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COMBINED APPROACH FOR ASPECT TERM EXTRACTION IN ASPECT-BASED SENTIMENT ANALYSIS

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Abstract
In the world of online news and social media, there is an ever increasing amount of textual data on the internet, and a large portion of it expresses subjective opinions. Sentiment Analysis (SA) termed as Opinion Mining, which is a method of automatically identify and extracting the subjective sentiments of a particular product or topic. Aspect Based Sentiment Analysis (ABSA) is a sub-field of SA which is used to extract more exact and refined opinions by splitting the text into aspects. The aim of this work is analyzing and implementing the method of Aspect Term Extraction (ATE) from user reviews on laptops and restaurants. The proposed method used Conditional Random Fields (CRF) which is able to optimize the use of features for classification. It is identified that the existing methods for SA failed to extract some implicit aspects in some cases. In this work, we proposed a new set of features to capture more semantic information from text and to improve the representation of a text. In aspect term extraction, these set of features are considered as additional positional features for giving training to the model of CRF. To extract missing implicit aspect terms, a set of rules are proposed and combined with the CRF approach to increase the efficiency of the aspect extraction. Detailed empirical evaluations are performed by experimenting with custom made features along with proposed features using a CRF supervised algorithm to accomplish the task of Aspect Term Extraction in terms of Recall, Precision and F-measure evaluation metrics adopted in the field. The improved performance in aspect term identification is observed by combining the proposed set of rules with the CRF algorithm. The performance of CRF algorithm is observed by comparing with other algorithms such as Decision Tree (DT), Naive Bayes (NB) and K-Nearest Neighbor (KNN) classifiers. The overall improvement in F1-Score of our proposed model shows an increment of 3% from that of the state-of-the-art methods.
Key words: Aspect term extraction, Sentiment analysis, Conditional Random Fields, Word Representation, Word POS tagging.

1. Introduction

Nowadays, online social media platforms like LinkedIn, Twitter and Facebook provide a valuable framework for individuals to share and discuss ideas and opinions regarding various topics, products, services, organizations, movies, political events and individuals to increase services and quality of organizations [1, 2] . SA also known as Opinion Mining (OM) is "the field of study that analyzes people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes" [3]. Subjectivity analysis is one step of a SA and the aim of subjective analysis is classifying subjective phrases into negative, positive, neutral or mixed.
The Sentiment classification can be achieved at various levels such as Sentence level, document level and at level of Aspect based on the amount of text considered. Document Level Sentiment Classification (DLSC) extracts the opinion on a document as either negative or positive [4]. Sentence Level Sentiment Classification (SLSC) SLSC is to categorize a sentence present in the document as either subjective or objective [5]. It categorizes the subjective sentence into negative (-), positive (+) or neutral (.) opinion. Aspect Level Sentiment Classification (ALSC) also called as ABSA is to recognize features of objects like Picture Quality and battery life which were commented by an opinion holder [6]. Therefore identification of Sentiment in a message at the level of its aspects is an interesting research area. The existing models and features for identification of sentiment at aspect level that

present in the messages might not suitable for short messages. There is a need of good analysis at the aspect level to determine what the author dislikes or likes about the entity. The ASBA also called as attribute based or feature based SA. The major goal of ALSC is identification of aspects along with express the sentiment of aspects. For example, the statement “the food is delicious but the service is very slow” states the reviewer specified opinion on two aspects such as service and food wherein the sentiment of service and food is negative and positive respectively.

ABSA establishes a relationship among the aspects of a product and their polarity. The aspects also called as attribute or feature of a product. The aspect identification is an important concept in sentiment analysis. There are two types of aspects such as implicit aspect [7] and explicit aspect [8]. Many tasks such as aspect sentiment classification, aspect extraction and aspect categorization are performed in ABSA. In this work, we concentrated on the aspect identification, extracting the aspects from the reviews dataset as well as identifying the implicit aspects using a set of rules in combination with the explicit aspects identified by the CRF with a set of features.

Section 2 explains the existing work on ABSA and SA. The proposed model is explained in the section 3. It contains the description on existing features, proposed features and explanation on rules in identifying the implicit aspect terms. In section 4, the description of dataset, evaluation measures, the empirical evaluations on the proposed system and analysis and observations on the obtained results. Finally in section 5, the conclusions of this work and possible future enhancements were discussed.

2. Related Work

All printed material, ZHANG; LIU, (2014) considered the aspect extraction as a task of sequence labeling because the aspects of a product occurred at a sequence in a sentence [9]. The study done by Chernyshevich (2014) focused in extraction of cross-domain features of product using CRF, and aimed to fulfill the aspect extraction also called as phrase-level sentiment classification [10]. Toh and Wang (2014) proposed a system to address the two sub tasks of ABSA track of SemEval 2014 competition [11]. Their system contains two classifiers such as linear classifier and CRF for Aspect Term Polarity Classification and Aspect Term Extraction (ATE) respectively. In the subtask of ATE, the authors extracted a variety of syntactic, lexical, semantic and cluster features from unlabeled data. They implement a set of general features, such as token, PoS, Head word, Dependency Relation, and Name list. Additional features that require external resources and/or complex processing are also used, such as WordNet Taxonomy, Word Cluster, and Name List Generated using Double Propagation.

The Saias (2015) proposed an opinion mining system Sentiue for Aspect Category Detection [12]. In their approach, they applied supervised machine learning classifier to select the aspect label based on the probabilities of the pair entity/attribute. The work done by Kumar et al. (2016) achieved best results in sentiment polarity classification about English laptops, Spanish restaurants and Turkish restaurants, and Scored second for English restaurants [13]. They used a set of word features such as Lemma, PoS, Chunk, Named entity information, and a set of syntactic features such as WordNet, Prefix and suffix, tf-idf, and Bag of words.

Ruder, Ghaffari and Breslin (2016) proposed an approach based on Convolution Neural Network (CNN) for both aspect-based sentiment analysis and aspect extraction [14]. They experimented with multiple language sub tasks of ABSA such as Aspect Term Polarity Classification and Aspect Term Extraction. The approach was applied on the domains Restaurants, Laptops, Phones, and Hotels. The sentiment towards an aspect was determined by concatenating the word embedding of aspects into an aspect vector and applies a convolution over it. The system proposed by Toh and Su (2016) was submitted to the subtasks of Opinion Target Extraction (OTE) and Aspect Category Detection (ACD) of SemEval 2016 [15]. Their system uses two classifiers such as sequential labeling classifiers and binary classifiers. Sequential labeling classifier was used for OTE. The binary classifiers was used for aspect category classification by training the classifier with single layer feed forward network. Besides extracting different features like cluster, syntactic and lexicon features, the authors explored deep learning systems usage to provide additional neural network features. Some of the features are Word embeddings, Name list, Token, Head Word and Word Cluster.

Zhou ET AL., (2015) proposed a representation learning approach for ACD to learn useful features automatically [16]. In their work, first they proposed a semi-supervised word embedding algorithm to attain continuous word representations from a large number of reviews dataset. Later, the authors produced hybrid and deeper features. Finally, they used hybrid features to train the logistic regression classifier for predicting the aspect category. The system proposed by Machacek (2016) models the task of ACD, where labels correspond to the entity-aspect pairs. Words from each sentence are used as individual binary features of that sentence. For each entity-aspect pair, all training sentences are used as positive or negative examples of that entity-aspect pair. The systems use features such as Lemma, PoS, Token, Stop words, Prices recognition, N-grams, Minimal word length, and Consecutive letters neutralization.

In [17], proposes two methods directed towards two fundamental points to opinion treatment: aspect-based sentiment analysis, which identifies expressions mention aspects and entities in a text, using natural language processing tools combined with machine learning algorithm and polarity attribution, which uses twenty-four features. The author proposed the classifier Simple Logistic which utilizes logistic linear regression models, using word features such as token, sentence split, PoS, Lemma, Dependency Parsing, and Co-reference. Kok et al.

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(2018) used restaurant reviews in their experiment and consider the ABSA task at the review-level [18]. The authors focused on the ontology enhanced methods which complement a standard machine learning algorithm. The sentiment classification was determined with SVM models by training with a variety of features. These features can be split into two groups such as generated features (sentence count, sentiment count, Aspect, ontology concepts, lemma) and adapted features (negation handling, ontology concept score, weights, synonyms and word window).
In [19], proposed an approach for the sub task of Sentiment polarity Classification task in ABSA. They used SemEval 2015 datasets of laptop and restaurant domains. In their experimentation, six different pattern classes such as syntactical, lexical, sentiment, semantic, surface and hybrid features are used with Support Vector Machine from lib SVM library. Features such as Word n-grams (unigram to fourgram), PoS n-grams (unigram to fourgram), Synset n-grams (unigram and bigram), Synset-PoS bigram, Negator-PoS bigram, Sentisynset unigram, Negator-sentisynset bigram are used. They observed that the performance of several patterns like negator-POS bigram, synset bigram and POS bigram was good for determining the aspect-based sentiment.
Movahedi et al. (2019) proposed a model which utilizes many attentions with various topic contexts [20]. This model enables different sentences of reviews based on various topics. They proposed Topic-Attention Network (TAN) and neural architecture to capture important words from different topics and applied it to the restaurant reviews in SemEval 2014 and 2016 datasets. The study by Xia et al. (2019) proposed an approach by using CRF algorithm for online review sentiment classification to retrieve emotional characteristics based on the domain dictionary from the fragments of the review to sentiment analysis [21]. Their approach depends on the accuracy and comprehensiveness of the dictionary. The weights are computed asymmetrically for the characteristic (feature) words before a SVM classifier is used to achieve the review's sentiment orientation in portrait style.

3. Proposed Model

The proposed approach as presented in Figure 1, contains six steps. The training and test datasets are in XML format. The training data of Restaurant dataset consists of 3041 reviews, training dataset of laptop dataset consists of 3045 reviews and test dataset for each domain contains 800 reviews. In the first step, the training and test datasets of both domains are preprocessed. Each review in the training dataset contains review sentence, aspect terms and aspects polarities. The reviews, aspect terms and its polarities are separated and collected in text format. The stem of each word is extracted from the review to remove semantic redundancy,. Stem word sequence is formed using the word sequence of each review. As a second step, the optimal feature set is identified from the empirical evaluations using machine learning algorithms. In third step, label sequence (IOB) is identified for the reviews in the training dataset using aspect terms presented in the reviews. CRF algorithm is trained using stem word sequences with its corresponding label sequences. In the fourth step, the trained CRF model is used to identify the label sequence for each review in the test dataset. In the fifth step, from the label sequence for each test review, its explicit aspect terms are extracted. In the sixth step, each test review is inputted to the manually crafted rule set to identify the implicit aspect terms that are not identified from the previous step. Aspect terms identified from the CRF model and crafted rules are combined to extract final list of aspect terms.

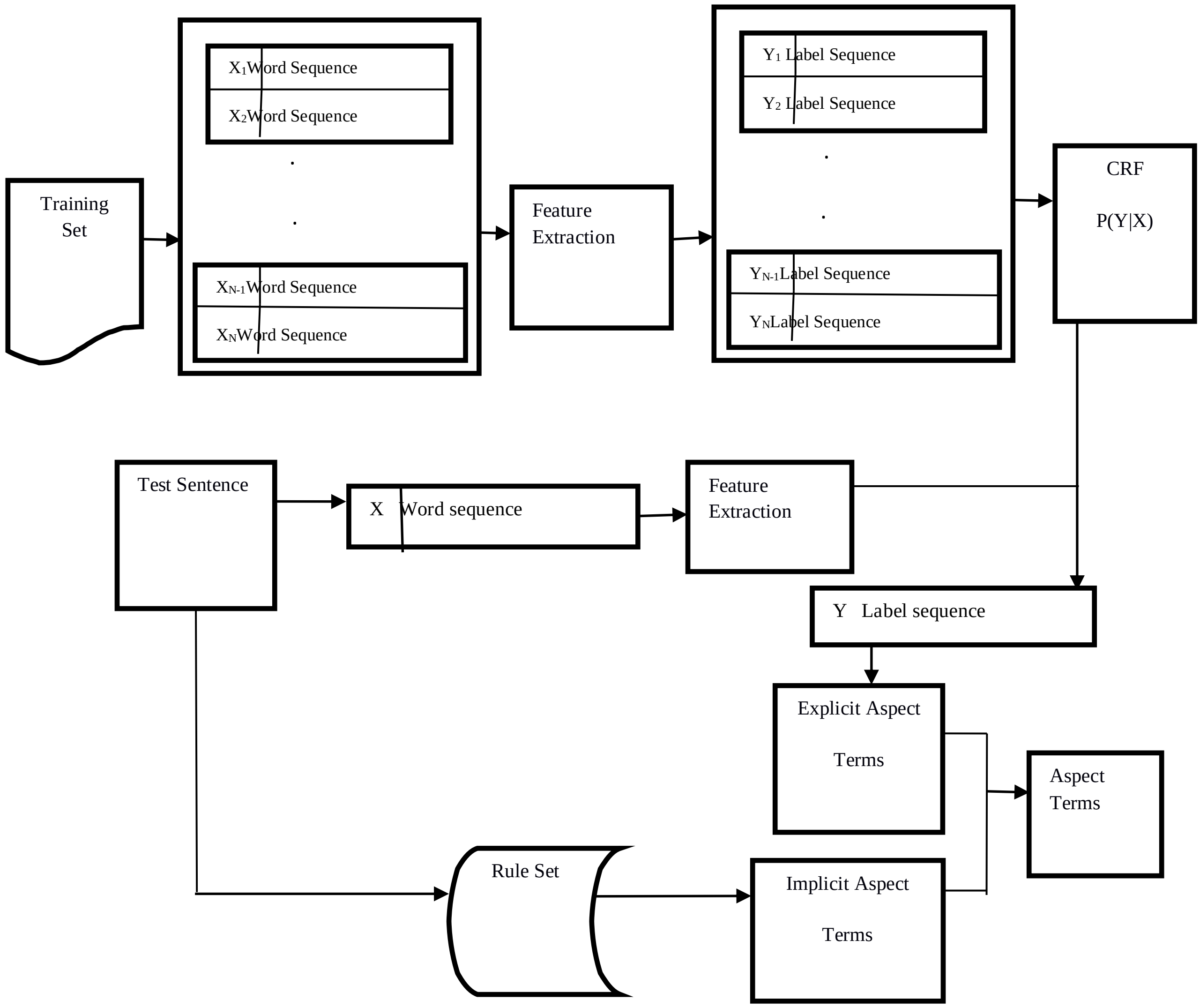

Fig. 1. The Proposed Combined Aspect Term Extraction Model

The list of most prominent features identified from the existing works, the proposed features to capture the semantic relations among the words presented in the reviews and manually crafted rules to extract the implicit aspect terms are presented below:

3.1 Features

The CRF model mainly depends on the set of features that are used in the model. Those features are described below:

i) **Local Context (LC):** The word and it succeeding and preceding words.
ii) **Words (W):** The occurrence **of a** Word on a given position in the context window.
iii) **Word N-Gram (WN): T**he word N-Grams (where N is ranging from 1 – 3) from the review dataset.
iv) **Parts of Speech (POS) tags:** The POS tags of the present word and POS tags of its next and previous words.
v) **Chunk (CH):** This feature determining the aspect terms boundaries. The POS taggers are used to identify the small phrases by using the sentences POS tag sequences.
vi)**Named Entity Recognition (NE):** The names of persons, organizations and locations are considered as Named Entities.
vii) **Dependency Tree (DT):** this is used to extract the adverbs and adjectives of the nouns in the tree.
viii) **Word Class (WC):** The Yelp dataset and skip gram model is used to compute Word2Vec for each word in the review. These word vectors are grouped into 300 clusters using K- Nearest Neighbor algorithm.
ix) **Word distance (WD):** The nearest noun phrase to sentiment word. Stanford POS tagger is used to find this feature.

3.2 Proposed Features

i) **Word Embedding (WE):** Vector representations of the words presented in the reviews capture the semantic and syntactic information in textual contents. Word Embeddings are produced using Continuous Bag Of Words

(CBOW) model of 300-dimensional word vectors using Word2Vec technique. This model is trained using the dataset of Google News. These word embeddings are inputted as a feature to CRF.

ii) **Word-POS clustering (WP): C**ombines words with POS tags of words to get the Word-POS feature. This feature is proposed to recognize the polysemy of the words. The Word-POS vector is trained using Yelp dataset with skip gram model. The WP clusters are formed using K-means algorithm to form 300 clusters.

3.3 Implicit Aspect Term Extraction Approach

There are set of rules are derived to extract implicit Aspect terms

Rule 1: If the sentiment word cannot determine the aspect term, search for the nearest aspect term with maximum window size of four as adjective which occurs usually before the term.

Rule 2: The mapping of Aspect-Sentiment word is based on the highest count and consider the aspect which is to be implied by the sentiment word.

Rule 3: If there is a noun-noun compound relationship with another word and a term is labeled as an aspect, then composed of combination of them marked as a multi word aspect term.

Rule 4: Is there exists a mod relation between two terms, one as a sentiment word and the other is a noun then it is an aspect term

Rule 5: If there as a conj relation between two terms, one a noun and Aspect term then the other term is an aspect term.

4. Results and Discussion

4.1 Machine learning Algorithms

The CRF model is able to learn from the feature patterns, in the data set and utilize that to do tasks on unseen data. Given a set of tagged data, we would like our model to learn how to correctly tag an unlabeled sentence it has not seen before. There are many methods for developing such models, mainly generative models and classification models. Conditional Random Fields (CRF) bring together the best of generative and classification models by combining key aspects of both. CRF model handle the sequence data by extending its functionality with MaxEnt model.

J48 is an implementation of decision tree algorithm which builds on the concept of Information entropy. The algorithm chooses the most informative features based on information gain. NB classifier is functioning based on Bayes theorem. IBk is an implementation of KNN classifier. It computes the distance between the feature vectors of both the training and the unseen example. The label of the unseen example is determined by using k-nearest neighbors training examples.

4.2 Datasets

SemEval 2014 competition introduced the sub task of aspect extraction for sentiment analysis of English dialect. SemEval competition provides datasets which are accepted widely by the researchers around the world. We use the reviews datasets of Restaurant and Laptop that was provided in the SemEval 2014 Challenge. The Restaurant dataset contains 3,041 training and 800 test sentences. The Laptop dataset contains 3045 training and 800 test sentences. The information of the datasets are presented in the Table 1. The Restaurant training dataset is annotated with aspect categories and aspect terms with its polarities. The Laptop training dataset is annotated with aspect terms with its polarities.

Table 1. Statistic of Dataset

Domain	**Training**	**Testing**	**Total**	**Aspect terms**	**Positive**	**Negative**	**No. of Categories**
Restaurant	3041	800	3841	3893	2892	1001	5
Laptop	3045	800	3845	2358	1328	994	-
Total	6085	1600	7686	6251	4220	1995	5

4.3 Performance measures

This metric is based on evaluating the count of correct aspect terms are retrieved through our approach. Using the known definitions of Recall (R), Precision (P) and F1 scores:

$$R = \frac{|S \cap G|}{|G|} P = \frac{|S \cap G|}{|S|} F1 = \frac{2 * P * R}{P + R}$$

S is System returned set of aspect terms.

G is set of correct aspect terms.

4.4 Empirical Evaluations and Discussion

The extracted features with the combination of rule set were used to train four different classifiers namely Conditional Random Filed (CRF) classifier, DT (J48) classifier, KNN (IBk) classifier and NB Classifier. The proposed model is trained and tested with proposed features in combination with manually crafted rules, the implementations of various machine learning algorithms are as CRF++ is an open source project to implement the model CRF (Conditional Random Fields) that allows for segmentation and labeling of sequential data. It is a supervised classification algorithm due to its capability of providing an easier way to define, interpret, and combine several features. The Weka 2.7 implementation of J48, IBk and Naive Bayes were used with 5 as the k value. The performance of the classifiers with the custom features, proposed features and rule set are evaluated on restaurant and laptop dataset and the results are presented in Table 2 and Table 3.

Table 2. Precision, Recall and F1-scores for the Restaurant Dataset

Classifier	Features	Precision	Recall	F1-Score
Conditional Random Field (CRF++)	Custom Features	83.54	78.71	81.05
	+Proposed Features	85.42	81.16	83.23
	+ Crafted Rule set	86.79	82.53	84.60
Decision Tree (J48)	Custom Features	81.34	76.98	79.09
	+Proposed Features	82.25	78.72	80.44
	+ Crafted Rule set	84.38	79.50	81.86
Naive Bayes (NB)	Custom Features	80.69	76.13	78.34
	+Proposed Features	81.54	77.58	79.51
	+ Crafted Rule set	83.63	78.52	80.99
K-Nearest Neighbor (IBk)	Custom Features	79.13	75.25	77.14
	+Proposed Features	80.25	76.81	78.49
	+ Crafted Rule set	81.03	77.45	79.19

Initially, the custom feature set is used to train the classifier on restaurant dataset and the performance of the classifier is measured with recall, precision and F1-score. From the results, it is identified that the precision value is more in compare with recall value. The performance of CRF++ classifier in extracting the aspect terms is high compared with J48, NB and IBk classifiers. The F1-scores for CRF++, J48, NB and IBk classifiers are 81.05, 79.09, 78.34 and 77.14 respectively. For next cycle of evaluations, the proposed feature set is combined with the existing feature set and the classifier performance is measured. From the Table 2, it is observed that the F1-values for CRF++, J48, NB and IBk are 83.23, 80.44, 79.51 and 78.49 correspondingly. With the combination of proposed feature set with custom feature set, the precision, recall and F1-scores are increased. The probable reason is that these features captures the semantic relations that exists among the words presented in the reviews. As a third cycle of empirical evaluations, implicit aspect terms are extracted using manually handy crated rules that are missed using classifiers with the feature set. These classifiers are combined with the previously extracted explicit aspect terms results in improving the recall, precision and F1-Score. The F1-Score values for the classifiers CRF++, J48, NB and IBk are 84.60, 81.86, 80.99 and 79.19 respectively.

Table 3. Precision, Recall and F1- score for the Laptop Dataset

Classifier	Features	Precision	Recall	F1-Score
Conditional Random Field (CRF++)	Custom Features	83.52	65.72	73.55
	+Proposed Features	85.30	66.53	74.75
	+ Crafted Rule set	88.34	68.31	77.04
Decision Tree (J48)	Custom Features	82.40	65.21	72.80
	+Proposed Features	84.15	65.83	73.87
	+ Crafted Rule set	86.52	67.70	75.96
Naive Bayes (NB)	Custom Features	81.83	64.74	72.29
	+Proposed Features	83.79	66.13	73.91
	+ Crafted Rule set	85.91	66.52	74.98
K-Nearest Neighbor (IBk)	Custom Features	81.24	63.50	71.28
	+Proposed Features	83.35	64.50	72.72

	+ Crafted Rule set	84.80	65.71	74.04

The classifiers CRF++, J48, NB and IBk are evaluated on Laptop dataset using the custom feature set. The performance of the classifiers with the measures such as recall, precision and F1-scores are shown in the Table 3. The F1-scores with custom based features are 73.55, 72.80, 72.29 and 71.28 for the classifiers CRF++, J48, NB and IBk respectively. After combining the proposed feature set with the custom feature set the overall score of the classifiers are increased by 1 to 1.5% . The classifiers sometimes fail to find valid aspects. In this case, a better result is produced by the rule-based approach. These classifiers suffer from low recall value on laptop domain because of the sparsity of the reviews compared with restaurant review dataset. To increase the recall value, rule-based approach is used to extract missing aspect terms from the reviews. The comparison of the F1-score values for the classifiers on the reviews datasets of Restaurant and Laptop using proposed aspect term model is shown in the Figure 2 and Figure 3 respectively. It is observed that the CRF++ implementation in aspect term extraction is superior when compared with other three classifiers. The performance of NB and KNN classifiers are comparable to each other. The performance of Decision Tree classifier is also high compared with NB, IBk and low compared with CRF++ implementation.

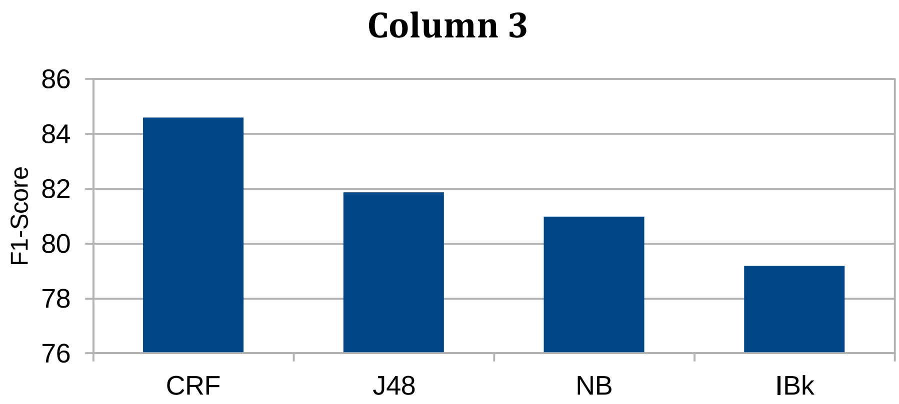

Figure 2. Classifier performance on Restaurant dataset

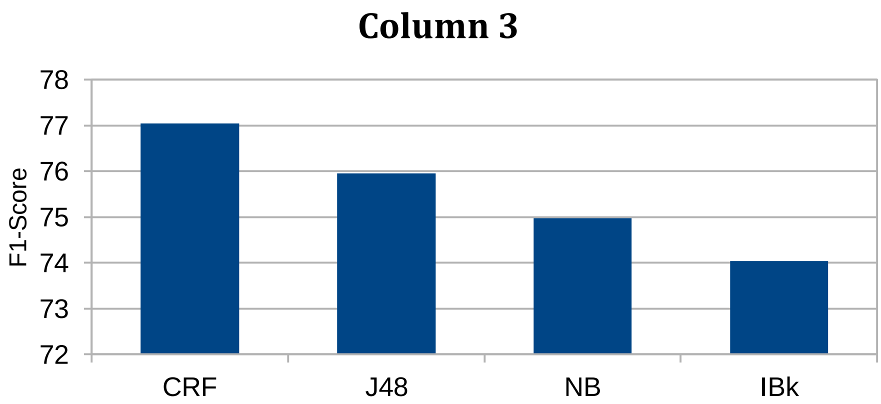

Figure 3. Classifier performance on Laptop Dataset

The recall, precision and F1-score values of the proposed system on reviews dataset of restaurant and laptop is compared with state-of-the-art methods and presented in the Tables 4 and 5. The proposed system is compared with baseline system presented by SemEval 2014 conference organizers. The DLIREC is the system submitted in the competition and scored highest F1-Score on restaurant dataset out of 24 teams participated in the competition. IHS_RD is the highest scoring system on laptop dataset in the competition. MFE-CRF is the model developed by Jin Zheng et al on same dataset in 2018. The model performance is compared the highest scoring systems participated in the competition and achieved 2% increment on laptop dataset and minor improvement on restaurant dataset. The proposed model is compared with these systems and achieved small improvement in restaurant dataset over MFE-CRF model and achieved 1% increase on laptop dataset compared with the MFE-CRF model. The proposed model has achieved 0.6% increase in F1-score on restaurant dataset compared with highest successful model DLIREC, presented in the competition and achieved 3% improvement in F1-score on laptop dataset compared with IHS_RD, the highest scoring system in the SemEval competition.

Table 4. Comparison of Proposed System with State of the Art Methods for the restaurant dataset

Term Extraction Model	Precision	Recall	F1-Score
Baseline	53.9	51.4	52.6
DLIREC	85.35	82.71	84.01
MFE-CRF	86.41	82.35	84.33
Proposed	86.79	82.53	84.60

Table 5. Comparison of Proposed System with State of the Art Methods for Laptop Dataset

Term Extraction Model	Precision	Recall	F1-Score
Baseline	40.1	38.1	39.1
IHS_RD	84.8	66.51	74.55
MFE-CRF	87.81	67.82	76.53
Proposed System	88.34	68.31	77.55

5. Conclusion and Possible extensions

In this paper, aspect term extraction in ABSA is addressed. Empirical evaluations are performed on two datasets from restaurant and laptop domains. Two features are proposed to capture the semantic relations exists among the words presented in the reviews. Word vector feature captures the word dependency relations and predicts the probable sequence of words with the knowledge on previous words present in the review. The word embeddings are produced by trained on Google news dataset. The second proposed feature addressed polysemy of words by joining words with POS tagging. Clusters are formed on these vectors to assign aspect terms to the nearest clusters. A rules set is used to extract implicit aspect terms that are missed from the classifiers in the identification using features. The proposed model has an overall improvement in F1-score compared with the state-of-the-art methods.Future work should investigate the ways of increasing recall without penalty for the obtained precision for laptop dataset. It is planned to explore the benefits of using neural networks for aspect term extraction in sentiment analysis. There is a need of comprehensive study on the proposed approach using additional features and classifiers.

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