

Sentiment Analysis Using Support Vector Machine

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Abstract—Sentiment analysis is treated as a classification task as it classifies the orientation of a text into either positive or negative. This paper describes experimental results that applied Support Vector Machine (SVM) on benchmark datasets to train a sentiment classifier. N-grams and different weighting scheme were used to extract the most classical features. It also explores Chi-Square weight features to select informative features for the classification. Experimental analysis reveals that by using Chi-Square feature selection may provide significant improvement on classification accuracy.

I. INTRODUCTION

Sentiment Analysis (or opinion mining) is defined as the task of finding the opinions of authors about specific entities [1]. Sentiment analysis in reviews is the process of exploring product reviews on the internet to determine the overall opinion [2][3]. Sentiment analysis is treated as a classification task as it classifies the orientation of a text into either positive or negative. Machine learning is one of the widely used approaches towards sentiment classification in addition to lexicon based methods and linguistic methods [4]. Sentiment analysis has been applied to broader area of research including consumer product reviews and services [1][5].

This work present experiments using machine learning open source data mining software tool. Research by [6] shows that during experiments, there is no single tool or technique that always achieves the best result. However, some achieve better results more often than the other. The experiments have been conducted using benchmarks datasets by [7][8] with several different term-weighting schemes for feature extraction and Chi-square for feature selection. Support Vector Machine (SVM) have been used for the classification process. The results was measured using Precision, Recall, Accuracy, F Measure and AUC for evaluating the effectiveness of the proposed method.

The remainder of this paper is organized as follows; Section 2 describes related works performed by other researchers in this field; Section 3 describes the proposed method to perform the experiment; and Section 4 describes the primary results and discussion obtained from the experiments. The last section presents the conclusions and suggested future work.

II. RELATED WORKS

In the area of sentiment analysis, many relevant researches have been developed in the recent years. The researches discover many issues of sentiment analysis in regards to domains

of the datasets, corpus types and size and also multilingual context. The research conducted by [9] dealt with sentiment analysis on twitter data. In terms of domains, [10] have revisited the field of sentiment analysis of a group of machine learning based methods in classifying cricket sports news articles. Another issues that relates to domains was investigated by [2] where applied the sentiment analysis of online movie reviews by combining different pre-processing methods. Research by [11] had explored a new research area applying Support Vector Machines (SVM) for testing different domains of data sets from movie reviews, topics from computers, hotels or music and also about opinions from digital cameras. Many studies also have been done in order to perform sentiment analysis in multilingual context. For example, sentiment classification methodologies were applied to English and Arabic Web forum postings. A wide array of English and Arabic stylistic attributes were included in the experiments besides syntactic features. The main purpose is to improve accuracy and identify key features for each sentiment class [13].

In order to address these issues, a suitable method of feature selection is required to extract the useful features before the classification is done. If the features used are reliable and robust then the classification performance can be increased. Excessive numbers of features not only increase computational time but also degrade classification accuracy. As a consequence, feature selection plays a critical role in text classification problems to speed up the computation as well as improving the accuracy [14].

III. PROPOSED METHOD

The aim of this experiment is to improve SVM on benchmark datasets by Pang Corpus [7] and Taboada Corpus [8]. The framework consists of preprocessing, feature extraction, feature selection and classification stages. The success measure will also be briefly explained in the following subsection.

A. Preprocessing Methods

The datasets will go through the pre-processing task of the text documents such as tokenization, stop word removal, lowercase conversion and stemming. Tokenization is the procedure of splitting a text into words, phrases, or other meaningful parts, namely tokens. Stop words are the words that are commonly encountered in texts without dependency to a particular topic such as conjunctions, prepositions, etc. Another preprocessing step is lowercase conversion. All uppercase characters are usually converted to their lowercase forms before the classification

stages. Finally, stemming process where we obtain root, stem of derived words. The commonly used stemming process for English is Porter Stem which was introduced by [15].

B. Datasets Description

For the preliminary experiments, we have used two label datasets which are 2000 positive and negative Movie Review Datasets from [7], and 400 positive and negative SFU Review Corpus Datasets from [8] for the experiments.

1) *Pang Corpus*: The corpus was prepared by [7] to classify movie reviews collected from IMDb.com. The collection consists of 2000 reviews (1000 positive samples and 1000 negative samples).

2) *Taboada Corpus*: This collection was prepared by [8] that includes 400 opinions collected from the website Epinions.com divided into 200 reviews classified as "recommended" (positive) and 200 as "not recommended" (negative). The datasets contains reviews about product and services such as movies, books, cars, phones and etc.

C. Feature extraction

Feature extraction is the process of transforming the input data into set of features. The performance of the machine learning process depends heavily on its features so it is crucial to chose the extract features. The objectives is to summarize and transform input data into a set of representation features (features vectors) that work appropriately to the classifier. On the other hand, one of our main goals is to applied several n-gram models which is unigrams, bigrams and trigrams to compare the influence of using different n-gram schemes.

1) *Term-weighting Scheme*: The calculation of the term-weighting scheme plays a crucial role in extracting the most classical features as an input to the classifier. The more classical the features, the better performance of the classifier will be. The experiments applied several term-weighting schemes, consists of Term Frequency Inverse Document Frequency (TFIDF), Binary Occurences (BO) and Term Occurences (TO) for each n-gram scheme to create the word vectors.

They are based on the following counts:

f_{ij} the number of occurences of term i in document j
 fd_j the total numbers of terms occuring in document j
 ft_i the total number of documents in which term i appears at least once

Based on these counts, there are 3 classes available to measure the importance of term i for document j , as denoted by v_{ij} :

- TFIDF - the tf/idf measure with $v_{ij} = \frac{f_{ij}}{fd_j} \log\left(\frac{|D|}{ft_i}\right)$, where $|D|$ is the total number of documents. The resulting vector for each document is normalized to the Euclidean unit length.
- BinaryOccurences(BO) - occurrences as a binary value $v_{ij} = \begin{cases} 1, & f_{ij} > 0 \\ 0, & \text{else} \end{cases}$
The resulting vector is not normalized.
- TermOccurences(TO) - the absolute number of occurrences of a term $v_{ij} = f_{ij}$ The resulting vector is not normalized.

D. Feature Selection

There are filter, wrapper, and embedded approaches for feature selection[16]. In the experiments, filter methods were used due to classifier independence and relatively low computation time of the filters[17][18].

1) *Chi-Square*: Filter attribute evaluation [17] of Chi-Square weight features were used to select informative features and ranking method was also applied in order to remove irrelevant features. One of the most popular feature selection approaches is CHI2. In statistics, the CHI2 test is used to examine independence of two events. The events, X and Y , are assumed to be independent if

$$p(XY) = p(X)p(Y). \quad (1)$$

In text feature selection, these two events correspond to occurrence of particular term and class, respectively. CHI2 information can be computed using formula below:

$$CHI2(t, C) = \sum_{t \in \{0,1\}} \sum_{C \in \{0,1\}} \frac{(N_{t,C} - E_{t,C})^2}{E_{t,C}} \quad (2)$$

N is the observed frequency and E is the expected frequency for each state of term t and class C (Manning, et al., 2008). CHI2 is a measure of how much expected counts E and observed counts N deviate from each other. A high value of CHI2 indicates that the hypothesis of independence is not correct. The occurrence of the term makes the occurrence of the class more likely if the two events are dependent. Consequently, the regarding term is relevant as a feature. CHI2 score of a term is calculated for individual classes. This score can be globalized over all classes in two ways. The first way is to compute the weighted average score for all classes while the second way is to choose the maximum score among all classes. In this paper, the former approach is preferred to globalize CHI2 value for all classes as in

$$\sum_{i=1}^M P(C_i) \cdot CHI2(t, C_i), \quad (3)$$

where $P(C_i)$ is the class probability and $CHI2(t, C_i)$ is the class specific CHI2 score of term t .

E. Text Classification Method Selection

Support Vector Machine(SVM) has been chosen for the classification in the experiments. The support-vector machines is a learning machine for two-group classification problems introduced by [19]. It is used to classify the texts as positives or negatives. SVM works well for text classification due to its advantages such as its potential to handle large features. Another advantage is SVM is robust when there is a sparse set of examples and also because most of the problem are linearly separable [20]. Support Vector Machine have shown promising results in previous research in sentiment analysis [21][22][9].

TABLE I. TABOADA CORPUS 10-FOLD CROSS-VALIDATION TRAINING RESULTS

		Accuracy	Precision	Recall	AUC
TFIDF	Unigrams(%)	73.21	75.17	71.43	0.804
	Bigrams(%)	70.00	70.59	72.14	0.756
	Trigrams(%)	63.57	63.30	67.14	0.682
BO	Unigrams(%)	67.14	62.35	89.29	0.764
	Bigrams(%)	59.29	56.30	90.71	0.685
	Trigrams(%)	58.93	56.15	90.71	0.648
TO	Unigrams(%)	59.29	55.80	92.14	0.734
	Bigrams(%)	56.43	54.08	90.71	0.699
	Trigrams(%)	56.07	53.92	94.29	0.642

F. Effectiveness Measures

Four effective measures that have been used in this study are based on confusion matrix output, which are True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN).

- Precision(P) = $TP/(TP+FP)$
- Recall(R) = $TP/(TP+FN)$
- Accuracy(A) = $(TP+TN)/(TP + TN + FP + FN)$
- AUC (Area under the (ROC) Curve) = $1/2 \cdot ((TP/(TP+FN)) + (TN/(TN+FP)))$
- F-Measure(Micro-averaging) = $2 \cdot (P \cdot R) / (P + R)$

The text categorization effectiveness is usually measured using the F1, accuracy, and AUC [23]. F1 measure is a combined effectiveness measure determined by precision and recall. The area under the ROC curve (AUC) has become a wide measurement of performance of supervised classification rules. However, the simple form of AUC is only applicable to the case of two classes.

IV. PRIMARY RESULTS AND DISCUSSION

Similar to other text classification problems, a training dataset and a separate testing dataset will be used to train the model and to assess its accuracy. Each set was divided into two parts one for training and the other for testing, by ratio 70:30, that is 70% parts used for training and 30% parts for testing. Three different weighting scheme were used to generate the word vectors which is word frequency in document and in the entire corpus (TFIDF), Binary Occurrence (BO) and Term Occurrence (TO). Support Vector Machine (SVM) was used for this experiment to classify the testing datasets as positives or negatives.

Table 1,2,3 and 4 shows the comparison of training and testing results in terms of AUCs on Taboada Corpus [8]. It can be seen from Table 1 and 2 that the AUCs of SVM from these tables is higher with unigram model regardless of weighting scheme used. The highest AUCs from Table 1 is 0.804 and AUCs value from Table 2 is 0.785. At the same time the highest accuracy obtained is 73.21% and also 71.05% from both tables. In terms of weighting scheme, TFIDF performs better in this experiments compared to Binary Occurrences (BO) and Term Occurrences (TO).

The datasets were tested with the testing model in order to measure the performance. Table 3 and 4 list the AUCs of

TABLE II. TABOADA CORPUS 3-FOLD CROSS-VALIDATION TRAINING RESULTS

		Accuracy	Precision	Recall	AUC
TFIDF	Unigrams(%)	71.05	69.93	73.56	0.785
	Bigrams(%)	69.62	67.77	74.22	0.754
	Trigrams(%)	58.92	57.92	64.97	0.620
BO	Unigrams(%)	64.63	59.37	92.85	0.756
	Bigrams(%)	59.27	55.52	93.54	0.710
	Trigrams(%)	57.84	54.75	91.41	0.617
TO	Unigrams(%)	60.70	56.41	94.26	0.734
	Bigrams(%)	56.42	53.74	92.14	0.702
	Trigrams(%)	54.27	52.48	91.43	0.612

TABLE III. TABOADA CORPUS 10-FOLD CROSS-VALIDATION TESTING RESULTS

		Accuracy	Precision	Recall	AUC
TFIDF	Unigrams(%)	77.50	75.74	83.33	0.847
	Bigrams(%)	73.33	71.59	83.33	0.817
	Trigrams(%)	67.50	63.53	88.33	0.736
BO	Unigrams(%)	52.50	51.45	95.00	0.819
	Bigrams(%)	50.00	50.00	100	0.819
	Trigrams(%)	50.00	50.00	100	0.739
TO	Unigrams(%)	58.33	55.42	91.67	0.775
	Bigrams(%)	53.33	51.91	100	0.836
	Trigrams(%)	50.00	50.00	100	0.744

TABLE IV. TABOADA CORPUS 3-FOLD CROSS-VALIDATION TESTING RESULTS

		Accuracy	Precision	Recall	AUC
TFIDF	Unigrams(%)	73.33	69.05	85.00	0.808
	Bigrams(%)	75.83	69.70	91.67	0.843
	Trigrams(%)	69.17	66.36	85.00	0.730
BO	Unigrams(%)	54.17	52.36	96.67	0.816
	Bigrams(%)	50.83	50.43	100	0.832
	Trigrams(%)	50.00	50.00	100	0.752
TO	Unigrams(%)	53.33	52.07	88.33	0.764
	Bigrams(%)	51.67	50.88	98.33	0.847
	Trigrams(%)	50.00	50.00	100	0.742

SVM during the testing process. The AUCs of SVM from Table 3 shows the value of AUCs is 0.847 with unigram model and TFIDF weighting scheme and the accuracy also achieved 77.50% while in Table 4, the highest value of AUCs is 0.847 with bigram model and Term Occurrences (TO) weighting scheme but with accuracy shows only 51.67%. The more stable results achieved when the AUCs value shows 0.843 with accuracy 75.83% but with bigram model and TFIDF weighting scheme.

In another experiments from Pang Corpus [7], Table 5 and 6 show the results of the AUCs for training process. Table 5 shows AUCs of SVM based on unigram models are superior when achieving 0.923 and accuracy 84.50% with BO weighting scheme. Table 6 also indicates the highest AUCs of SVM is 0.918 and accuracy 83.14% with unigram model and BO weighting scheme.

Table 7 and 8 shows the results of AUCs for testing process. The results also consistent with training results where the highest AUCs and accuracy obtained with unigram models and BO weighting scheme. From table 7, the highest AUCs

TABLE V. PANG CORPUS 10-FOLD CROSS-VALIDATION TRAINING RESULTS

		Accuracy	Precision	Recall	AUC
TFIDF	Unigrams(%)	82.50	84.10	80.43	0.909
	Bigrams(%)	66.36	66.49	65.86	0.725
	Trigrams(%)	52.57	52.23	53.43	0.549
BO	Unigrams(%)	84.50	84.49	84.86	0.923
	Bigrams(%)	63.93	63.62	64.86	0.705
	Trigrams(%)	52.29	53.04	68.00	0.553
TO	Unigrams(%)	81.50	79.63	85.14	0.893
	Bigrams(%)	66.29	65.58	68.57	0.725
	Trigrams(%)	51.57	50.72	78.57	0.555

TABLE VI. PANG CORPUS 3-FOLD CROSS-VALIDATION TRAINING RESULTS

		Accuracy	Precision	Recall	AUC
TFIDF	Unigrams(%)	81.71	82.94	79.86	0.895
	Bigrams(%)	64.35	64.54	63.71	0.715
	Trigrams(%)	52.64	55.63	42.31	0.554
BO	Unigrams(%)	83.14	82.53	84.29	0.918
	Bigrams(%)	62.14	61.69	63.70	0.691
	Trigrams(%)	53.50	52.12	85.71	0.559
TO	Unigrams(%)	79.64	77.85	83.71	0.879
	Bigrams(%)	63.21	62.78	64.99	0.709
	Trigrams(%)	52.93	51.78	85.71	0.557

TABLE VII. PANG CORPUS 10-FOLD CROSS-VALIDATION TESTING RESULTS

		Accuracy	Precision	Recall	AUC
TFIDF	Unigrams(%)	79.83	78.92	81.67	0.870
	Bigrams(%)	67.67	69.07	66.33	0.744
	Trigrams(%)	54.83	60.82	26.00	0.546
BO	Unigrams(%)	83.50	84.39	82.33	0.917
	Bigrams(%)	65.67	68.18	59.00	0.728
	Trigrams(%)	55.33	66.02	20.67	0.547
TO	Unigrams(%)	78.50	79.29	77.33	0.863
	Bigrams(%)	63.83	65.97	57	0.718
	Trigrams(%)	55.00	63.15	21.33	0.551

is 0.917 and accuracy is 83.50% while from table 8 , the highest AUCs is 0.904 and accuracy is 83.83%.From this overall results, unigram model outperform other ngrams model and this is consistent with the results reported by [21] that unigrams outperformed bigrams when performing the sentiment classification of movie reviews. Binary Occurences (BO) weighting scheme plays a crucial role in extracting the most representative features as an input to the classifier for Pang Corpus.Meanwhile, unigram models and TFIDF weighting scheme play an important role for the classifier performance in Taboada Corpus.

Table 9 and 10 indicates the comparison of feature selection methods with respect to F-measure on Taboada Corpus, respectively. It can be seen from Table 9 and 10 that the F-measure of SVM based on Chi-square is significantly improved compared to previous experiment without feature selection. The value of F-measure is achieved 0.89 and accuracy achieved 89.17% which is higher than the results obtained from previous experiments. Table 10 also shows the value of F-measure is 0.882 and accuracy achieved 88.33% which is also higher than the previous results without feature selection for Taboada

TABLE VIII. PANG CORPUS 3-FOLD CROSS-VALIDATION TESTING RESULTS

		Accuracy	Precision	Recall	AUC
TFIDF	Unigrams(%)	75.00	74.74	75.67	0.832
	Bigrams(%)	62.67	63.11	61.33	0.668
	Trigrams(%)	55.50	62.49	27.67	0.536
BO	Unigrams(%)	83.83	85.06	82.33	0.904
	Bigrams(%)	61.67	63.49	54.67	0.690
	Trigrams(%)	54.33	62.35	22.00	0.534
TO	Unigrams(%)	77.00	79.16	74.00	0.844
	Bigrams(%)	61.67	64.53	52.00	0.672
	Trigrams(%)	53.00	58.95	20.00	0.537

TABLE IX. THE CLASSIFICATION RESULTS AFTER CHI-SQUARE FEATURE-SELECTION WITH RESPECT TO F MEASURE ON TABOADA CORPUS FROM 10 FOLD CROSS VALIDATION RESULTS

		Accuracy	Precision	Recall	F Measure
TFIDF	Chi(%)	54.17%	0.761	0.542	0.42
BO	Chi(%)	89.17%	0.911	0.892	0.89
TO	Chi(%)	88.33%	0.894	0.883	0.883

TABLE X. THE CLASSIFICATION RESULTS AFTER CHI-SQUARE FEATURE-SELECTION WITH RESPECT TO F-MEASURE ON TABOADA CORPUS FROM 3 FOLD CROSS VALIDATION RESULTS

		Accuracy	Precision	Recall	F-Measure
TFIDF	Chi(%)	51.67%	0.754	0.517	0.369
BO	Chi(%)	88.33%	0.899	0.883	0.882
TO	Chi(%)	83.33%	0.847	0.833	0.832

TABLE XI. THE CLASSIFICATION RESULTS AFTER CHI-SQUARE FEATURE-SELECTION WITH RESPECT TO F-MEASURE ON PANG CORPUS FROM 10 FOLD CROSS VALIDATION RESULTS

		Accuracy	Precision	Recall	F Measure
TFIDF	Chi(%)	81.00%	0.854	0.81	0.804
BO	Chi(%)	88.83%	0.889	0.888	0.888
TO	Chi(%)	89.17%	0.892	0.892	0.892

TABLE XII. THE CLASSIFICATION RESULTS AFTER CHI-SQUARE FEATURE-SELECTION WITH RESPECT TO F-MEASURE ON PANG CORPUS FROM 3 FOLD CROSS VALIDATION RESULTS

		Accuracy	Precision	Recall	F Measure
TFIDF	Chi(%)	75.17%	0.831	0.752	0.736
BO	Chi(%)	87.33%	0.874	0.873	0.873
TO	Chi(%)	86.17%	0.863	0.862	0.862

Corpus.

Table 11 and 12 lists the F-measure of SVM on Pang Corpus based on Chi-Square feature selection, respectively. The results of F-measure of SVM from table 11 is superior as compared to the results without feature selection. The value of F-measure is achieved 0.892 and accuracy is 89.17%. Table 12 also indicates the results is superior as compared to previous experiments where the value of F-measure is 0.873 and accuracy is 87.33%.

The overall results shows that the process of selecting the features based on their chi-squared statistics value helped reducing the dimensionality and the noise in the text, allowing a high performance of the classifier that could be comparable to topic categorization [2]. It also shows that the prediction

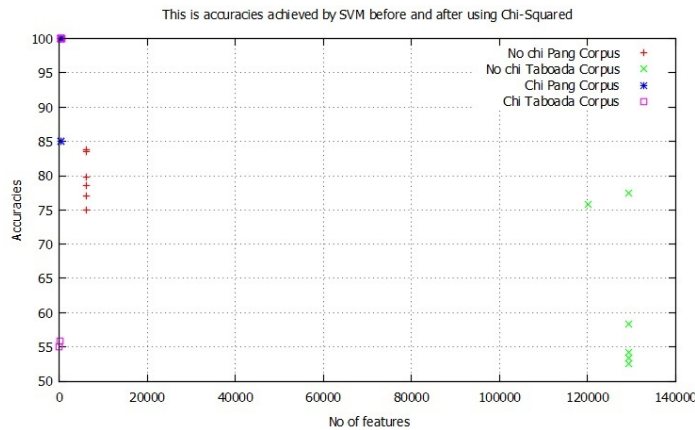


Fig. 1. The correlation between accuracies and no of features before and after using Chi-Squared

accuracies by using SVM achieved higher when the number of features selected is fewer [2] as well as other factors that might affect the classifier performance such as domains and corpus size [11].

V. CONCLUSION

In our research, benchmark datasets were used to train a sentiment classifier based on Support Vector Machine(SVM) that uses n-grams and different weighting scheme as an input to the classifier. From the observations, it can be concluded that unigrams outperform other n-grams models for both datasets while Binary Occurences (BO) and TFIDF weighting scheme plays a crucial role in extracting the most classical features for Pang Corpus and Taboada Corpus. The results also shows that by using chi-square feature selection will significantly improved the classification accuracy for both datasets.

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