An Intelligent Model for Co-Extraction of Opinion Words and Targets from Online Reviews Using Expectation Maximization

Dr. N. Shanmuga Priya [1], R. Nanthini [2], R. Padmanatharathinam [3]

[1] *Associate Professor and Head, Department of Computer Applications, Dr. SNS Rajalakshmi College of Arts & Science, Coimbatore, Tamil Nadu, India*

[2, 3] *PG Student, II MCA, Department of Computer Applications, Dr. SNS Rajalakshmi College of Arts & Science, Coimbatore, Tamil Nadu, India*

Abstract: The vital tasks of opinion mining is Mining opinion targets and words from the web reviews. The main aim is to notice opinion relations between words. During this paper, a novel Expectation Maximization (EM) is projected for opinion relations within the sort of alignment method. Subsequently graph-based co-ranking algorithm is studied. And at the last, a candidate who has higher confidence is extracted. As compared with different strategies, this model is creating the task of opinion relations, for large-span relations additionally. As Compared with the syntax technique, the word alignment model is appearance for negative effects of when yearning for on-line texts. The experimental results show that this model obtains higher precision as Compared to the part supervised alignment model. Once projected system searches for candidate confidence, it gets to understand that higher-degree vertices within the EM algorithm are decreasing the probability of the generation of error

Keywords: Opinion Mining, Opinion Targets Extraction, Opinion Words Extraction, Expectation Maximization.

1. INTRODUCTION

The Internet and WWW have turned today's world into global village. Over the years technology has significantly changed the way people communicate. How they feel, what they like or dislike, people like to share it online. Proper mining and analysis of public feelings or opinions can bring a miracle to existing business profit. For the same purpose instead of exclusive public opinion polling, machine learning tools are preferred. Few researchers are trying to interpret it with the help of linguistic approach. But the reviews or opinion of the customers' also known as user-generated content has the characteristics such as incomplete, grammatically incorrect, weakly structured etc. This causes degradation in the performance of the opinion mining task [1]. Whereas, few researchers are trying to apply statistical measures for the same. Both the methods have their own pros and cons. In this paper, we have proposed a hybrid approach by integrating both the linguistic as well as statistics approach into a single unified framework. The key objective of our task is to co-extract the feature and opinion pair from customers reviews. Let's view the unstructured corpus a combination of a set of grammatically correct and a set of grammatically incorrect sentences. For the grammatically correct sentence, use syntactic pattern-based rules to extract the features and opinion pairs. For the set of sentences not interpreted by the syntactic parser, apply word alignment technique to extract probable feature opinion pair.

Mining opinion targets and opinion words from on-line reviews are vital tasks for fine-grained opinion mining, the key element of that involves detection opinion relations among words with the fast development of internet 2.0, an enormous variety of product reviews are developing on the net. From these reviews, customers will get primary assessments of product info and direct superintendence of their purchase actions. Means, makers will get immediate feedback and opportunities to boost the standard of their merchandise. Thus, mining opinions from on-line reviews has become associate degree progressively imperative activity and has attracted a good deal of attention from researchers [2]. To extract and analyze opinions from on-line reviews, it's unacceptable to just get the sentiment a few products. In most cases, customers expect to search out fine-grained sentiments regarding a facet or feature of a product that's reviewed. Mining opinions from online reviews is a fundamental step in obtaining the overall sentiment of a product. Detection of opinion relations among the words play an important role in the opinion target (OT) and opinion word (OW) extraction. In this paper, Partially Supervised Word Alignment Model is used to find opinion relations among words. Graph based co-ranking algorithm is used in estimating the confidence of each OT and OW. Candidates having confidence value higher than the threshold are extracted as final OT and OW. We propose a hybrid method that considers semantic relations along with opinion relations that result in fine grained opinion target (OT) and opinion word (OW) extraction [3].

In this paper, planned a completely unique approach supported the expectation model, which regards characteristic opinion relations as an alignment method. Then, a graph-based co-ranking algorithm is exploited to estimate the confidence of every candidate. Finally, candidates with higher confidence are extracted as opinion targets or opinion words. Compared to previous strategies supported the closest neighbor rules, our model captures opinion relations a lot of exactly, particularly for long-span relations. Compared to syntax-based strategies, our word alignment model effectively alleviates the negative effects of parsing errors once managing informal on-line texts. Above all, compared to the standard unsupervised alignment model, the planned model obtains higher preciseness thanks to the usage of partial superintendence. Additionally, once estimating candidate confidence, we have a tendency to punish higher-degree vertices in our graph based mostly co-ranking algorithm to decrease the chance of error generation. The paper is organized in following sections: section two describes the connected work on mining product options and opinion extraction, section three planned algorithms, and section four Experimental results and section five conclusions and future work.

2. LITERATURE REVIEW

The task of identifying the opinion relations among the words is the important component. To overcome the challenges present in nearest neighbour and syntactic patterns methods to extract (OT) and (OW), we use alignment-based method along with graph based co-ranking to extract OT and OW. To accurately mine opinion relations, It use Word Alignment Model (WAM). Opinion modifier can find its corresponding opinion target using word alignment [9]. As there is no restriction on the window size, WAM captures long-span modified relations. Word alignment model is trained in an unsupervised method. This results in unsatisfactory quality of alignment. This is overcome by supervised training that certainly improves the alignment quality.

Yu Bai Jian, S., et al., (2021), addressed the Aspect Sentiment Triplet Extraction (ASTE) is the task of extracting triplets of aspect terms, their associated sentiments, and the opinion terms that provide evidence for the expressed sentiments [4]. Previous approaches to ASTE usually simultaneously extract all three components or first identify the aspect and opinion terms, then pair them up to predict their sentiment polarities. In this work, we present a novel paradigm, ASTE-RL, by regarding the aspect and opinion terms as arguments of the expressed sentiment in a hierarchical reinforcement learning (RL) framework. It first focuses on sentiments expressed in a sentence, and then identifies the target aspect and opinion terms for that sentiment. This takes into account the mutual interactions among the triplet's components while improving exploration and sample efficiency. Furthermore, this hierarchical RL setup enables us to deal with multiple and overlapping triplets. In our experiments, we evaluate our model on existing datasets from laptop and restaurant domains and show that it achieves state-of-the-art performance.

Miao, Z., et al., (2020), proposed the solution to opinion mining, which is the problem of extracting aspects, opinions, and sentiments from text [5]. One method to mine opinions is to leverage the recent success of pre-trained language models which can be fine-tuned to obtain high-quality extractions from reviews. However, fine-tuning language models still requires a non-trivial amount of training data. Author studied the problem of how to significantly reduce the amount of labeled training data required in fine-tuning language models for opinion mining. It describe, an opinion mining system developed over a language model that is fine-tuned through semi-supervised learning with augmented data. A novelty of is its clever use of a two-prong approach to achieve state-of-the-art (SOTA) performance with little labeled training data through: (1) data augmentation to automatically generate more labeled training data from existing ones, and (2) a semi-supervised learning technique to leverage the massive amount of unlabeled data in addition to the (limited amount of) labeled data. It shows with extensive experiments that performs comparably and can even exceed previous SOTA results on several opinion mining tasks with only half the training data required. Furthermore, it achieves new SOTA results when all training data are leveraged.

Zhao, R., et al., (2023), aims to extract a structured summary or key points organised as positive and negative viewpoints towards a common aspect or topic. Most recent works for unsupervised key point extraction is largely built on sentence clustering or opinion summarization based on the popularity of opinions expressed in text [6]. However, these methods tend to generate aspect clusters with incoherent sentences, conflicting viewpoints, and redundant aspects. To address these problems, The authors proposed a novel unsupervised Contrastive Opinion Extraction model, called Cone, which learns disentangled latent aspect and sentiment representations based on pseudo aspect and sentiment labels by combining contrastive learning with iterative aspect/sentiment clustering refinement. Apart from being able to extract contrastive opinions, it is also able to quantify the relative popularity of aspects and their associated sentiment distributions. The model has been evaluated on both a hotel review dataset and a Twitter dataset about COVID vaccines. The results show that despite using no label supervision or aspect-denoted seed words, Cone outperforms a number of competitive baselines on contrastive opinion extraction. The results of Cone can be used to offer a better recommendation of products and services online.

Zhou, J., et al., (2023) focus on the extraction of opinions and their corresponding targets has gained significant interest recently, as it offers valuable insights into Opinion Mining (OM) at a granular level [7]. Opinion and target terms to be extracted by existing OM tasks need to be explicitly present in reviews. Targets that are not present but implied in contextual semantics are neglected by existing OM tasks, even though an investigation reported that about 60% of reviews contain implicit targets. To enable implicit target extraction, a novel task named Mining Opinions towards Implicit Targets (MOIT) under the fine-grained OM, is proposed to extract both opinions and their corresponding implicit targets, enabling a more comprehensive analysis of reviews. To set up the basis for follow-up research on MOIT, two large-scale datasets were constructed as resources in two languages, where the Chinese dataset was built from scratch via a standard human annotation process, and the English dataset was built semi-automatically through machine translation and manual checking. The proposed MOIT task extends the field of OM research, and the datasets and models establish a foundation for future studies in this area.

Sun, K., et al., (2023) aims to extract the targets (or aspects) on which opinions have been expressed. Recent work focus on cross-domain OTE, which is typically encountered in real-world scenarios, where the testing and training distributions differ [8]. Most methods use domain adversarial neural networks that aim to reduce the domain gap between the labelled source and unlabelled target domains to improve target domain performance. However, this approach only aligns feature distributions and does not account for class-wise feature alignment, leading to suboptimal results. Semi-supervised learning (SSL) has been explored as a solution, but is limited by the quality of pseudo-labels generated by the model. Inspired by the theoretical foundations in domain adaptation, propose a new SSL approach that opts for selecting target samples whose model output from a domain-specific teacher and student network disagree on the unlabelled target data, in an effort to boost the target domain performance. Extensive experiments on benchmark cross-domain OTE datasets show that this approach is effective and performs consistently well in settings with large domain shifts.

3. PROPOSED SYSTEM

In this paper, present a feature-based product ranking technique that mines varied client reviews. First determine product options and analyze their frequencies. For every feature, we tend to determine subjective and comparative sentences in reviews. Here, assign sentiment orientations to those sentences. It models the relationships among product by exploitation the knowledge obtained from client reviews, by constructing a weighted and directed graph. Here, tend to mine this graph to see relative quality of product. Experiments on camera and TV reviews demonstrate the results of the planned techniques [10].

As a result of the user convenience moreover as dependability, and also the product value there are the massive numbers of shoppers are selecting one amongst the most effective thanks to on-line shopping on-line shopping. Now days, on-line looking are far more well-liked within the world [11]. And this makes terribly profitable to client. To create buying the selections is predicated on solely footage and short descriptions of the merchandise, and it is terribly tough for patrons to buying the customers; because the range of product being sold on-line is will increase. On the opposite hand, client reviews, i.e. Text describing options of the merchandise, their comparisons and experiences of explicit product give an expensive supply quantity of data to match product.

And to create the nice buying selections, on-line retailers like Amazon.com, and flipcart.com enable us customers to feature reviews of product that they need purchased. These reviews become numerous to help the opposite customers. Historically, many shoppers have used skilled rankings. To assign the rank to the merchandise, then it is terribly useful for the client to pick the merchandise and its quality like smart in quality or dangerous. Moreover, the merchandise typically has multiple product options, their blessings and a few drawbacks, that play an important role in several manners [12]. Totally different customers could also be curious about different options of a product, and their preferences might vary consequently.

It describe the method to produce product feature summary extracted from customer reviews using semi supervised EM. The summary produced by the system is displayed in the form of tree view which consists of customer review sentiment and system processed sentiment [13].

- **System Management Module:** The system management module consists of system graphical user interface. The user interface mainly consists of two forms. The first form includes block of reviews and the reviews can be added dynamically. For adding the reviews, vocabulary generated by the system is to be considered which consists of a specific structure in which the review should be added such that every review should have some numerical value embedded in it. It also consists of a control which learns the complete block of reviews. After learning the reviews, a particular review is selected and analyzed. Its summary is displayed graphically in tree view in second form. The system proposed uses Open NLP library as machine learning based tool kit for natural language processing of a text and SharpNLP which is collection of tools of natural language processing. It provides common NLP tasks such as a splitter, a part-of-speech tagger, a tokenizer, a chunker, a parser, a name entity extraction and interface to WordNet lexical base which are driven by maximum entropy models processed by SharpEntropy library. Open NLP is based on maximum entropy based model and perceptron based machine learning. In addition, the SharpWordNet is provided by SharpNLP which is WordNet database library. In the proposed system, the Open NLP tasks performed are splitting, tokenizing and POS tagging.
- **POS tagging Module:** The text analysis systems mainly consist of a tagger as an important component. The significance of part-of-speech (POS) tagging for analysis and language processing is, they provide much amount of information about words and their tags. The tagger categorizes the given text into a set of lexical or part-of-speech tags such as noun, verb, adjective, adverb etc. The POS tags assigned to each word are the symbolic representation of such categorized word such as (NN) noun, (VB) verb, (JJ) adjective, (RB) adverb etc. Most commonly used tag set is the Penn tree bank tag set which consists of 45 tags.
- **Splitting:** The sentence splitter is useful for obtaining an array of words from the given sentence. The basic and simple sentence splitter used is („.") but it is the limited way of dividing the sentences of a paragraph of a text. Therefore, to handle most cases correctly, the extended splitters used are („.") („!") („?") The input text is scanned and whenever it comes across any of these characters, it should decide whether or not it is the end of the sentence. To decide this, maximum entropy model comes into the picture.
- **Tokenizing Sentences:** One of the steps in NLP tasks is to identify basic units called tokens which cannot be decomposed further in the processing. The tokens are nothing but the English words with the combination of which a sentence in a text is constructed. It is obvious, proper analysis or generation cannot be carried out without segregating these basic units. The simplest way to recognize the words in the given text is to use space marks as explicit delimiters. But these space marks may misled by overlooking distinguish complex units such as English idioms or fixed expressions. The system uses a Tokenize method of EnglishMaximumEntropyTokenizer object.
- **Part-Of-Speech Tagging:** The words in the sentence are assigned part-of-speech, this task of assigning is called as part-of-speech tagging abbreviated as POS tagging. The array of tokens obtained from the tokenization process is fed to the POS tagger. The result generated is also an array of tags of same length as that of tokenizer array such that the index of tag array matches with the index of token array. The POS tags are coded abbreviations, which follow the scheme of PennTree bank, which is a linguistic corpus developed by University of Pennsylvania. The AllTags ( ) method provides all possible list of tags that follow PennTree bank description. The POS tagger was trained by the maximum entropy model which used the text from the oldest Wall Street Journal and Brown Corpus. The POS tagger is controlled by providing it with a POS lookup list. The

constructor used by the system are EnglishMaximumEntropyPosTagger constructors, to specify the POS lookup list, there are two possible alternatives either by a POSLookupList or a by file path. The lookup list includes a text file with a word and its possible POS tags on each line, such that if a tagged word is found in the lookup list, the possible tags specified by the list are restricted by the POS tagger such that it selects the correct tag. It basically splits an input paragraph into sentences, each sentence is tokenized, and then Tag method POS tags the sentence.

- **Parsing and Dependency Analysis:** The NLP algorithms task is to perform parsing and produce a parser tree. A parser splits the customer review into a split tree which is a syntactic structure. The parse tree generated is constituency based parse tree which includes phrase grammar structure. The system generates the parse tree using a class named as EnglishTreebankParser class in which the most probable the ranked parse tree is generated. The object created is the root node in the tree such that the objects which generated are the best guess for the customer review. The tree generated can be traversed using GetChildren () method and has a property the Parent property. The parse node has tagset which has all tags of Penn Treebank found in Type property and which is equal to a MaximumEntropyParser. The output of parser is the textual representation of a parse tree graph.
- **Feature Extraction:** The system extracts the features based on frequent nouns and noun phrases which occur in the review after using a POS tagger. The opinions expressed by many customers are first indentified for mining of product feature candidate, related opinion and technical feature value extraction.

3.1. Proposed Methodology

First choose real on-line reviews from totally different domains and languages because the analysis datasets. Here, to compare our methodology to many progressive ways on opinion target/word extraction. Here, tend to gift the most framework of our methodology [14]. As mentioned, to regard extracting opinion targets/words as a co-ranking method. It is to assume that each one nouns/noun phrases in sentences are opinion target candidates, and every verb are considered potential opinion words, that are wide adopted by previous ways. Every candidate are assigned a confidence, and candidates with higher confidence than a threshold are extracted because the opinion targets or opinion words. To assign a confidence to every candidate, our basic motivation is as follows.

“If a word is probably going to be associate degree opinion word, the nouns with that that word contains a modified relation can have higher confidence as opinion target. If a noun is an opinion target, the word that modified it'll be extremely doubtless to be an opinion word".

It can see that the confidence of a candidate (opinion target or opinion word) is jointly determined by its neighbors per the opinion associations among them. At the same time, every candidate might impudence its neighbors. This can be an iterative reinforcement method. The Fig. 1.1. Says that once a specific client wills on-line looking, then per that exact product he or she ought to post reviews i.e. Feedback of client regarding product. Those reviews could also be either positive or negative. The matter of analyzing the net reviews of client on product and generating the outline for those reviews by exploitation changed Expectation Maximization algorithm that summarizes review reckoning on options and technical feature worth extracted from the reviews. When causing the reviews, system can send reviews to the server. Server can apply filter for those review. Filter is applied to separate positive or negative review in order that extraction of positive reviews and negative reviews are done. Moreover as separation of words those are substantive are extracted. For this separation Hill climbing algorithm is employed. Server can determine keyword for this partly supervise algorithm is employed and can assign polarity to them during this positive and negative sentence is distinguished.

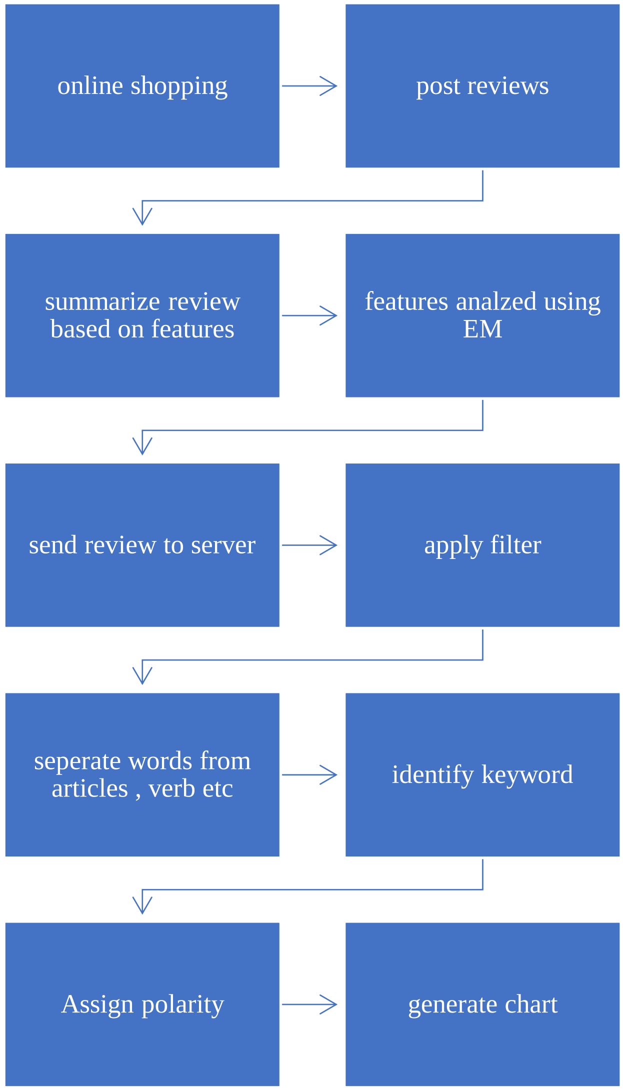

Fig 3.1: - overall process of proposed architecture of system

The required extractions for the system square measure performed exploitation semi-supervised learning that uses Expectation Maximization (EM) formula. This opinion retrieval module is that the "E-step" of EM formula and consists of following extractions:

1) Product Feature Candidate Extraction

The product feature candidate extraction is completed by considering the labelled sentence and when parsing the noun phrases within the review indicate the merchandise feature candidate.

For example: This phone contains a colorful and massive screen, however its LCD resolution is incredibly unsatisfactory.

Product candidate feature: phone, LCD screen.

2) Connected Feature Extraction:

Related feature is that the opinion expressed within the review. The system uses adjectives and adverbs as opinion words that square measure searched within the dissect tree generated antecedently.

For example: This phone has a colorful and big screen, but its LCD resolution is very disappointing.

Related feature opinion: colorful, LCD resolution

The pseudo code for above extractions is as follows:

Pseudo Code:

```
Input: IT: set of tag
TS: tokenize sentence (noun list)
Output: Feature value, Review Sentiment
If (IT=Proper noun (“NNP”) or IT=noun(“NN”)) // Check for the nouns in the tag set.
{
If (IT=Cardinal Number (“CD”) or IT=determiner (“DT”))
// check the predecessor of nouns has a numerical value and determiner
 {
 Featurevalue=TS [i-1] element
 }
}
If (IT=adjective (“JJ”) or IT=verb(“VBN”))// check if the tag is adjective or verb
 {
Review Sentiment = IT;
If (IT= Adverb ("RB"))// check the adjective or verb is preceded by an adverb
 {
Review sentiment=TS [i-1] element + TS [i] element
 }
Else if (IT= Cardinal Number (“CD”)) // check if the adjective or verb is preceded by a cardinal number
 {
 Featurevalue= TS[i-1] element
 Technical feature value=CD
 Reviewsentiment= sentiment string
 }
}
```

4. EXPERIMENTAL RESULTS

The three datasets are selected to evaluate the WAM method [15]. The datasets are CRD, COAE, and Large. The first customer review data (CRD) has the reviews for five products and the second dataset COFE 2008 contains the Chinese reviews for four products include camera, car, laptop, and phone. The last dataset large has the reviews on three domains includes restaurant, hotel, mp3 [16].

i) Precision Comparison

The number of customers exhibiting precision rate in the specified range of threshold values is specifically brought out in Fig 4.1. From the figure it is well know that the proposed work providing the better precision results than the existing works. The reason is that the computational complexity of the proposed method is high which leads to increase in precision rate. When the number of customers increases the precision rate of the proposed system gets increased.

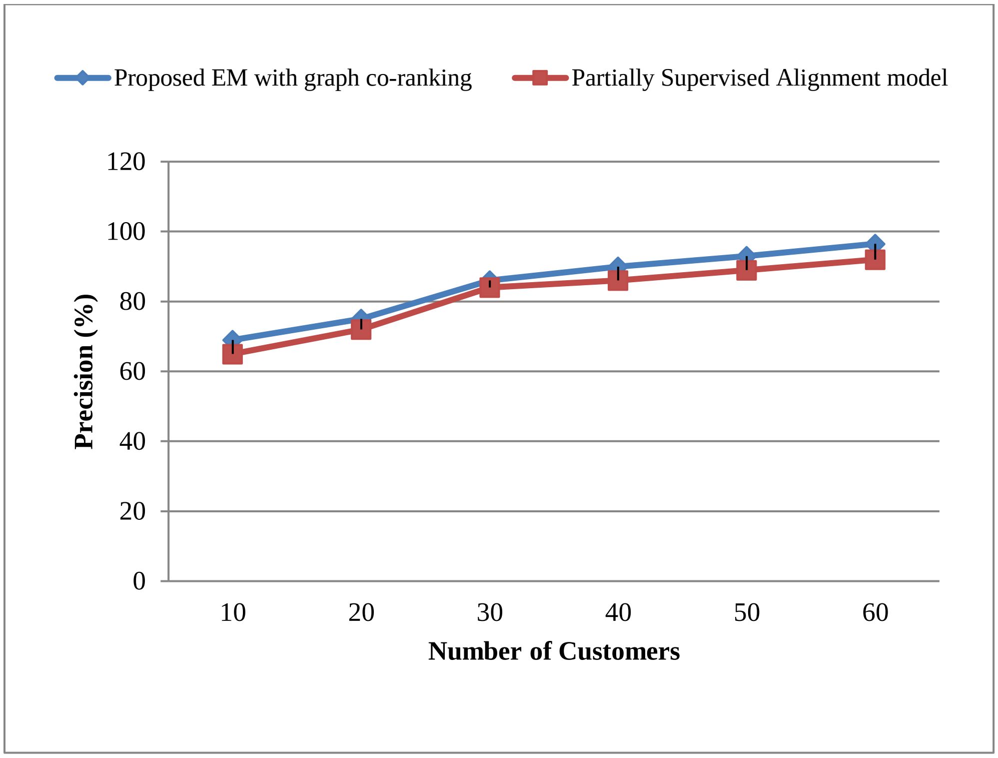

Fig 4.1: - Precision comparison

ii) False positive rate (FPR) Comparison

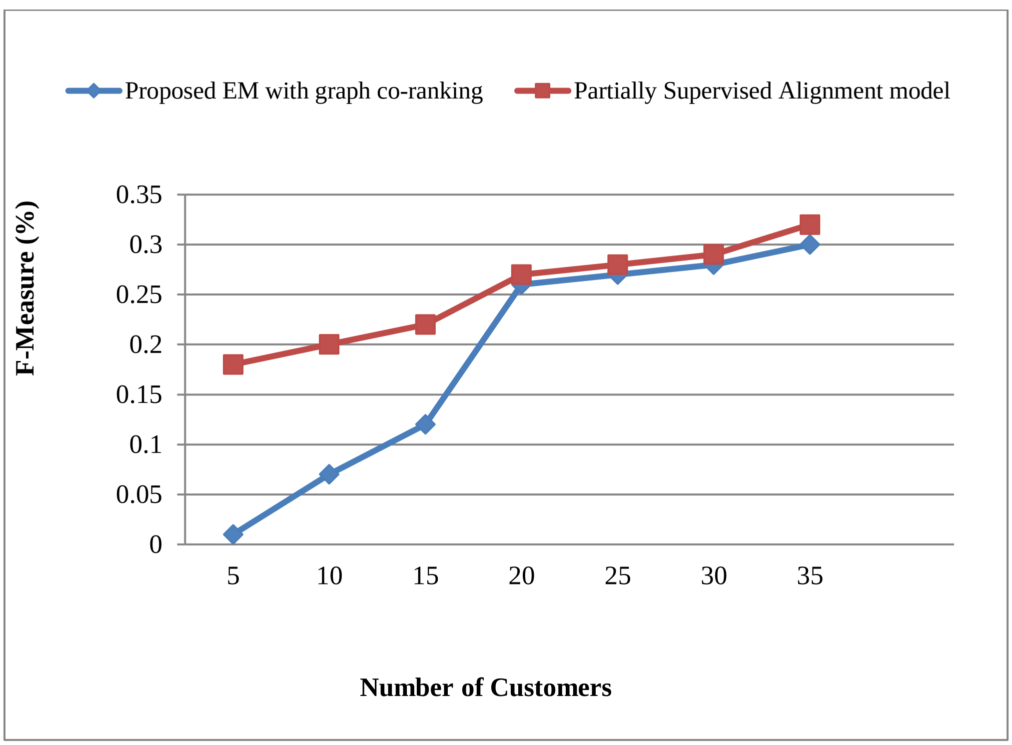

Fig. 4.2: - False Positive Rate Comparison

Figure 4.2 shows the graph of false positive rate in percentage. The proposed method have low false positive rate 10% which is significantly improve co-extracting rate and accuracy when compared to the existing method.

ii) Accuracy Comparison

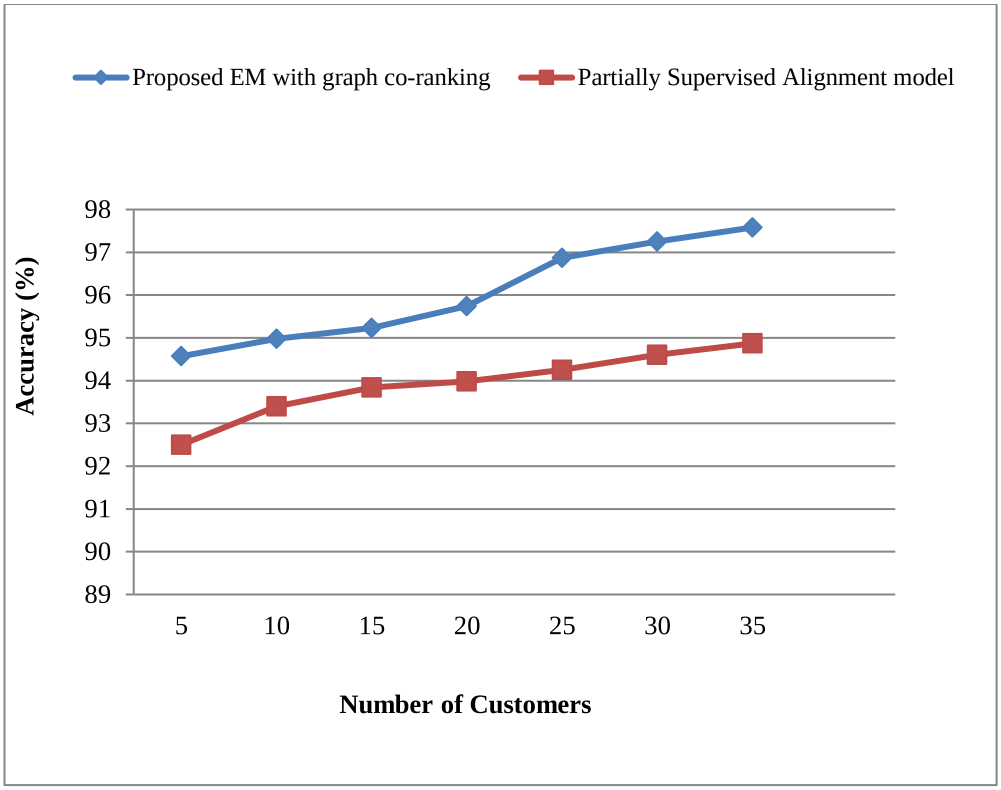

Fig 4.3: - Accuracy Comparison

Prediction and detection accuracy of the proposed method achieves higher classification accuracy than the existing classification method and the accuracy result is illustrated in Figure 4.3, since the proposed methods select the important words in the customer review

5. CONCLUSION

In this paper a complete unique technique by creating use of word alignment model, for co-extraction of opinion targets further as co-extraction of opinion words. The goal is to specializing in detection of the opinion relations that square measure gift in between opinion targets and opinion words. As compared with previous technique that relies on nearest neighbor rules and syntactic patterns, this planned technique captures opinion relations. Due to this advantage, this technique is a lot of helpful for extraction of opinion target and opinion word. After that, to concentrate on to generate Opinion Relation Graph to point out all the candidates and detected opinion relations between them.

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