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Evaluation of Polarity Features for Sentiment Analysis on Product Reviews

Lubna Zafar[1], Anees Qamar[2], Jawad Zareen[3]

[1] Department of Computer Science and Information Technology, University of Poonch Rawalakot, Azad Kashmir, Pakistan. Email: Lubnazaffar@upr.edu.pk
[2] Department of Computer Science and Information Technology, Women University Bagh, Azad Kashmir, Pakistan.
[3] Department of Education, University of Poonch Rawalakot Azad Kashmir, Pakistan.

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ABSTRACT

Customers express their opinions about products online, which influence potential buyers. This feedback is valuable for manufacturers to enhance their products. Sentiment analysis, which categorizes sentiments as positive, negative, or neutral, is crucial but challenging. Despite recent advancements, several research gaps persist. Firstly, prior studies have explored polarity features independently or in partial combinations, lacking comprehensive evaluation across annotated datasets. Secondly, most methods classify sentiments as merely positive or negative, overlooking nuances like intensity levels (e.g., strong positive, weak negative). Lastly, existing approaches often employ diverse classifiers on disparate datasets, lacking standardized comparison. To address these gaps, this research examines adjective, adverb, and verb polarity features both independently and in various combinations (Adjective-Adverb, Adjective-Verb, Adverb-Verb, and Adjective-Adverb-Verb). The findings demonstrate that adjectives can accurately classify sentiments into seven intensity levels. Notably, the Naïve Bayes classifier achieves high precision (0.984) when utilizing adjectives alone and (0.981) when combined with adverbs, outperforming other classifiers across six evaluated combinations.

Corresponding Author's Email: Lubnazaffar@upr.edu.pk

1. Introduction

The advancement in the area of e-commerce has led to a fast change in the process of trading. The rate of reviews is accelerating due to the predominant tendency of customers to express their opinions about products on the internet. A huge number of reviews are available for a particular product and it has become difficult for a new customer to read all reviews about a single product and then make a decision about that product. New customers check and rely on these opinions. Manual efforts take more time to analyze these reviews.

As, extracting reviews from the web, finding users opinions from the textual data and then classifying them as positive, negative, and neutral is a difficult and time taking task. So, an automatic technique is essential in opinion mining to classify the opinions as positive, negative, and neutral. Therefore, sentiment analysis aims to automate the process of reviews based on opinion summarization of reviews like positive, negative, or neutral. It focuses on given text and determines its sentiment in terms of positive, negative, or neutral text. So, sentiment analysis has become a challenging research issue due to these reasons. In this research, sentiment analysis polarity feature evaluation architecture is used that restricts on adjectives, adverbs, and verbs.

The primary objectives revolve around:

(1) Assessing polarity features, involving (i) evaluating the features of adjectives, adverbs, and verbs individually, and (ii) examining combinations such as Adjective-Adverb Combination (AAC), Adjective-Verb Combination (AVC), Adverb-Verb Combination (AVC), and

Adjective-Adverb-Verb Combination (AAVC) at the sentence level post POS (Parts-of-Speech) tagging.

(2) Intensity of polarity features. To calculate intensity of these features and classify them into seven different sentiment polarities i.e. strong positive, positive, weak positive, strong negative, negative, weak negative and neutral using Sentiwordnet. Sentiwordnet is used for scoring of these features and the score lies between -1 to +1 and classifies the reviews into these seven different sentiment polarities.

(3) Evaluation of polarity features on six different machine learning classifiers that are Naïve Bayes, K-Star, TreeJ48, Random Forest, VFI, and Random Tree on adjectives, adverbs, and verbs alone and also apply Naïve Bayes classifier on all combinations using Weka with a dataset comprising 53,258 reviews of office products gathered from Amazon.

Below are the research questions:

1. What are the most effective polarity features for sentiment analysis on product reviews?
2. How do different sentiment lexicons perform in capturing sentiment polarity in product reviews?
3. Can the combination of multiple polarity features improve the overall accuracy and reliability of sentiment analysis on product reviews?

The objective of this research is to evaluate the effectiveness of polarity features for sentiment analysis on product reviews. Polarity features refer to linguistic cues, sentiment lexicons, or other indicators used to determine the sentiment polarity (positive, negative, or neutral) of a given text. By conducting this evaluation, the aim is to enhance the accuracy and robustness of sentiment analysis systems, particularly in the context of analyzing product reviews, which are often rich in sentiment and opinions.

Section 2 provides a review of related research works, while Section 3 delves into the methodology before proceeding further details of studies and the results come in Section 4. Section 5, contains result visualization and in section 6, discussion of research findings is concluded.

2. Literature Survey

Presently, sentiment analysis primarily concentrates on categorizing polarities such as positive, negative, and neutral within reviews that convey sentiments, aiming to determine the polarity of a sentence within a document.

2.1. Senetence Level Sentiment Analysis

Some previous studies on sentiment analysis focus on sentence level sentiment polarities using a BOW (bag-of-word) model to address and solve the polarity shift problem (Kolekar et al., 2016) by detecting, modifying, and removing negation from the text. This paper also deals with opinion features. The users' opinions are identified about a product based on their online reviews. A sentence level sentiment analysis is proposed (Fang & Zhan, 2015) using online product reviews. An algorithm is also proposed and implemented for negative sentences identification and sentiment score computation. Sentiment analysis have been done on different levels like document level, aspect level and sentence level. Another technique is proposed (Subrahmanian & Reforgiato, 2008) to find the polarity of a sentiment at sentence level by combinations of Adjective-Verb-Adverb (AVA). Adverbs and adjectives combination technique is used to extract the opinion (Bethard, Yu, Thornton, Hatzivassiloglou, & Jurafsky, 2004) at the sentence level.

2.2. Natural Language Processing

A technique called semantic orientation was proposed (Mehta, Patil, Patil, Somani, & Varma, 2016) which automatically finds the frequently used terms in online reviews, for this an Unsupervised approach/Natural language processing (NLP) is used that automatically extract meanings of a text from natural language (Bethard et al., 2004; Sri & Ajitha, 2016; Subrahmanian & Reforgiato, 2008; Vermeij, 2005), and uses corpus based approach to determine the sentiments in patterns of words to find the co-occurrence which also uses resources/lexicon like Sentiwordnet, Wikictionary, to find the emotional similarities between words. This approach is used to determine the words sentiments by using antonyms and synonyms.

2.3. Dictionary Based Sentiment Analysis

A Sentiwordnet algorithm (Tomar & Sharma, 2016) was proposed to find the polarity at sentence level. POS (Parts- of-Speech) tagger is used to determine polarity of text by proposing a new Sentiwordnet algorithm. On document level an Adverb-Adjective-Noun-Verb (AANV) combinations in sentiment analysis is proposed (Sarkar, Mallick, & Mitra, 2012). AANV technique is based on the analysis of adverbs, adjectives, abstract nouns, and categorized verbs. This technique defines a set of general axioms. Entropy, Conditional Entropy, and Information Gain concepts have been used to evaluate the proposed system. Adverb-Adjective Combination is very important in sentiment analysis but Adverb-Adjective-Noun (AAN) (Sing, Sarkar, & Mitra, 2012) combination proposed and it provides better results instead of using Adverb-Adjective Combination only. Adverb-Adjective Combination (AAC) (Benamara, Cesarano, Picariello, Recupero, & Subrahmanian, 2007) gives high Pearson correlations than previously used algorithms that did not use Adverb-Adjective Combination. A manually scored adjectives and adverbs (Yu & Hatzivassiloglou, 2003) sum based scoring method is used in sentiment analysis, while using a template based method (Chklovski, 2006) to set values of sentiments at a degree of (Mehta et al., 2016; Subrahmanian & Reforgiato, 2008) scale is also proposed.

A few experiments on subjectivity and polarity classifications of topic- and genre-independent blog posts, using linguistic feature, verb class information is performed and the online Wikipedia dictionary (Chesley, Vincent, Xu, & Srihari, 2006) is used for identifying the polarity of adjectives. The framework Hu04 (Vermeij, 2005), which summarizes online users reviews by extracting opinions on product features and classifies them as positive or negative opinions is expanded in this paper as shown in Table 1.

Though much work has been done and conducted in sentiment analysis covering the Adjective-Adverb-Verb-Noun combinations but no research focuses on this area on a comprehensive dataset i.e. (i) feature evaluation of adjectives, adverbs, and verbs alone (ii) Adjective-Adverb Combination (AAC), Adjective-Verb Combination (AVC) , Adverb-Verb Combination (AVC), and Adjective-Adverb-Verb Combination (AAVC) at sentence level and to identify the intensity of these polarity features and classifies them into seven different sentiment polarities i.e. strong positive, positive, weak positive, strong negative, negative, weak negative, and neutral. Polarity feature evaluation improves the performance and also provides the more precise results to the customers who want to purchase the product online. In this study, the research questions include:

1. What are the most effective polarity features for sentiment analysis on product reviews?
2. How do different sentiment lexicons perform in capturing sentiment polarity in product reviews?
3. Can the combination of multiple polarity features improve the overall accuracy and reliability of sentiment analysis on product reviews?

3. Proposed Methodology

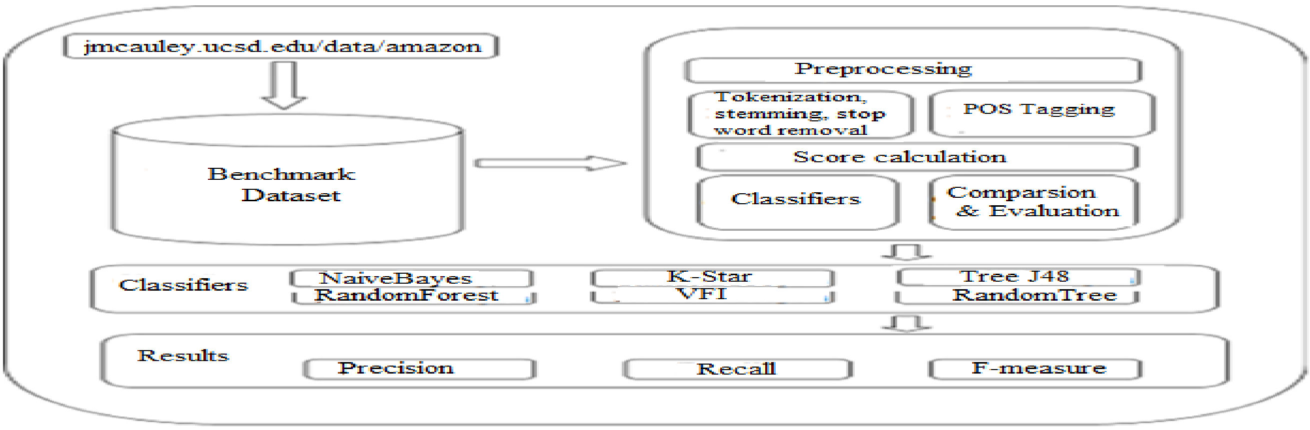
Amazon is an online shopping website that lets its customers to share their opinions and real time messages online about a product. Amazon receives millions of users reviews per day and these reviews turned into a gold mine for the companies to analyze their brands by mining the sentiments of product reviews. The goal of the polarity feature evaluation technique is to isolate polarity features associated with adjectives, verbs and adverbs identify the sentiments they convey, and subsequently categorize them based on their polarity. Figure 1 shows the proposed polarity feature evaluation architecture.

Table 1: Previous research on sentiment analysis

Author name, Year	Approaches	Intensity	Classifiers	Strength	Weakness	Results
Nilam et al. 2016	Natural Processing Language	Yes (positive, negative, neutral)	No	Address polarity shift problem on sentence level	Document level polarity classification not addressed	Opinion features as positive and negative ,neutral
Jalpa et al.	Natural			Review	Spam reviews can be	Reduces time

2016	Processing Language	No	No	Summarization and extract product attributes	detected and removed	complexity
Jenitha et al. 2016	Dictionary based	No	No	Find frequently used terms	Polarity Feature evaluation	30% accuracy achieved
Sherin et al. 2015	Unsupervised learning	No	No	Adverb +Adjective, Adverb + verb combination	Score of implicit features	3% improved accuracy from previous method
Xing et al. 2015	Machine Learning	No	Yes	Polarity classification at sentence level and review level	Implicit sentences and features evaluation	F1= 0.73 review level F1= 0.8 sentence level
Deepak et al. 2016	Natural Processing Language	Yes (positive, negative)	No	Sentiwordnet based algorithm,	Addition of module to check spelling mistakes	69.1% accuracy
Souvik et al. 2012	Entropy, Conditional Entropy and Information Gain	No	No	Adverb-Adjective Noun-Verb (AANV) combiantion	Test on machine learning techniques	Correlation score = 0.561
Sing et al. 2012	Linguistic analysis	Yes (Adverbs degrees, abstract noun, domain specific adjective)	No	Adjective-Noun (AAN) combination	Adjective-Adverb Noun combination can be addressed	Adjectives performs beter
Farah et al. 2006	Linguistic analysis	Yes (adverbs of degree up to 5 categories	No	Adverb-Adjective combinations (AACs).	Adverbs of time or adverbs of frequency can be identified	Higher accuracy based on Pearson correlation
Subrahm -anian et al. 2008	Linguistic analysis	No	No	Adjective , Verb & Adverb (AVA) combination	Adverb-Adjective Noun(AAN) combination	Achieves better results
Bethard et al. 2004	Discuss machine Learning approaches , dictionary based and corpus based	No	No	Related work of opinion mining in detail	Extracting polarity features	approaches have tried to tackle challenges
H. Yu et al. 2003	unsupervised, statistical techniques	Yes (positive, negative)	Yes	Present a Bayesian classifier	Extracting polarity features at sentence level	Achieves 91%accuracy
Chklo-vski et al. 2006	GrainPile (a user interface)	No	No	Aggregations of Assessments of degree to which a given property holds for a given entity	Extracting polarity features on social networking sites	Strongly outperform an interpretation free, co occurrence based method
Paula et al. 2006	Wikipedia dictionary	Yes (objective, positive, negative)	No	Subjectivity and Polarity classifications of topic- linguistic feature(adjectives types, verb)	Extracting polarity features Adjectives verbs-adverbs	Adjective accuracy 90.9%
Vermeij et al. 2005	Machine learning	No	Yes	Sentence level	Not good on large data sets	F measure=82

Figure 1: Proposed Methodology



3.1. Data Set

The dataset is collected from the online platform at jmcauley.ucsd.edu/data/amazon . There are total 53,258 reviews in the dataset. Each review consists of the following: 1) reviewerId, 2) productId, 3) reviewerName, 4) helpful, 5) review text, 6) overall, 7) summary, and 8) review time. Reviews are downloaded from the above mentioned URL and then stored in the database. Benchmark dataset is also downloaded and is based on star scale ratings from 1 - 5 stars.

3.2. Preprocessing

Preprocessing is the first phase in the sentiment analysis which applies and removes all raw data in the reviews. Preprocessing avoids the unnecessary overhead of sentiment analysis process and improves the accuracy. In reviews, customers use symbols, periods, apostrophes, hyphens, non-alphabetic characters like numbers and smileys. In this paper, three main steps are involved in preprocessing: tokenization, stemming, and stop word removal. Tokenization is the process of breaking a sequence of strings into pieces such as phrases, symbols, words, and keywords called tokens. Tokens can be the individual words or the full sentences. For example, Apple iPhone is very good. Output: 'Apple', ' iPhone' 'is', very', ‘good' break the string in tokens.

Stemming is the process of removing morphological affixes from words. It is the process of reducing a word into its root form. For example, the word look, looks and looking all stem into look which is the original and correct word. The pre-processing also involves stop words removal. All punctuation periods, hyphens, non-alphabetic characters like smileys, numbers and apostrophes are removed from the given dataset of reviews.

3.3. POS tagging and polarity features evaluation

Part-of-Speech (POS) tagging is the next step in sentiment analysis. This refers to the process of categorizing a word according to its grammatical function, enabling comprehension of its role within the sentence. Parts of speech are verb, adjective, adverb, noun, pronoun, preposition, interjection and conjunction.

Part-of-speech taggers typically take a sequence of words (i.e. a sentence) as input, and provide a list of tuples as output, where each word is associated with the related tag as shown in Table 2. Stanford parser (Subrahmanian & Reforgiato, 2008) is used for POS tagging on the given file of reviews. For example, ('iPhone', / 'NN'), ('is', /'VB'), ('very', / 'RB'), ('good', /'JJ'). Following the application of POS tagging on the provided file, proceed to extract polarity features limited to adjectives, verbs and adverbs from the tagged file. Subsequently, create three distinct files as these components tend to convey more sentiment within a given text.

Table 2: POS tags

Part-of-Speech (POS)	Abbreviation
Adjective	JJ
Adverb	RB
Conjunction	CC
Determiner	DT
Noun	NN
Number	CD
Preposition	IN
Pronoun	PR
Verb	VB

3.4. Sentiment score calculation

Adjectives, adverbs, and verbs scores are calculated by using Sentiwordnet after applying POS tagging. Sentiwordnet is a lexical resource publically available for opinion mining. Sentiwordnet is a database for the English language that groups English words into synonyms known as synset. Each synset has three sentiment scores: positive, negative, and neutral.

Sentiwordnet is used for score calculation of each word. Score of each adjective, adverb, and verb is calculated and stored in database. Scoring of any word will be either -1 to +1 using Sentiwordnet polarity categorization. -1 is considered as negative polarity, 0 as neutral and +1 as positive.

Adjectives, adverbs, and verbs scores are calculated separately and then classified into seven different intensities like strong positive, positive, weak positive, strong negative, negative, weak negative, and neutral as shown below in Table 3. An example of polarity classification is shown in Table 4. Positive Score (Pos score) and Negative score (Neg score) of a word obtained from Sentiwordnet as shown in algorithm in Table 3.

Table 3: Polarity feature classification

Score= Neg score – Pos score

```
 if (averageScore >= 0.75)
return "strong positive";
else if (averageScore > 0.25 && averageScore < 0.5)
 return "positive";
else if (averageScore >= 0.5)
 return " weak positive";
else if (averageScore < 0 && averageScore >= -0.25)
return "negative";
else if (averageScore < -0.25 && averageScore >= -0.5)
return " weak negative";
else if (averageScore <= -0.75)
return "strong negative";
return "neutral";
```

Table 4: Polarity feature classification example

Word	Score	Sentiment
best	0.75	Strong positive
appreciate	0.5	Weak positive
good	0.375	positive
serious	-0.75	Strong negative
same	-0.375	Weak negative
long	-0.25	negative
portable	0	neutral

4. Experimental results

Dataset used in this paper for evaluation of the work is the office product reviews. Dataset consists of 53,258 reviews about different types of calculators such as: HP-9100A simple calculator, HP-48 scientific calculator and HP-12C programmable calculator. Evaluation measures are precision, recall, and f-measure and machine learning algorithms are used for testing the dataset. Dataset is divided into 100 equal size subsets. In these 100 subsets, 10 subset is treated as testing data set for the classification models, and the remaining 90 subsets are used as training data sets. The cross-validation process is repeated 10 times and 10 subsets used one time as validation data. Now, the classifier calculates the average result from these folds and generates a single value. The evaluation measures used in this research are precision, recall, and f-measure that varies with the dataset used. Equations for precision, recall, and f-measure are (Naive Bayes);

$$Precision = \frac{no.of\ relevant\ features\ retrieved}{no.of\ relevant\ features\ retrieved} \quad (1)$$

$$Recall = \frac{no.of\ relevant\ features\ retrieved}{no.of\ relevant\ features\ in\ the\ collection} \quad (2)$$

$$F\ measure = \frac{2 * Precision * Recall}{Precision + Recall} \quad (3)$$

By using Naïve Bayes classifier on adjectives alone, it achieved 0.984 precision while adverbs achieved 0.941 and verbs have 0.969 precision as shown in Figure 2 (a). Naive Bayes classifier are a set of supervised learning algorithms. It is based on applying Bayes' theorem with the "naive" assumption of independence between every pair of features. For each class it calculates the posterior probability and for the class makes a prediction with the highest probability.

The classifier settings are as follows; on training set (x (i) , y(i)) for i = 1 . . . n, where each x (i) is a vector, and each y (i) is in {1, 2, . . . , j} Here, j is an integer specifying the number of classes in the problem. By using K-Star classifier on adjectives alone, it achieved 0.983 precision while adverbs achieved 0.866 and verbs have 0.937 precision as shown in Figure 2 (b). K* is an instance-based classifier. The K* function can be calculated as where P* is the probability of all transformational paths from instance x to y. It can also be interpreted as the probability that x will arrive at y (Naive Bayes):

$$K * \ (yi, x) = -Ln\ \mathrm{P} * yi, x)$$

By using Tree J48 classifier on adjectives alone, it achieved 0.975 precision while adverbs achieved 0.952 and verbs have 0.932 precision as shown in Figure 2 (c). Tree J48 applied which proceeds by dividing the data into local sets using a series of recursive splits. It utilizes all training data to search for the best splitting of the data to generate the tree.

The training data is a set A= {a_1, a_2…} of already classified samples. Each sample a_i consists of a p-dimensional vector (b_{1,i},b_{2,i},…..b_{p,i}), where the b_j represent attribute values or features of the sample, as well as the class in which a_i falls (Naive Bayes). By using VFI (Voting features intervals) classifier on adjectives alone, it achieved 0.994 precision while adverbs achieved 0.965 and verbs have 0.969 precision as shown in Figure 2 (d).

VFI (voting feature intervals) in which intervals are implemented for each attribute around each class. In VFI each feature involves in the classification. Every feature gives a vote for each class total of the n classes. So there are total m votes for each class. The predicted class will be the class with highest (Naive Bayes). This classification algorithm works very fast.

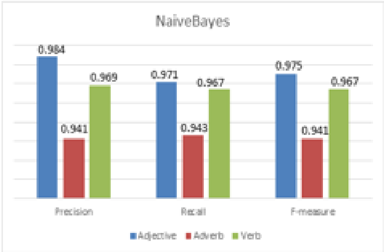
$$feature\ vote\ [f, c] = \frac{\boldsymbol{interval\_class\_count}\ [\boldsymbol{f}, \boldsymbol{i}, \boldsymbol{c}]}{\boldsymbol{class\_count}[\boldsymbol{c}]} \quad (5)$$

By using Random Forest classifier on adjectives alone, it achieved 0.976 precision while adverbs achieved 0.953 and verbs have 0.933 precision as shown in Figure 2 (e). Random Forest classifier use a technique known as bagging. The data instances produce multiple training subsets from the training data by resampling them multiple times. A random forest uses various sub-samples of the dataset and improve the predictive accuracy by using the average. The original input sample size is always the same as the sub-sample size. The process in random forests is to consider the original data as class 1 and to create a synthetic second class of the same size that will be labeled as class 2.

The synthetic second class is created by sampling at random from the univariate distributions of the original data. A single member of class two is created - the first coordinate is sampled from the N values {x(1,n)}. The second coordinate is sampled independently from the N values {x(2,n)}, and so forth. By using Random Tree classifier on adjectives alone, it achieved 0.974 precision while adverbs achieved 0.952 and verbs have 0.932 precision as shown in Figure 2 (f).

This shows that if only adjectives are used in our sentences then it conveys more sentiment than adverbs and verbs. Random Trees are trained on different training sets with the same parameters. These sets are created using a bootstrap procedure from the original training set: choose the same number of vectors randomly as in the original set for the training set. A random subset of each node finds the best split in the trained tree and a new subset is generated with each node.

Figure 2: Feature Evaluation of Adjective-Adverb-Verb alone, on (a) NaïveBayes (b) K-Star (c) Tree J48 (d) VFI (e) Random Forest (f) Random Tree



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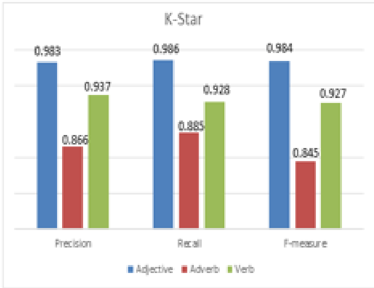

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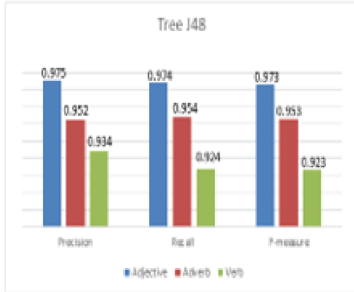

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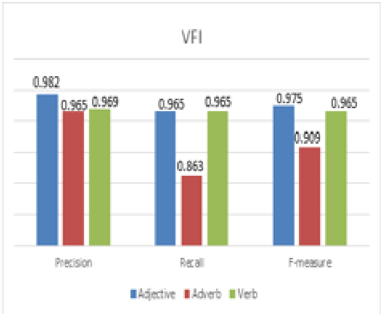

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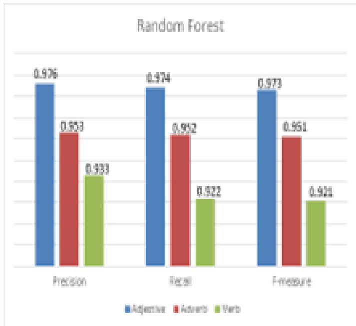
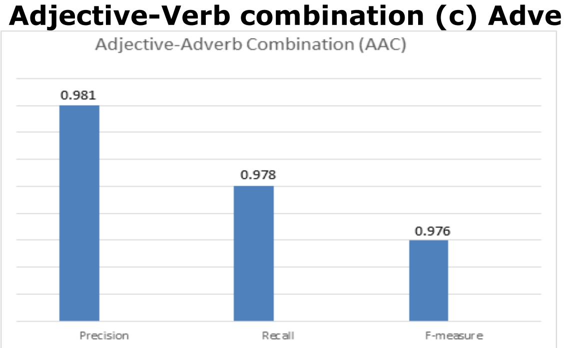


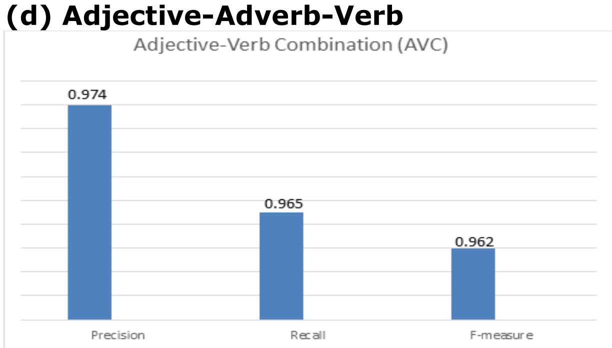
(e)

(f)

Figure 3: Feature Evaluation on Naïve Bayes (a) Adjective-Adverb combination (b) Adjective-Verb combination (c) Adverb-Verb (d) Adjective-Adverb-Verb



(a)



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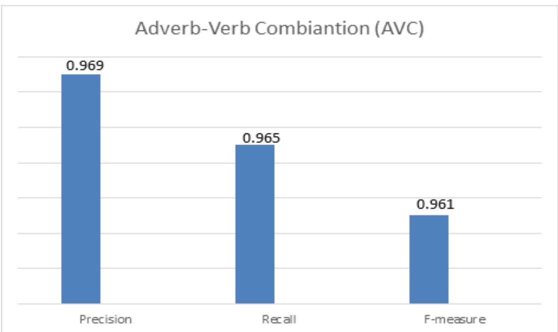

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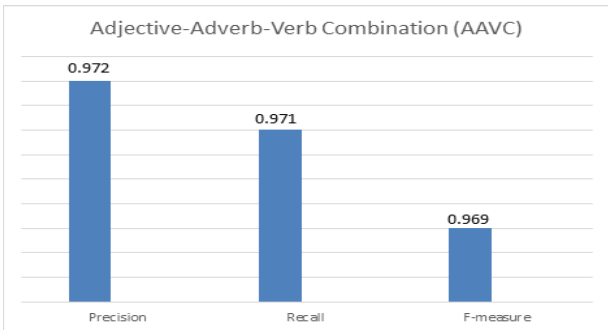

(d)

Further, combinations of Adjective-Adverb, Adjective-Verb and Adverb-Verb on Naïve Bayes classifier is tested. Adjective-Adverb achieved 0.981 precision as shown in Figure 3 (a). The combination of Adjective-Verb achieved 0.974 precision as shown in Figure 3 (b). Adverb-

Verb combination achieved 0.969 precision as shown in Figure 3 (c) and combination of Adjective-Adverb-Verb achieved 0.972 precision as shown in Figure 3 (d), on Naïve Bayes classifier.

Evaluation result shows that adjectives achieved highest precision, recall and f-measure whether used alone or with the combinations of adjective- adverb and gave best sentiments when evaluated on Naïve Bayes classifier as compared to other machine learning classifiers. The Naïve Bayes classifier achieved best results on adjectives alone 0.983 precision and on Adjective-Adverb Combination (AAC) it achieved 0.981 precision from the list of evaluated six classifiers.

5. Conclusion

This study utilizes a sentiment analysis approach to extract polarity features from user reviews, focusing on adjectives, adverbs, and verbs at the sentence level through POS tagging. The intensity of these features is calculated and classified into seven sentiment polarities using Sentiwordnet. We evaluated polarity features individually and in combinations using established classifiers across a dataset of 53,258 reviews of office products from Amazon. Among six classifiers, the Naïve Bayes classifier achieved high precision rates of 0.984 for adjectives alone and 0.981 for Adjective-Adverb Combinations (AAC). Our findings suggest that this research can assist companies in managing their online reputation and enhancing product development, marketing strategies, and customer relationship management by understanding customer preferences. Future research directions include exploring negation features and symbols, as well as extending the analysis to languages other than English. Additionally, identifying the contextual nuances in natural language remains a challenge for the research community. In conclusion, this study offers valuable insights into sentiment analysis methodologies and their practical applications, with implications for various industries and domains.

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