be on the co-extraction task of sentiment and topic lexicons in a target domain where they do not have any labeled data, but have plenty of labeled data in a source domain. The goal is to leverage the knowledge extracted from the source domain to help lexicon co-extraction in the target domain. To address this problem, a two-stage domain adaptation method was proposed. In the first step, they build a bridge between the source and target domains by identifying some common sentiment words as sentiment seeds in the target domain, such as “good”, “bad”, “nice”, etc. After that, they generate topic seeds in the target domain by mining some general syntactic relation patterns between the sentiment and topic words from the source domain.

In the second step, they propose a Relational Adaptive bootstrapping algorithm to expand the seeds in the target domain. The proposed method can utilize useful labeled data from the source domain as well as exploit the relationships between the topic and sentiment words to propagate information for lexicon construction in the target domain. Experimental results show that the proposed method is effective for cross-domain lexicon co-extraction in summary, they have three main contributions: 1) they give a systematic study on cross-domain sentiment analysis in word level. While, most of previous work focused on document level. 2) A new two-step domain adaptation framework, with a novel Relational Adaptive bootstrapping algorithm for seed expansion is proposed. 3) They conduct extensive evaluation, and the experimental results demonstrate the effectiveness of these methods.

Sentiment or topic lexicon extraction is to identify the sentiment or topic words from text. In the past, many machine learning techniques have been proposed for this task. They proposed an association-rule-based method to extract topic words and a dictionary-based method to identify sentiment words, independently. They proposed a method to identify subjective adjectives and nouns using word clustering based on their distributional similarity. Proposed a relaxed labeling approach to utilize linguistic rules for opinion polarity detection.

Proposed System

Mining opinion targets and opinion words from online reviews are important tasks for fine-grained opinion mining, the key component of which involves detecting opinion relations among words. A novel approach based on the Partially Supervised Word Alignment model is proposed.

Partially Supervised Word Alignment Model (PSWAM)

The standard word alignment model is usually trained in a completely unsupervised manner, which may not obtain precise alignment results. Thus, to improve alignment performance, a partial supervision will be performed in a monolingual scenario where every sentence is replicated so that each sentence pair consists of two identical sentences in the same language to

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generate a parall corpus for mining opinion relations in sentences and estimate the associations between words by incorporating partial alignment links into the alignment process. Here, the partial alignment links are regarded as constraints for the trained alignment model to obtain better alignment results, as shown in Figure 4.1.

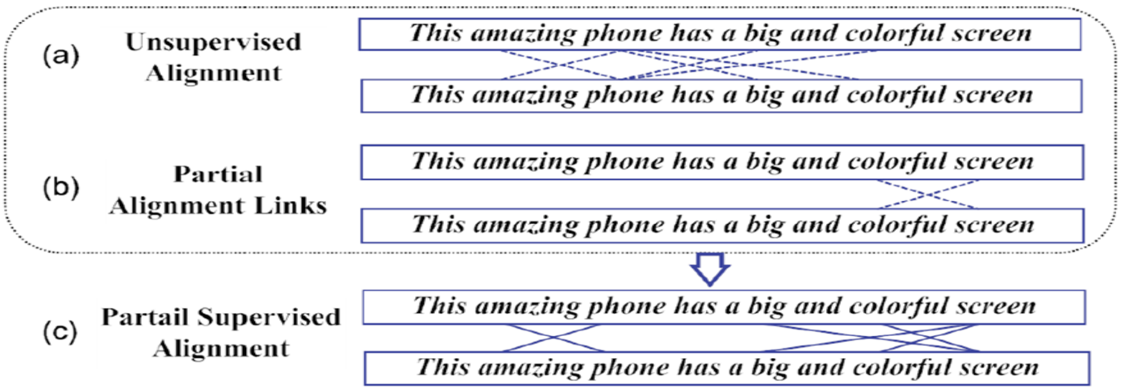


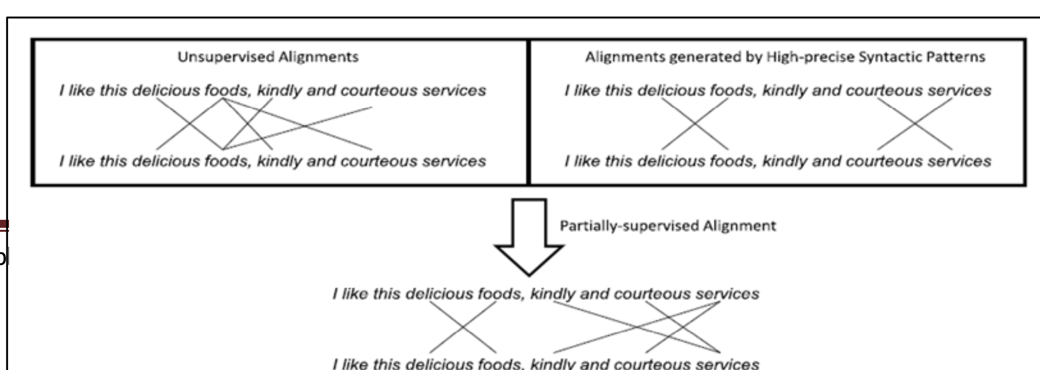
Figure 4 Mining Opinion Relations between Words Using PSWAModel

Formally, given the partial alignment links Â = {(i,a_i) | i ϵ [1,n] | a_i ϵ [1,n]} the optimal alignment Ã in Eq. (1) is rewritten:

$$A^* = \underset{A}{argmax}\, P(A \,|\, S, \hat{A}).$$

Partially Supervised Word Alignment Model

PSWAM is proposed in a monolingual scenario to mine opinion relations in sentences and estimate the associations between opinion target candidates and potential opinion words by incorporating partial alignment links into the alignment process that is generated by the use of pos tagging, where a potential opinion relation is comprised of an opinion target candidate and its corresponding modified word.



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Estimating Candidate Confidence for Opinion Targets/Words

The extraction of opinion targets/words will be regarded as a ranking process. All nouns/noun phrases in sentences are assumed to be an opinion target candidates, and all adjectives/verbs are regarded as potential opinion words, each candidate will be assigned a confidence, and candidates with higher confidence than a threshold are extracted as the opinion targets or opinion words. To assign a confidence to each candidate, the basic motivation is as follows. "If a word is likely to be an opinion word, the nouns/ noun phrases with which that word has a modified relation will have higher confidence as opinion targets. If a noun/noun phrase is an opinion target, the word that modifies it will be highly likely to be an opinion word", thus the confidence of a candidate (opinion target or opinion word) is collectively determined by its corresponding modified words according to the opinion associations among them. Simultaneously, each candidate may influence its neighbors. This is an iterative reinforcement process.

To model this process, a bipartite undirected graph G = (V, E, W) is constructed, named as Opinion Relation Graph. In G, $V = V^t \cup V^o$ denotes the set of vertices, of which there are two types: $v^t \in V^t$ denote opinion target candidates (the white nodes in Figure 4.3) and $v^o \in V^o$ denote opinion word candidates (the gray nodes in Figure 4.3). E is the edge set of the graph, where $e_{ij} \in E$ means that there is an opinion relation between two vertices. It is worth noting that the edges e_{ij} only exist between v^t and v^o and there is no edge between the two of the same types of vertices. $w_{ij} \in W$ means the weight of the edge e_{ij}, which reflects the opinion association between these two vertices.

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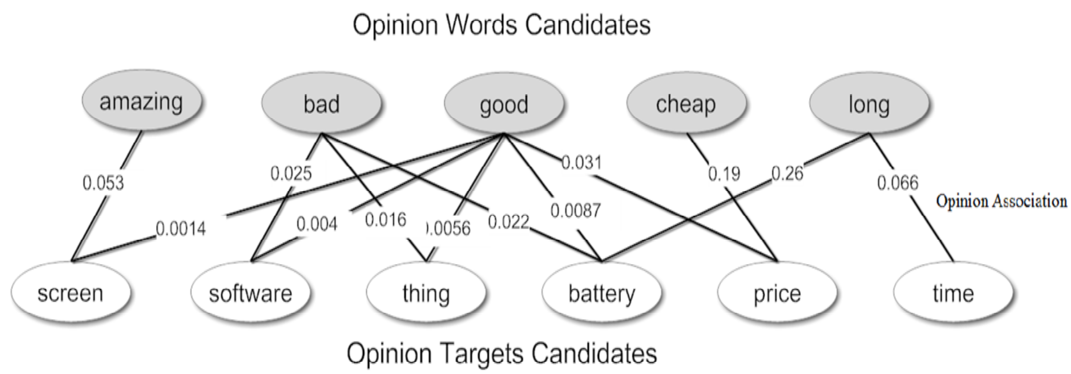

Figure 6 Opinion relation graph

Calculating the Opi

From the alignment results, a set of word pairs is obtained, each of which is composed of a noun/noun phrase (opinion target candidate) and its corresponding modified word (opinion word candidate). Next, the alignment probabilities between a potential opinion target w_t and a potential opinion word w_o are estimated using Eq. 4.2:

$$P(w_t \mid w_o) = \frac{Count(w_t, w_o)}{Count(w_o)},$$

Where $P(w_t|w_o)$ means the alignment probability between these two words. Similarly, the alignment probability $P(w_o|w_t)$ is obtained by changing the alignment direction in the alignment process. Next, the opinion association $OA(w_t,w_o)$ between w_t and w_o is estimated as shown in Eq. 4.3:

$OA(w_t, w_o) = M_{to} = (\alpha * P(w_t \mid w_o) + (1-\alpha)P(w_o \mid w_t))^{-1}$ Where α is the harmonic factor used to combine these two alignment probabilities and its value is equal to 0.5.

Calculating Candidate Confidence

After mining the opinion association between opinion target candidates and opinion word candidates. Then the confidence of each opinion target/word candidate will be calculated, and the candidates with higher confidence than a threshold are extracted as opinion targets or opinion words. Two candidates are assumed to belong to a similar category if they are modified by similar opinion words or modify similar opinion targets. If one of them

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expected to be an opinion target/word, the other one has a high probability of being an opinion target/word. The confidence of each candidate can be estimated as shown in Eq. 4.4:

$$C_t = (1-\mu) \times M_{to} \times C_o + \mu \times I_t,$$
$$C_o = (1-\mu) \times M_{to}^T \times C_t + \mu \times I_o,$$

Where the C_t and C_o are the confidence of an opinion target candidate and opinion word candidate which is initially generated randomly. M_{to} records opinion associations among candidates. $m_{ij} \in M_{to}$ means the opinion association between the ith opinion target candidate and the jth opinion word candidate, which can be computed by using Eq. 4.3. In Eq. 4.4, it can be seen that C_t and C_o are determined by two parts. One is $M_{to} \times C_o$ and $M_{to} \times C_t$, which mean that the confidence of an opinion target (opinion word) candidate is obtained through confidences of all opinion word (opinion target) candidates according to their opinion associations. The other ones are I_t and I_o, which denote prior knowledge of candidates being opinion targets and opinion words, respectively. $\mu \in [0,1]$ means the impact of prior knowledge on the final results. When $\mu = 1$, candidate confidence is completely determined by prior knowledge, and when $\mu = 0$, candidate confidence is determined by candidate opinion relevance.

RESULTS

Data Sets and Evaluation Metrics

In the experimental results different datasets are used to show the performance of the proposed technique.

Data Sets

Customer Review Datasets (CRD) has been used in the experimentation, which includes English reviews of five products { APEX AD2600 DVD Player (D1), Canon G3 Camera (D2), Creative Labs mp3 player (D3), Nikon coolpix Camera 4300 (D4), Nokia 6610 phone (D5)} which was crawled from the "http://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html" web site.

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Where #OW and #OT stand for the numbers of annotated opinion words and opinion targets, respectively.

Table 1 the Detailed Information of Data Sets

Dataset	Domain	Language	# Sentence	# OW	# OT
CRD	D1	English	50	110	97
	D2	English	50	109	83
	D3	English	50	72	83
	D4	English	50	68	49
	D5	English	50	85	82

In the experiments, reviews are first segmented into sentences according to punctuation. Next, sentences are tokenized, with part-of-speech tagged using the Stanford NLP tool. All the important features from each review sentences in each dataset are going to be extracted which consist of the most important words as being the opinion targets (nouns) and the opinion words (verbs/adjectives) which then is stored in a term of relation or table called as ARFF file (Attribute – Relation File Format).

Experimental Results using Customer Review Datasets

After constructing the ARFF file that contains all the prefetched features and then use this ARFF file with the WEKA tool, different classification techniques that includes (Naive Bayes classifier, support vector SMO classifier and J48-C 0.25-M 2 classifier) are going to be tested on the customer review datasets that consist of reviews for five different products.By using the results obtained after applying the classification techniques on the Customer Review Datasets, we will calculate the average values for Precision, Recall and F – Measure along with the accuracy. The average results for NB, SMO and J48 classifiers on customer review datasets, among the different classification techniques SMO Classifier shows better results.

Naive Bayes Classifier									
OT			OW			OT + OW			
P	R	F	P	R	F	P	R	F	classes
0.404	0.720	0.518	0.320	0.620	0.422	0.310	0.800	0.447	D1

0.796	0.780	0.788	0.784	0.800	0.792	0.828	0.960	0.889	D2
0.596	0.560	0.577	0.420	0.420	0.420	1.000	0.260	0.413	D3
0.558	0.480	0.516	0.696	0.320	0.438	0.520	0.260	0.347	D4
0.727	0.320	0.444	0.448	0.260	0.329	0.640	0.320	0.427	D5

Table 2 Experimental Results on Customer Review Datasets using Naive Bayes Classifier

SMO Classifier									
OT			OW			OT + OW			
P	R	F	P	R	F	P	R	F	classes
0.394	0.860	0.541	0.351	0.660	0.458	0.312	0.960	0.471	D1
0.896	0.860	0.878	0.800	0.960	0.873	0.980	1.000	0.990	D2
0.853	0.580	0.690	0.760	0.380	0.507	0.947	0.360	0.522	D3
0.758	0.500	0.602	0.543	0.500	0.521	0.600	0.120	0.200	D4
0.808	0.420	0.553	0.520	0.260	0.347	0.813	0.260	0.394	D5

Table 3 Experimental Results on Customer Review Datasets using SMO Classifier

J48-C 0.25-M 2 Classifier									
OT			OW			OT + OW			
P	R	F	P	R	F	P	R	F	classes
0.312	0.880	0.461	0.296	0.800	0.432	0.264	0.940	0.412	D1
0.795	0.700	0.745	0.821	0.920	0.868	0.875	0.840	0.857	D2
0.742	0.460	0.568	0.400	0.240	0.300	0.667	0.120	0.203	D3
0.688	0.220	0.333	0.706	0.240	0.358	0.714	0.100	0.175	D4
0.833	0.300	0.441	0.667	0.160	0.258	0.625	0.100	0.172	D5

Table 4 Experimental Results on Customer Review Datasets using J48 Classifier

	OT			OW			OT + OW		
	NB	SMO	J48	NB	SMO	J48	NB	SMO	J48
Avg.P	0.616	0.742	0.674	0.534	0.595	0.578	0.660	0.730	0.629
Avg.R	0.572	0.644	0.512	0.484	0.552	0.472	0.520	0.540	0.420

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Avg.F	0.569	0.653	0.510	0.480	0.541	0.443	0.504	0.515	0.364
Accuracy	0.572	0.644	0.512	0.484	0.552	0.472	0.520	0.540	0.420

Table 5 Average Results for NB, SMO and J48 classifiers on CRD

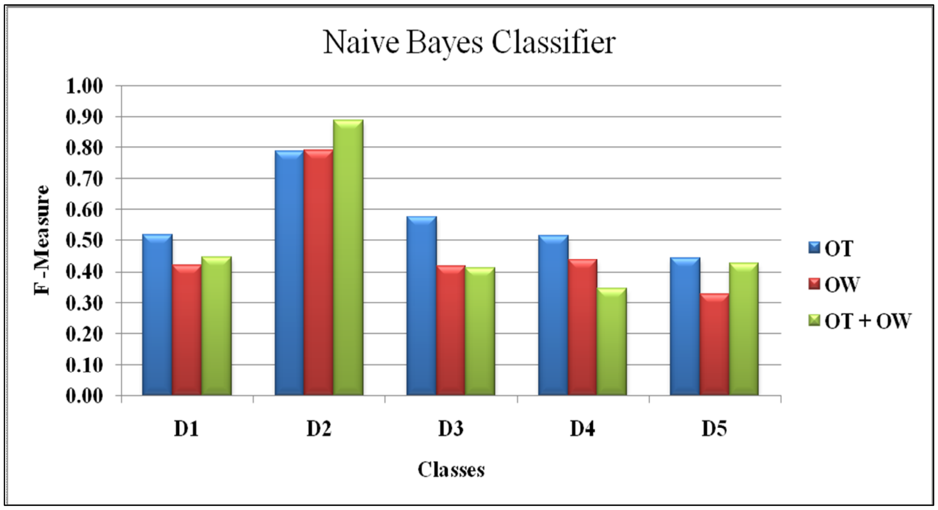


Figure 7 Chart Representation of the experimental results using Naive Bayes Classifier

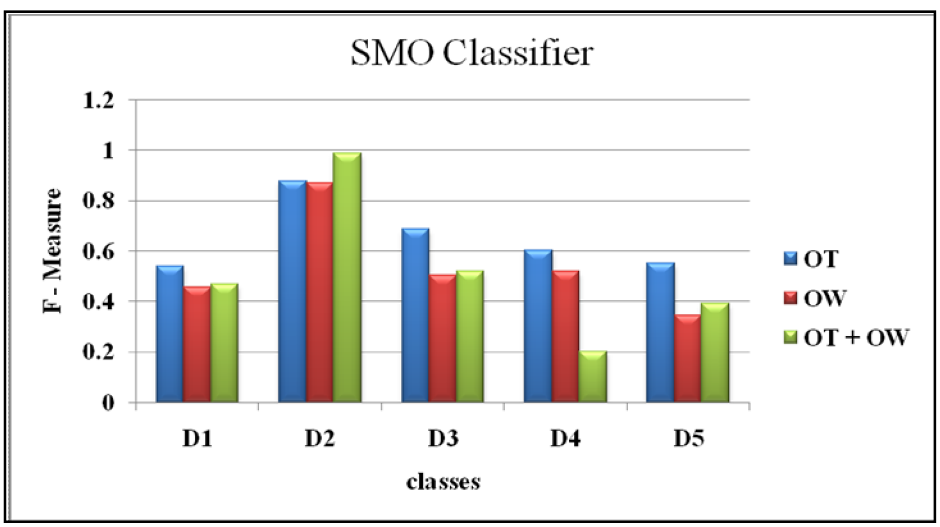
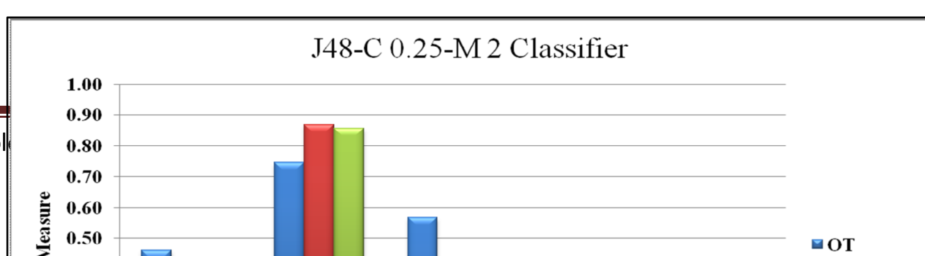


Figure 8 Chart Representation of the experimental results using SMO Classifier



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The use of different classification techniques that reflects the importance of the words in each review sentence in the customer reviews datasets where these words represent the extraction of the opinion targets (OT) and the opinion words (OW) after taking the F-Measure of each product dataset, in which the first (OT) represent the object about which users express their opinions, typically as nouns or noun phrases, and the second (OW) is defines as the words that are used to express users' opinions As a result, opinion targets usually are product features or attributes, and constructing an opinion words lexicon is also important because the lexicon is beneficial for identifying opinion expressions. Among the different classification techniques SMO classifier shows better results for the extraction of the opinion targets (OT), the opinion words (OW) and (OT + OW) after taking the F-Measure of each product review dataset..

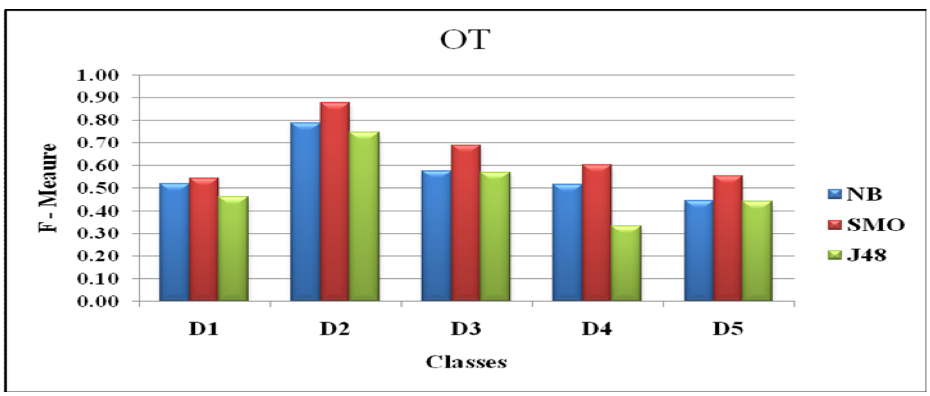

Figure 10 Chart Representation of the Opinion Targets extraction using NB, SMO, J48 Classifiers

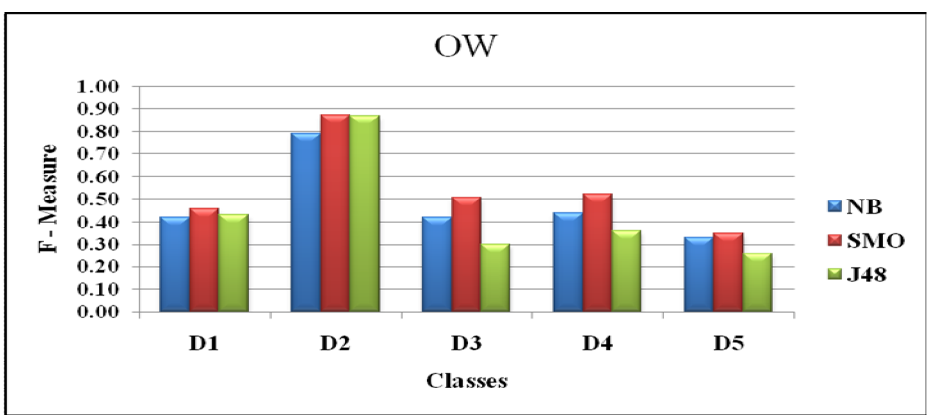

Figure 11 Chart Representation of the Opinion Words extraction using NB, SMO, J48 Classifiers

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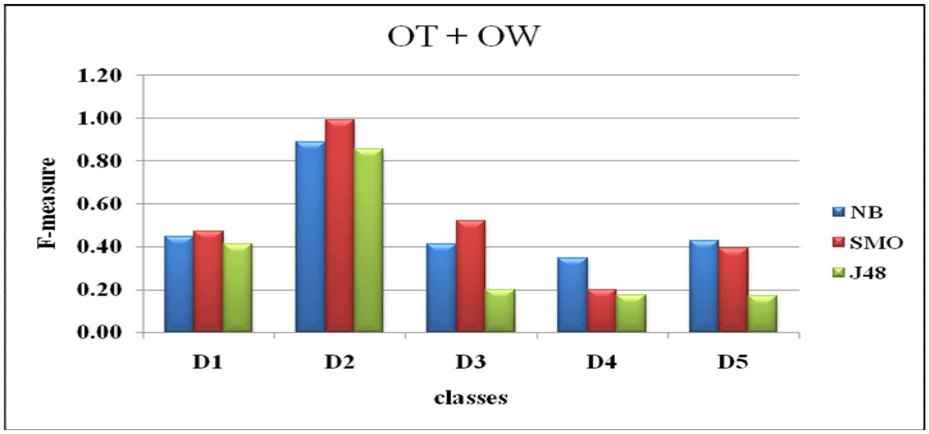

Figure 12 Chart Representation of the Opinion targets and Opinion Words extractions using NB, SMO, J48 Classifiers

Test Cases

A Test case is a set of input data and expected results that exercises a component with the purpose of causing failure and detecting faults. Test case is an explicit set of instructions designed to detect a particular class of defect in a software system, by bringing about a failure. A Test case can give rise to many tests. Test cases can be divided in to two types. First one is Positive test cases and second one is negative test cases. The positive test cases are conducted by the developer intention is to get the output. In negative test cases are conducted by the developer intention is to don't get the output.

S .No	Test case Description	Actual Value	Expected Value	Result
1	Select a Dataset and apply POS Tagging	Dataset selection done	Partially supervised data available and separated by "/"	True
2	Perform Candidate Extraction	Partially Supervised candidate extraction done	Generates Opinion Target candidates & Opinion Word candidates	True

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3	Calculate Opinion Associations	Opinion Targets , Opinion words generated	Probability of Opinion target & opinion word	True
4	Checking the threshold and confidence	Find opinion targets & opinion words	Opinion Target, Opinion Target Confidence, Opinion word, opinion word confidence available	**True**

Table 6 Positive Test Cases

S .No	Test case Description	Actual Value	Expected Value	Result
1	Select a Dataset and apply POS Tagging	Dataset selection done	Partially supervised data not available	False
2	Perform Candidate Extraction	Partially Supervised candidate extraction done	Does not Generates Opinion Target candidates & Opinion Word candidates	False
3	Calculate Opinion Associations	Opinion Targets , Opinion words generated	Probability of Opinion target & opinion word is not generated	False
4	Checking the threshold and confidence	Find opinion targets & opinion words	Opinion Target, Opinion Target Confidence, Opinion word, opinion word confidence available with reverse relation	**False**

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Table 7 Negative Test Cases

Conclusion

The project proposes a novel method for co-extracting opinion targets and opinion words by using a Partially Supervised Word Alignment Model. The main contribution is focused on detecting opinion relations between opinion targets and opinion words. Compared to previous nearest-neighbor rules, the PSWAM does not constrain identifying modified relations to a limited window; therefore, it can capture more complex relations, such as long-span modified relations. Compared to syntactic information, the PSWAM is more robust because it effectively avoiding noises from syntactic parsing errors when dealing with informal texts. Thus, it's reasonable to expect that PSWAM is likely to yield better performance than traditional methods. Next, All nouns/noun phrases in sentences are assumed to be an opinion target candidates, and all adjectives/verbs are regarded as potential opinion words. The extracted opinion targets, opinion words and the combination of (opinion targets + opinion words) from customer reviews dataset is stored in a term of ARFF file which is linked with the WEKA tool. Different classification techniques that include (Naive Bayes Classifier, Support Vector SMO Classifier and J48 Classifier) are going to be tested on the customer review datasets. Among the different classification techniques SMO classifier shows better results for the extraction of the opinion targets (OT), the opinion words (OW) and (OT + OW) after taking the F-Measure of each product review dataset.

Future Enhancements

In future work, additional types of relations will be considered between words, such as topical relations. This is may be beneficial for co-extracting opinion targets and opinion words. These methods usually adopted coarser techniques, such as frequency statistics and phrase detection, to detect the proper opinion targets/words. Product reviews, comments and feedback could be in different languages (English, Urdu, Arabic, French etc), therefore to tackle each language according to its orientation is a challenging task that can be handled as an enhancement to this work.

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