Analysis on Lexicon Based Approach for Automatic Product Aspect Extraction

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Abstract— **In many applications related to opinion mining and sentiment classification, it is necessary to compute the semantic orientation of certain opinion expressions on an object. Many researchers suggest that semantic orientation depends on application domains. Moreover, semantic orientation depends on the specific feature that an opinion is expressed on it. In this paper, we introduce an effective approach to opinion lexicon expansion automatically. We use small set of seed lexicon and dependency relations to extract opinion words and then, we expand it automatically from a larger set of unannotated documents. To do this, we proposed an unsupervised algorithm based on double propagation. Our method was evaluated in three different domains (headphones, hotels and car), using a corpus of product reviews which opinions were annotated at the feature level. We conclude that our method produces feature-level opinion lexicons with better precision and recall that domain-independent opinion lexicons without using annotated documents.**

Index Terms—**Opinion Extraction, Opinion Lexicon Expansion, Dependency Relations, Feature Extraction**

I. Introduction

Opinion mining also known as sentiment analysis is the computational study of subjective information towards different entities. Entities usually refer to products, organizations, services or/and their features, functions, components and attributes. Opinion mining is a major task of Natural Language Processing (NLP) that studies methods for identifying and extracting opinions from written text, such as product reviews, discussion groups, forums and blogs. It makes the Web an extensive and excellent source of information to gather opinions about a specific object. With the undeniable growth of the Web, individuals and organizations are using online content for their buying and manufacturing decision-making.

Every time someone attempts to discover what other people think about something on the Web, the response is an enormous amount of data, which makes it difficult to find useful information easily. For organizations, tracking customer feedback can help to measure the level of satisfaction and make optimal manufacturing and selling decisions. Due to human mental and physical limitations, it is difficult to manually gather and analyze the massive amount of information on the Web. Therefore, a system that can automatically summaries documents is increasingly desirable. Such a system extracts relevant information and presents it in a manner that is easy to read and understand in order to make informed decisions.

Usually, there are two types of textual information in customer reviews: objective statements, which represent facts, and subjective statements, which symbolize opinions or perceptions. Opinion mining can be studied at three different levels, namely document, sentence and feature levels Pang and Lee, (2008). A document-level sentiment analysis classifies an opinionated document e.g., a product review based on the overall sentiment of the entire document. It assumes that the entire document expresses a single opinion. Likewise, a sentence level sentiment analysis classifies sentiment on a sentence level. However, not every sentence is a subjective sentence Wilson et al., (2005).

Even though opinion mining at document and sentence levels is valuable, neither discover exactly what people like and dislike. An opinionated text on a particular entity does not mean that the author likes or dislikes every single feature of the entity. “The Canon camera is amazing; it is better than the Samsung camera,” is an example of a product review that express positive opinion about one product and a negative opinion on another product. It is not valid to classify and generalize the sentiment on both products. To obtain fine-grained opinions, it is necessary to examine the feature level Liu, (2015).

The feature level is also known as feature-based opinion mining, which identifies and extracts opinions and their targets. Feature Based opinion mining has three main tasks: first, identify and extract product features; then determine opinion words and their polarities; and finally map the relationship between features and opinions. If FBOM was applied to the previous example, the system should identify “Canon camera”, then identify the opinion “amazing”, and finally map the relation in which the opinion corresponds to “Canon camera” not “Samsung camera”.

Aspect-based opinion mining from customer reviews is a challenging problem for opinion mining and sentiment analysis. This research contributes to methods to identify and extract product features and sentiment from customer reviews by employing natural language processing (NLP) in unsupervised learning techniques. The contributions of the proposed system are as follows;

- This system contributes an approach to extract opinions and product features simultaneously and iteratively.
- This system also considers verb features, verb opinions and context dependent opinion words by using only dependency relations.

This work focuses on analyzing a large corpus of online reviews about products. Opinion lexicon expansion and aspects extraction tasks are performed simultaneously based on double propagation using the dependency relations. Firstly, word tokenization, part-of speech tagging and syntax or dependency parsing are done to process the sentences of the input datasets. StandfordfordCoreNLP dependency parser is used to identify dependency relations. To process the propagation, the system only requires a seed opinion lexicon. The idea of the propagation approach is first to extract opinion words and features using the seed opinion lexicon and then use the newly extracted opinion words and features for new features and opinion words extraction.

The algorithm ends until no more opinion words and features can be identified. In this way, even if the seed opinion lexicon is small, features can still be extracted with high recall and at the same time the opinion lexicon is also expanded. Incorrect features are removed by using general word set obtained from WordNet and NLTK. Finally, input sentences are classified their polarity orientations such as positive or negative by using Vader lexicon. By this way, opinion lexicon is expanded automatically.

The paper is organized as follows. Section 2 describes some related works of the proposed system. Section 3 to 8 show detailed and step by step procedures of the proposed system. Section 9 expresses the experimental results and analysis of the proposed system. Finally, section 10 concludes the proposed system.

II. RELATED WORKS

Many research has been done about opinion word extraction. In general, the existing work can be categorized as corpora-based and dictionary-based approaches. Our work falls into the corpora-based approaches.

Recent corpora-based approach is proposed by Kanayama and Nasukawa (2006). However, their method for finding candidates would have low recall if the occurrences of seed words in the data are infrequent or an unknown opinion word has no known opinion words in its context. Besides, the statistical estimation can be unreliable if the corpus is small, which is a common problem for statistical approaches [14].

In dictionary-based approaches, Kamps et al. (2004) take advantage of WordNet to construct a synonymy network by connecting pairs of synonymous words. The semantic orientation of a word is decided by its shortest paths to two seed words "good" and "bad" which are chosen as representatives of positive and negative orientations [13] [18].

Guang et al. (2011) used a bootstrapping based method to expand opinion words and to extract targets. To perform the tasks, they considered syntactic relations between opinion words and targets. However, the authors only considered adjective opinions. The authors did not consider verb opinion. The extraction rules used in their system are only direct relations between product features and opinions. So, some dependency relations are still missing [8] [23].

Qian Liu (2013) proposed a logic programming approach for aspect extraction. In their system, they implemented double propagation in Answer Set Programming using 8 ASP rules. The recall is low because correct aspects were pruned as incorrect features and they considered only direct relations. Moreover, their approach may miss some infrequent features because this method extracted frequent noun or noun phrases as product features [14] [22].

Sentiments may be narrated as opinions, ideas or as judgements manifested by emotions by Boiy et al., (2007). As Kadam and Joglekar, (2013) stated, “One of the challenges related to sentiment analysis is identifying the objects of the study of opinions and subjectivity. Quirk defines private state as something that is not open to objective observation or verification in Kadam and Joglekar, (2013). These private states include emotions, opinions and speculations. Computational linguistics mainly focuses on opinions rather than on sentiments, feelings or emotions. The terms ‘sentiment’ and ‘opinion’ are often used interchangeably in the literature.

According to Banitaan et al., (2010), Binali et al., (2009), and Glance et al., (2004), there are different categories of entities. A broad overview organizes them into four entity categories that represent different types of words in a review text. These four categories are components, functions, features, and opinions. Some entities may not fit in any category. Therefore, a fifth category, “other” is formed and left open for any suggested categories.

Another essential issue, after discovering entities, is to assign them to the right opinions and right products; this is called “entity assignment”. Some reviews may have direct opinions assigned to direct entities, which are explicitly mentioned in the sentence. Other reviews may contain entities or opinions that are implied and difficult to assign. These two issues are crucial, as without discovering which entities the review talked about and without assigning the corresponding opinions to the correct entity, the opinion mining is of no use A.M. Popescu, and O. Etzioni, (2007).

There are some proposed techniques to discover and assign entities. [Ding et al., 2009] proposed a solution to discover entities by discovering linguistic patterns and then using them to extract entities. They also proposed a technique for assigning entities depending on extracting entities of comparative sentences, such as the example of Camera S300 in Kansal, H. and Toshniwal, D., (2014).

As another attempt to create a lexicon-based approach for sentiment mining, Alhazmi et al. (2013) linked the Arabic WordNet to ESWN through the provided synset offset information. The efficiency of the lexicon for sentiment mining was not evaluated.

Agarwal et al., (2015) employed dependency relations between words to extract features from text based on ConceptNet ontology. Afterwards they used a method called "mRMR", which works as a feature selection scheme to eliminate redundant information. [Somprasertsri and Lalitrojwong, 2010] presented a method that extracts opinions and product features considering the syntactic and semantic information and based on dependency relations and ontology knowledge.Zhao et al (2015) presented a new method called joint propagation and refinement for mining opinion words and targets. The authors used frequency based threshold to prune incorrect targets. So, targets that are not occurred frequently, i.e. infrequent features are removed in their system. Threshold need to be raised to improve the precision which will affect the recall [31].

Our approach extracts not only domain independent opinion words but also context dependent opinion words.

III. SEED LEXICONS

The proposed system are evaluated with two lexicons as seeds, Bing Liu Lexicon with 6786 positive and negative words developed by Hu and Bing Liu and NRC Affect Intensity Lexicon with nearly 6000 words developed from National Research Council of Canada. In opinion lexicon expansion, the proposed approach and Qiu's approach are evaluated with two types of evaluation; on all words including seeds and on newly extracted words without considering the seeds. This is because we intended to consider this system to evaluate different lexicon as seeds and different number of seed words.

IV. DATASETS AND ANNOTATION

Amazon product reviews datasets are used for the experiment. The first three datasets are annotated by Qian Liu and Bing Liu, University of Illinois at Chicago, (IJCAI, 2015) [20]. Opinions are manually collected from Dataset according to Bing Liu's lexicon, Vader lexicon and Sent WordNet. To get consistency, we check whether the collected words are contained in these three lexicons.

V. RULES FOR FEATURES AND OPINIONS EXTRACTION

In this section, we describe how to extract opinion and product features using extraction rules. They are the most important tasks for text sentiment analysis, which has attracted much attention from many researchers. We used the extraction rules and patterns proposed in the previous work (Wai et al., ICIS 2017) [20].

Based on the relations between features and opinions, there are four main rules in the double propagation;

1. Extracting features using opinion words
2. Extracting features using the extracted features
3. Extracting opinion words using the extracted features
4. Extracting opinion words using both the given and the extracted opinion words

In the following extraction rules, O is opinion word, H is the third word, {O} is a set of seed opinion lexicon, F is product feature, and O-Dep is part-of-speech information and dependency relations. {JJ}, {VB} and {NN} are sets of POS tags of potential opinion words and features, respectively. And {DR} contains dependency relations between features and opinions such as mod, pnmod, subj, s, obj, obj2, and conj. We used rule 1 and 2 to extract features, and rule 3 and 4 use to extract opinion words. Moreover, we also used some additional patterns to extract features and opinions.

Table 1. Extraction rules using dependency relations

Rule No.	Observations	Constraints	Outputs
R11	O →O-De →F F→F-Dep→O	O∈{O}, O-Dep ∈{DR} F-Dep ∈ {DR}POS(F)∈ {NN, VB}	F=Feature
R12	O→O-Dep→H←O-Dep←F	O∈{O}, O-Dep∈{DR} Fdep∈{DR} POS(F)∈ {NN, VB}	F=Feature
R13	O→O-Dep→H→F-Dep→F O←O-ep←H←F-Dep←F	F_i ∈{F} F_i-Dep=F_j-Dep POS(F_j) ∈ {NN}	F=Feature
R22	F_i →F_i -Fep→F_j	F_i ∈{F} F_i-Dep=F_j-Dep POS (F_j) ∈{NN}	F=Feature
R31	O → O-Dep → F F→F-Dep→O	F∈{F}, O-Dep∈{DR} F-Dep∈{DR} POS(O) ∈{JJ, VB}	O=Opinion
R32	O→O-Dep→H←O-Dep←F	F∈{F}, O-Dep∈{DR} F-Dep∈{DR} POS(O) ∈ {JJ, VB}	O=Opinion
R33	O→O-Dep→H→F-Dep→F O←O-Dep←H←F-Dep←F	F∈{F}, O-Dep∈ {DR} F-Dep∈ {DR} POS(O) ∈ {JJ, VB}	O=Opinion

R41	$O_i \rightarrow O_i$-Dep $\rightarrow O_j$	$O_j \in$ {O}, O_i-Dep$\in${CONJ}, POS (O_j) $\in${JJ}	O=Opinion
R42	$O_i \rightarrow O_i$-Dep$\rightarrow$H$\leftarrow O_j$-Dep$\leftarrow O_j$	$O_i \in${O} O_i-Dep=O_j-ep, POS (O j) $\in${JJ}	O=Opinion

In this section this system takes raw data as input and xml tag and ascii code characters are removed. After that, word tokenization, part-of speech tagging and dependency identification between words are done by using StandfordfordCoreNLP dependency parser. We used the algorithm also from [17]. Table 1 shows the general overview of the observation, constraints and output of the extraction rules.

VI. Feature Based Automatic Opinion Lexicon Expansion

The extraction process uses a rule-based approach using the relations defined in above. The system assumed opinion words to be adjectives, adverbs and verbs in some cases.

The primary idea is that opinion words are usually associated with product features in some ways. Thus, opinion words can be recognized by identified features, and features can be identified by known opinion words. So, the extracted opinion words and product features are used to identify new opinion words and new product features. The extraction process ends when no more opinion words or product features can be found. Detailed explanation of feature and opinion extraction are shown in the above algorithm [17] [20].

In the extraction rules, O is opinion word, H is the third word, {O} is a set of seed lexicon, F is product feature, and O-Dep is part-of-speech information and dependency relations. {JJ}, {VB} and {NN} are sets of POS tags of potential opinion words and features, respectively. And {DR} contains dependency relations between features and opinions such as mod, pnmod, subj, s, obj, obj2, and conj [20].We used rule 1 and 2 to extract features. Rule 3 and 4 are used to extract opinion words. Moreover, we also used some additional patterns to extract features and opinions [20] [26].

A. *"no" Pattern.*

"No" pattern means that the word "no" is followed by a noun/noun phrase. For example, people can say "no USB". Here "USB" is a feature of phone. People often use this pattern in product reviews to express their short opinions on features [20].

B. *"To" Pattern.*

"To" pattern means that the word "to" is followed by verb infinitive (based form). For example, "slow to download", "easy to set up", "easy to hook up". In these sentences, the words "download", "set up", "hook up" are verb product features [20].

C. *"Verb + Adjective" Patterns.*

This pattern means that subject is followed by verb and then followed by adjective. For example, "The output image gets worse if we block more of the frequencies." In this sentence, "worse" is an opinion word. So, we proposed a pattern to extract this kind of sentences [20].

VII. Nigram Feature Extraction

Two consecutive words are extracted if their POS tags conform to any of the patterns in Table 2. For example, the pattern in line 2 means that two consecutive words are extracted if the first word is an adverb and the second word is an adjective but the third word (which is not extracted) cannot be a noun. NNP and NNPS are avoided so that the names of entities in the review cannot influence the classification [1] [19] [20] [26].

Table 2. Patterns of tags for extracting two-word phrases

First word	Second word	Third word (not extracted)
JJ	NN or NNS	anything
RB, RBR, or RBS	JJ	not NN nor NNS
JJ	JJ	not NN nor NNS
NN or NNS	JJ	not NN nor NNS
RB, RBR, or RBS	VB, VBD, VBN, or VBG	anything

Bigram features are extracted by using dependency relations compound for noun compound words e.g., battery life and compound-prt for noun and preposition compound words e.g. set up, heat up. Other n-gram words are extracted by using TextBlob tool. Since there are false negative rate in textblob, the output from textblob are matched with n-grams corpus. To match the textblob output, this system use n-gram corpus by collecting n-gram words contain in the datasets from Google N-gram Corpora.

Table 3. Patterns of tags for extracting two-word phrases

Compound Word	Relation	Example
Noun + Noun	nn	Battery life, picture quality, screen resolution
Adjective + Noun	amod	Electrical connectivity, dead pixels, viewing angle
Verb + Preposition	prt	Set up, hook up, heat up
Verb + Noun	vmod, dobj	Recommended camera, appreciate picture

VIII. Context Dependent Opinion Words

Context dependent opinion means that a word may indicate different opinions in the same domain. This system can extract context dependent opinion words by using R31, R32 and R33 with dependency relations of amod and cop. Table 4 shows some context dependent opinion words extracted from the proposed system.

Table 4. Context dependent opinion words

Longer battery life	positive	Longer run time	negative
Low price	positive	Low audio volume	negative
Small cost	positive	My house is small	negative
Big crisp screen	positive	Big problem	negative
Much more	positive	Much lower	negative

IX. Experimental Results And Analysis

The performance of the proposed system is evaluated by measuring the evaluation criteria as shown in the above section according to the extracted features and their corresponding opinions from customer reviews. For experiment, we use core i7 processor with 2.20 GHz speed (2 gen), 4GB RAM with 665.3 MHz speed and 64-bit Ubuntu OS, and, the proposed system is implemented with python programming language (PyCharm IDE for python.

In this research, 10 reviews datasets are chosen to test the proposed system as resources for experiment. 8 product review datasets are collected from https://www.cs.uic.edu/~liub/FBS/sentiment-analyssas. Among them, three datasets; computer, router and speaker are annotated by: Qian Liu, Bing Liu, 2015, School of Computer Science and Engineering, Southeast University, China and Department of Computer Science, University of Illinois at Chicago, USA. And, another 2 datasets; restaurant and hotel are obtained from SemEval research group. SemEval (Semantic Evaluation) is an ongoing series of evaluations of computational semantic analysis systems, organized under the umbrella of SIGLEX, the Special Interest Group on the Lexicon of the Association for Computational Linguistics (ACL). The rests are annotated and used in (Ding, Liu and Yu, WSDM-2008), which improves the lexicon-based method proposed in (Hu and Liu, KDD-2004). Table 5.2 shows the information of dataset according to their names, the number of sentences and the number of features.

Table 5 shows the domains according to their names, the number of sentences and the number of opinions. This performance of opinion words expansion is evaluated in term of precision (P), recall (R) and f1-measure (F1).

Table 5. Dataset used for experiment

Dataset	no of sentences	no of features	no of opinions
Restaurant	1083	1193	463
Hotel	266	212	185
Router	245	304	207
Speaker	291	435	227
Computer	239	346	215
IPod	161	293	214
Linksys Router	192	375	193
Nokia 6000	363	633	277
Norton	210	302	185
Diaper Champ	212	239	169

In opinion lexicon expansion, the proposed approach and Qiu's approach are evaluated with two types of evaluation; on all words including seeds and on newly extracted words without considering the seeds. The proposed system used two lexicons) as the seed. 10 different seeds number such as S100, S500, S1000, etc. words from Bing Liu's lexicon and NRC Affect Intensity lexicon. In this case, S means seed. This is because we intended to consider this system to evaluate different lexicon as seeds and different number of seed words.

The comparative results of the proposed approach with Bing Liu seed, the proposed approach with NRC seed, Qiu's approach with Bing Liu seed and Qiu's approach with NRC seed are shown in figure 1, 2 and 3. Note that all metrics (precision, recall, and F-score) are computed on the newly extracted opinion words. This is an important point because only the new extractions are meaningful. Using all the extracted words to compute precision and recall is not appropriate as they can include many words that are already in the seed list. The comparative results of precision on newly extracted opinion words between the proposed approach and Qiu's approach with different seed numbers and seed lexicons are described in figure 1.

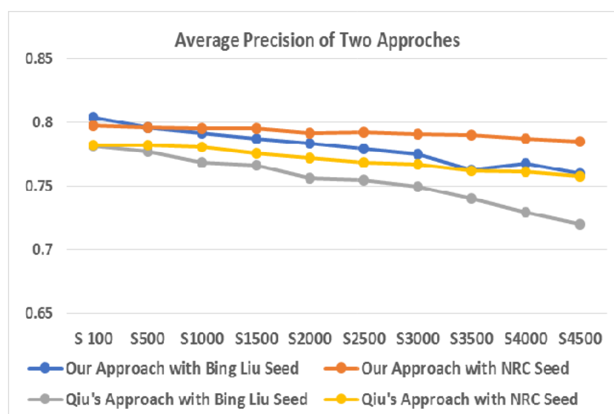

Figure 1. Comparison of Precision of Opinion Extraction

As shown in figure, the proposed approach outperforms in precision for all different seed numbers although the seed lexicons are changed. The proposed approach gets 78% average precision while Qiu's approach 76% average precision.

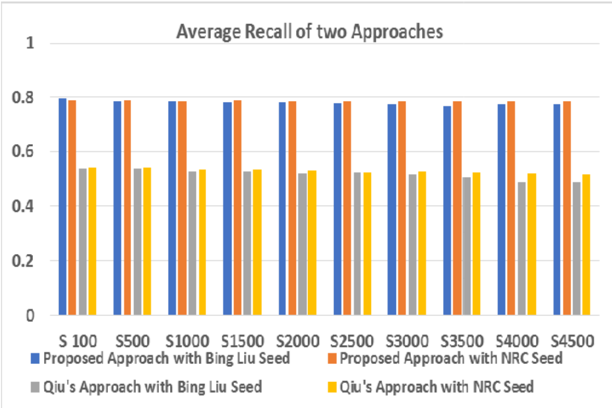

Figure 2. Comparison of Recall of Opinion Extraction

The average f1-score of the proposed approach and Qiu's approach using two seed lexicons and different seed numbers are described in figure 3. The proposed approach performs better than the Qiu's approach for all seed numbers in both seed lexicons. The proposed approach has 78% average f1-score whereas Qiu's approach gets only 61% average f1-score.

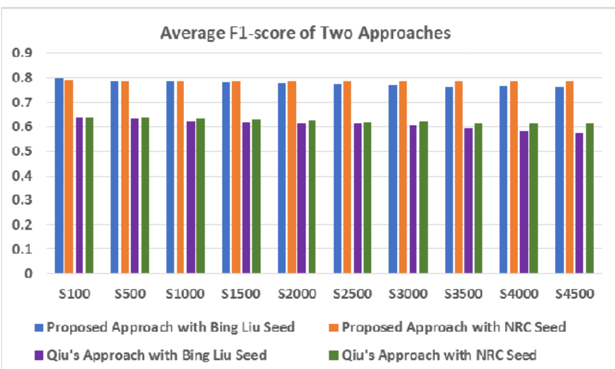

Figure 3. Comparison of F1-measure of Opinion Extraction

The comparison of false negative rate or missing rate on newly extracted opinion words with different seed numbers are described in figure 4. According to the results, Qiu's approach are much more FNR than the proposed approach. This shows that the proposed has less missing words to extract.

The proposed Approach are tested with different seed lexicons and different datasets to evaluate the computational time. Different datasets from different domains are used to test the domain independency.

In this analysis, all datasets get acceptable results except ABSA Hotel dataset. Moreover, the computational time of the proposed approach and state of the art approach are calculated in various cases in order to determine the efficiency and complexity. It is measured in seconds.

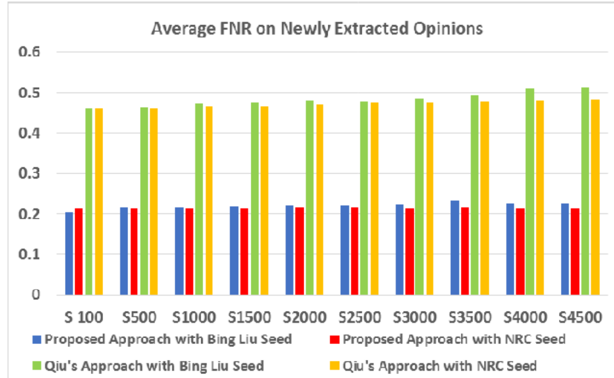

Figure 4. Comparison of FNR of Opinion Extraction

In this evaluation, only ABSA Restaurant dataset get about 40 seconds in computational time because the numbers of sentences contained in this dataset are 5 times larger than other datasets. The worst-case time complexity of the proposed algorithm is at most O (N*N) which is common with algorithms in text processing applications that involve nested iterations over the data set.

The computational time depends on the number sentences and number of seeds. When the number of and number of seed are large, the computational time take longer than the small number of seeds and sentences. Figure 5 shows the comparison of computational time in seconds of the proposed approach and Qiu's approach. According to the experimental results, Qiu's approach average 3 seconds faster than the proposed approach in all seed numbers.

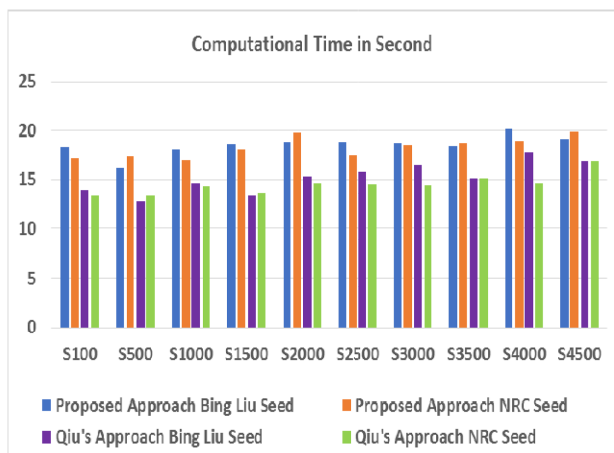

Figure 5. Comparison of Computational Time for Opinion Extraction

X. Conclusion

Opinion mining or sentiment analysis analyzes people's opinions, appraisals, attitudes, and emotions toward entities, individuals, issues, events, topics, and their attributes. When people need to make a decision, they often seek out the opinions of others. This is true not only for individuals but also for organizations. This work has been explored a number of methods to feature and opinion extraction including dictionaries, machine learning, statistical techniques and natural language processing techniques. In this work, an unsupervised corpus-based method to opinion lexicon expansion and feature extraction is proposed. Features and opinions words are extracted simultaneously by using the proposed algorithm. If the opinion words of the datasets does not contain in the seed lexicon, the system can extract more words rather than that contain less words in the seed.

The system has been tested with different datasets and different seed numbers. This method has a major advantage that the dictionary based method does not have. It can help find domain- and context specific opinion words and their orientations using a domain corpus. The proposed method have experimented with the use of rule base method to extract features and opinion from customer reviews. Unlike the existing method, context dependent opinion words can be extracted and get domain independencies. According to experimental results, the proposed system works well in all datasets that contain verb features and verb opinions and get domain independency without using training examples. The system works well in customer reviews, especially in product review datasets.

REFERENCES

[1] Bing Liu, "Web Data Mining", 2nd edition, Springer, Department of Computer Science, University of Illinois, Chicago, USA.
[2] Bing Liu, "Sentiment Analysis and Opinion Mining", Morgan& Claypool Publishers, May 2012, pp.16-29.
[3] Bo Pang and Lillian Lee., "Using very simple statistics for review search: An exploration". In Proceedings of the International Conference on Computational Linguistics (COLING), 2008. Poster paper.
[4] C.J. Hutto and Eric Gilbert, "VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Texts", Association for the Advancement of Artificial Intelligent AAAI, www.aaai.org, 2014,
[5] Ebrahim et al. "Sentiment Classification of online Product Reviews Using Product features", International Journal of Information Processing and Management (IJIPM), Volume3, Number3. July 2012.
[6] Esuli, Andrea and Fabrizio Sebastiani. 2005. Determining the semantic orientation of terms through gloss classification. In Proceedings of CIKM'05, pages 617–624.
[7] Fabíola S. F. Pereira, "Mining Comparative Sentences from Social Media Text", In Proceedings of DMNLP, Workshop at ECML/PKDD, Nancy, France, 2014.
[8] Guang Qiu et al., "Opinion Word Expansion and Target Extraction through Double Propagation", Proceeding of the Association for Computational Linguistics ACL, 2011, pp. 10-27
[9] Hatzivassiloglou, Vasileios and Kathleen R. McKeown. 1997. Predicting the semantic orientation of adjectives. In Proceedings of ACL'97, pages 174–181.
[10] Hu, M and Liu, B., "Mining and Summarizing Customer Reviews", Knowledge Discovery & Data Mining KDD'04, 2004
[11] J. Ashok Kumar and S. Abirami, "An Experimental Study of Feature Extraction Techniques in Opinion Mining", International Journal on Soft Computing, Artificial Intelligence and Applications (IJSCAI), Vol.4, No.1, February 2015.
[12] Jindal, N. and Liu, B., "Mining Comparative Sentences and Relations", Proceeding of the American Association for Artificial Intelligence AAAI'06, 2006.
[13] Kamps, Jaap, Maarten Marx, Robert J. Mokken, and Maarten de Rijke. 2004. Using wordnet to measure semantic orientation of adjectives. In Proceedings of LREC'04, pages 1115–1118.
[14] Kanayama, Hiroshi and Tetsuya Nasukawa. 2006. Fully automatic lexicon expansion for domain-oriented sentiment analysis. In Proceedings of EMNLP'06, pages 355–363.
[15] Kim, Soo-Min and Eduard Hovy. 2004. Determining the sentiment of opinions. In Proceedings of COLING'04, pages 1367–1373.
[16] Kobayashi, Nozomi, Kentaro Inui, and Yuji Matsumoto. 2007. Extracting aspect-evaluation and aspect-of relations in opinion mining. In Proceedings of EMNLP'07.
[17] Lei Zhang et al., "Extracting and Ranking Product Features in Opinion Documents", Proceeding of the International Conference on Computational Linguistics (Coling), 2010, pp1462-1470
[18] Murthy Ganapathibhotla and Bing Liu, "Mining Opinions in Comparative Sentences", Proceedings of the 22nd International Conference on Computational Linguistic, Manchester, August, pp. 241-248, 2008.
[19] Maria Pontiki et al., "Aspect Based Sentiment Analysis", Association for Computational Linguistics (ACL), San Diego, California, June 16-17, 2016
[20] Myat Su Wai anf Sint Sint Aung (2017), "Simultaneous Opinion Lexicon Expansion and Product Feature Extraction", 16th IEEE/ACIS International Conference on Computer and Information Science ICIS, 2017, May 24-26, 2017.
[21] Priyanka R. Shirsath and Ujwala M. Patil, "Getting Better Alternatives by Comparable Entity Mining": A Survey, International Journal of Innovative Research in Computer and Communication Engineering, Vol. 3, Issue 6, June 2015, ISSN (Online): 2320-9801
[22] Qian Liu, "A Logic Programming Approach to Aspect Extraction in Opinion Mining", IEEE WC/ACM International Conference, 2013.
[23] Qian Liu, Zhiqiang Gao, Bing Liu and Yuanlin Zhang. "Automated Rule Selection for Aspect Extraction in Opinion Mining." Proceedings of International Joint Conference on Artificial Intelligence (IJCAI-2015), July 25-31, 2015.
[24] S Padmaja and Prof. S Sameen Fatima, "Opinion Mining and Sentiment Analysis –An Assessment of Peoples' Belief: A Survey", International Journal of Ad hoc, Sensor & Ubiquitous Computing (IJASUC), Vol.4, No.1, February 2013
[25] Seon Yang and Youngjoong Ko, "Extracting Comparative Sentences from Korean Text Documents Using Comparative Lexical Patterns and Machine Learning Techniques", Proceedings of the ACL-IJCNLP 2009 Conference, Short Papers, pages 153–156, Suntec, Singapore, 4August 2009.
[26] Sint Sint Aung and Myat Su Wai, "Domain Independent Feature Extraction using Rule Based Approach", Advances in Science, Technology and Engineering Systems Journal Vol. 3, No. 1, 2018.
[27] Sun Yongmei and Huo Hua "Research on Domain-independent Opinion Target Extraction", International Journal of Hybrid Information Technology, Vol.8, No.1 (2015), pp.237-248
[28] Takamura, Hiroya, Takashi Inui, and Manabu Okumura. 2005. Extracting semantic orientations of words using spin model. In Proceedings of ACL'05, pages 133–140.
[29] Zhao et al., "Joint Propagation and Refinement for Mining Opinion Words and Targets", IEEE Data Mining Workshop, 2014, pp.417-424