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Sentiment Learning from Imbalanced Dataset: An Ensemble Based Method

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ABSTRACT

More people are buying products online and expressing their opinions on the products through online reviews. Sentiment analysis is used to extract opinion related information from the reviews and the extracted results can benefit both consumers and manufacturers. Much work on machine learning based sentiment classification has been carried out on balanced datasets. However, the real time sentiment analysis is a challenging machine learning task, due to the imbalanced nature of positive and negative sentiments. Sentiment analysis becomes complex when learning from imbalanced data sets, very few minority class instances cannot present sufficient information and result in performance degrading significantly. Modifying the data distribution or the classifier are the traditional approaches for dealing with the class imbalance problem. In this work, we propose to apply a combination of both approaches. We propose a modification in ensemble based bagging algorithm and also in sampling method used for data distribution, so as to solve class imbalance problem to improve the classification performance. We found that the modified bagged ensemble makes an improvement in predicting performance in terms of the receiver operating characteristic curve (ROC). The results also show that the modified bagging model performs better in terms of area under the receiver operating characteristic curve (AUC) in imbalanced dataset.

***Keywords*:** sentiment, classifier, opinion, learning, reviews.

Mathematics Subject Classification 2000: 68T01 Artificial Intelligence General, 68T50 Natural language processing

1. INTRODUCTION

With the rapid growth of social media and massive volume of online reviews in digital form, the need to organize them arises (Abbasi et al., 2008). Sentiment Analysis can be generally defined as the extraction of users' opinions from textual data. The huge and ever-growing amount of data available makes it worth to investigate the extraction of user's feelings at different levels of granularity. Classification being an

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active area of research, techniques for classification can be broadly categorized into supervised and unsupervised approaches. Machine learning based classification methods is a prominent and emerging area of research in various fields in recent years (De Falco et al.,2007; Tomescu et al.,2007; El Sehiemy et al.,2013). Machine learning based sentiment classification research has also evolved from classifying whole documents, to classifying each sentence, to classifying each separate feature of the product (Cambria et al., 2013; Tsytsarau et al., 2012; Pang et al., 2008). However, all the existing machine learning methods assume the balance between negative and positive samples in the labeled data (Ali et al., 2013; Moraes et al., 2013; Tang et al., 2009; Pang et al., 2008; Pang et al., 2002). But a more common case in real time application is where the class distribution is highly imbalanced (either positive or negative sentiment dominates). Imbalanced data sets correspond to domains where there are many more instances of some classes than others. The class with more samples is the majority class, and the class with lesser samples is the minority class (Chawla, 2005; He et al., 2009; Sun et al., 2009). Many of the previous studies have used a balanced dataset, however, in the product domain it is commonly the case that the ratio of positive and negative reviews is imbalanced (Zhang et al., 2011; Ye et al., 2009; Prabowo et al., 2009; Dave et al., 2003). Unfortunately, very few works have been carried out using an imbalanced dataset in sentiment classification (Burns et al., 2011). Classification on imbalanced dataset always causes problems because standard machine learning algorithms tend to be overwhelmed by the large classes and ignore the small ones. Some solutions to the class imbalance problem have been proposed at both data level and algorithm level in other data mining applications (Chawla, 2005; Sun et al., 2009; He et al., 2009). At the data level, various re-sampling techniques are applied to balance class distribution. At the algorithm level, solutions are proposed by adjusting algorithm itself. Among the classification algorithms, ensemble systems have drawn more and more attention because of their flexible characteristics. More researchers have been working on ensemble models and proved that it can reduce errors. This motivates us to investigate the effect of the imbalanced dataset in sentiment classification (Su et al., 2013; Wang et al., 2014; Li et al., 2012; Whitehead et al., 2008; Oza et al., 2008).

The contribution of the research work is as follows: Our system architecture takes online product reviews as input for each of the classifiers and outputs the dataset split into positive and negative reviews. A word vector model is developed using unigram, bigram and trigram product attributes as feature for classification. In this work, we propose to apply a combination of data level modification and algorithm level modification. We propose a modification in the existing bagging method to perform better in imbalanced data domains. A modification is also proposed in the sampling method of bagging approach such that the class distribution in the sampled subsets are altered to make base learners perform uniformly for both of the classes. The proposed modification makes the sampled subset to have equal numbers of majority and minority examples. The results are also compared with individual statistical model i.e. Support vector machine and existing bagging method. This paper is outlined as follows. Section 2 narrates the related work. The problem design is given in Section 3. The classification methods used is discussed in Section 4. Experimental discussion is discussed in Section 5. Section 6 presents the various results obtained. Section 7 concludes our work.

2. REVIEW OF LITERATURE

Sentiment analysis has been the work of many researchers over the past years. The focus of this research is on polarity sentiment analysis of customer product reviews (Moraes et al., 2013; Tsytsarau et

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al., 2011; Tang et al., 2009; Pang et al., 2004). From the literature, it is found that the machine learning approach applied mostly belongs to supervised learning for sentiment classification in balanced data distribution (Moraes et al., 2013; Vinodhini et al., 2013; Zhang et al., 2011; Ye et al., 2009; Prabowo et al., 2009; Tan et al., 2009; Pang et al., 2008; Dave et al., 2003; Pang et al., 2002). Among classification methods used, support vector machines have been extensively studied and have shown remarkable success in sentiment classification applications (Vinodhini et al., 2014; Ye et al., 2009; Abbasi et al., 2008; Pang et al., 2002). Also a few studies exist on classifying customer's sentiment orientations of products using a combination of classifiers in balanced data distribution (Su et al., 2013; Wang et al., 2013; Li et al., 2012; Whitehead et al., 2008; Oza et al., 2008). They showed that the generalization ability of an ensemble method is usually much stronger than that of a single learner, which makes ensemble methods very attractive. However, most of these studies mainly focus on classifying customer's sentiment orientations of products using individual classifier and also on balanced data distribution. Except the work of Burns et al. (2011), the literature does not contribute much work using machine learning approaches for sentiment classification in imbalanced data distribution. Burns et al. (2011) in their work compared, dynamic language model and naive bayes classifier. Experiments have been carried out to determine the consistency of results when the datasets are of different sizes and also the effect of a balanced or unbalanced dataset. The experimental results indicate that both the algorithms over a realistic unbalanced dataset can achieve better results than the balanced data sets commonly used in research.

However, the real time sentiment analysis is a challenging machine learning task, due to the imbalanced nature of positive and negative sentiments. This motivates us to deal with imbalanced data sets for sentiment classification. Sentiment analysis becomes complex when learning from imbalanced data sets, very few minority class instances cannot present sufficient information and result in performance degrading significantly. Modifying the data distribution or the classification algorithm is the traditional approaches to dealing with the class imbalance problem in other application areas of research (Chawla, 2005; Sun et al., 2009; He et al., 2009). In this work, we propose to apply a combination of both approaches. We propose a modification in ensemble based bagging algorithm and also in sampling method used for data distribution, so as to solve a class imbalance problem to improve the classification performance.

3 . PROBLEM DESIGN

The methodology of the work is summarized below for developing and validating the classification models (Fig 1.).

i. Perform data preprocessing and segregate the features (product attributes).
ii. Develop word vector for imbalanced dataset using unigram, bigram and trigram attributes.
iii. Develop the classification models using the respective training data set.
    a. Develop support vector machine model.
    b. Develop bagged ensemble model.
    c. Develop the modified bagged ensemble model.
iv. Classify the class (positive or negative) of each review in the test data set of all data models.

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v. Compare the classification results with actual results.

vi. Compute the area under the curve value from the ROC curves of learning models.

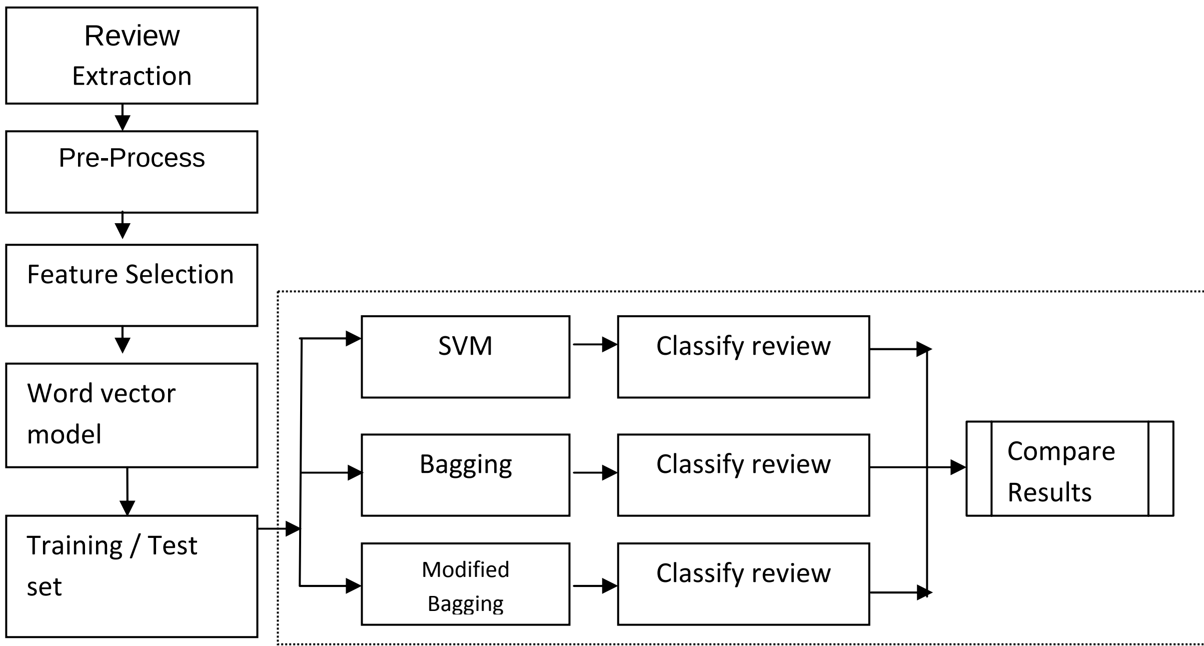

Fig 1. Problem design.

4. CLASSIFICATION METHODS

4.1. Support Vector Machine (SVM)

SVM are often considered as the classifier that makes the greatest accuracy outcomes in text classification issues. They function by building a hyper plane with maximum Euclidean range to the nearest exercising cases. SVM signifies cases as factors in area which are planned to a high-dimensional area where the planned cases of individual sessions are separated by an as large as possible tangential range to the hyper plane. New cases are planned in that same area, and based on which part of the hyper plane they are placed, they are expected to fit in with a certain category. SVM hyper planes are completely established by a relatively small part of the training circumstances, which are known as the support vectors. The relaxations of the exercising data have no impact on the qualified classifier. SVM have been applied efficiently in text classification and in a large range of series handling programs. We specifically chose SVM to attack the problem of imbalanced data because SVM is based on strong theoretical foundations. Its unique learning mechanism makes it an interesting candidate for dealing with

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imbalanced data sets, since SVM only takes into account those instances that are close to the boundary, i.e. the support vectors, for building its model (Moraes et al., 2013).

4.2. Bagged ensemble

Ensemble learning is a machine learning paradigm where multiple learners are trained to solve the same problem. In contrast to ordinary machine learning approaches which try to learn one hypothesis from training data, ensemble methods try to construct a set of hypotheses and combine them to use. An ensemble contains a number of learners which are usually called base learners. The generalization ability of an ensemble is usually much stronger than that of base learners. However, the original bagging chooses each bootstrap sample independently of the class labels, which results in the class distribution of each subset not being exactly the same as the original class distribution (Rokach, L., 2010). The pseudocode of bagging is as follows (Fig.2.)

Data set D={(x1, y1), (x2, y2),…(xn, yn),};

Base learning algorithm L;

Number of learning rounds T // T=5

***Process**:*

for t=1,…,T

Dt =Bootstrap(D); % Generate a bootstrap sample from D

ft=L(Dt) % Train a base learner ht from the bootstrap sample

end

***Ouput:**f(x)= argmaxy∈YΣt=1*

T 1 (y= ft (x)) % the value

of 1(a) is 1 if a is true and 0 otherwise

Fig.2 Pseudocode of Bagging.

4.3. Modified bagging (M-Bagging)

Ensemble based technique is used to deal with imbalanced data sets to address the class imbalance problem (Li.W. et al., 2012). Modified bagging is a variation of bagging ensemble approach. In the modified bagging approach, the data set (D) is sampled into sub samples which are used to train different base learners. The variation proposed in the modified bagging approach, is to construct consecutive subset of dataset based on the importance of the instances rather than bootstrap sampling. The

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importance of the instances is based on the instances that improve the diversity. The subset of samples thus created consists of a uniform distribution of easy and difficult instances. The instances which are misclassified by the ensemble classifier formed of these classifiers, which did not use the instance to be trained are called as difficult instances. The difficult instances always have a high priority to be included to the next subset of data. The easy instances have a lower priority to be added into the next data subset. The pseudo code for modified bagging is shown in Fig. 3.

D, a set of d training tuples;
K, the number of models in the ensemble; // K=5
A, learning scheme (SVM)
N, bootstrap size
Output: *A composite model, M*.*
Process:
initialize weight for error value (W_{new}) // W_{new} =0.5
repeat
W_{old}= W_{new}
initialize subset (S) size as null
repeat
Select a random instance(R) from D
Classify R by out of bag classifier
if true then
Place R in S with probability p where p= W_{old} /(1- W_{old})
else
Place R in S
end if
until size(S) < N
apply the base learner model to the subset (S).
calculate the error of out of bag classifier (W_{new})
until W_{new} > W_{old}

Fig 3. Pseudo code for modified bagging.

5. Experiment

We collected the review sentences from the Amazon reviews website. A crawler is developed in Java to randomly download positive reviews and negative reviews of three different products (digital camera, mobile phone and laptop). We found that, except clearly positive feedback and negative feedback, there are borderline and neutral reviews in between. We manually discard a review if it is not clearly aligned towards positive or negative sentiment. For our binary classification problem, we selected positive and negative reviews to establish the corpus. The polarity dataset obtained is a set of product review sentences of product which were labeled as positive or negative. This data set contains reviews of three different products (digital camera, mobile phone and laptop). There are 1800 annotated reviews for digital camera and the data are obtained in plain text format. For our binary classification problem, we have considered only 900 positive reviews and 125 negative reviews of digital camera (Data source of knowledge flow Fig 4.). In the product domain, it is typical that there are substantially more positive

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reviews compared to negative reviews. For each of the positive and negative review sentences, the product attributes discussed in the review sentences are collected. The unique characteristic of words representing the product attributes in a review sentence is that they are mostly nouns by Parts of speech (POS) tagging (Cambria et al., 2013; He et al., 2009). POS tagger (Stanford) is applied to find out the product features. The words representing product attributes in review sentences can be unigram, bigram or trigram. Product attributes selected as features for classification model have a higher impact on the orientation of the text than the other words in the same text. Unique unigram, bigram and trigram product features are grouped, which results in a final list of product attributes (features) of size 207. Similar process is repeated for other two product reviews. In terms of these, the descriptions of review dataset model (model I, II & III) to be used in the experiment are given in Table 1 and the sample product features identified for model I to build the word vector model is listed in Table 2.

Table 1. Description of dataset.

Product	Model	No.of Reviews	Feature	Features Data type	Class label Data type	No. of Features	Vector matrix	Positive Reviews	Negative reviews	Imbalance- ratio
Camera Review	Model I	1025	unigrams, bigrams, trigrams	Integer	Binomial	207 (137 +52 +18)	1025X 208	900	125	7:1
Mobile review	Model II	900	unigrams, bigrams, trigrams	Integer	Binomial	176 (118 + 47+11)	900 X 177	800	100	8:1
Laptop review	Model III	880	unigrams, bigrams, trigrams	Integer	Binomial	102 (74 + 23 +5)	880 X 103	800	80	10:1

Table 2. Sample Features.

Sample Features identified for Model I (unigrams, bigrams, trigrams)
camera ,digital camera, canon g, price, quality, lens, lcd, viewfinder, light auto correction, manual, picture, strap, optical zoom, size, megapixel, lag, metering option, movie mode, battery life, mp, download ,image download, compactflash, use, lag time, zoom, auto mode, software, speed, hot shoe flash, made, macro, mb memory card, raw format, casing, exposure control, option, indoor image quality, manual function.

The review sentences are pre processed (Preprocess in knowledge flow Fig 4.). The following are the steps done in data preprocessing. Tokenize to split the texts of a review sentence. Transform the upper case letters to lower case to reduce ambiguity. Then stop words are filtered to remove common English

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words. Porter stemmer is then used for stemming to reduce words to their base or stem. After preprocessing, the reviews are represented as unordered collections of words and the features are modeled as a bag of words. In this experiment, three types of n grams are used (unigram, bigram and trigram).A word vector representation of review sentences is created for model I (String to word vector in Fig 4.). The word vector set can then be reused and applied for various classifications. And the feature weighting is TF-IDF.

After creating the word vector model, each sample in the vector model is labeled as positive or negative class (Class Assigner in knowledge flow Fig 4.).Ten fold cross validation (Cross validation Folder Maker in knowledge flow Fig 4.) is used for evaluation of classifier used (SVM in knowledge flow Fig 4.). Then the performances of classifiers used are measured after tenfold cross validation. Visual representation of classifier performance is obtained (model performance in knowledge flow Fig 4.)

The implementation is done using the data mining tool Weka. Weka is a modeling tool in which user can select Weka components from a tool bar, place them on a layout canvas and connect them together in order to form a "knowledge flow" for processing and analyzing data. All the classifiers make use of the default values for the parameters available in the tool. The modified bagging is implemented using the Filter option available in the Weka Explorer. The knowledge flow representation of the various experiments used is shown in Fig 4.Fig 5 gives the knowledge flow representation of bagging classification model. Though modification is done in bagging algorithmic model, a sample knowledge flow representation of modified bagging classification model is shown in Fig 6.

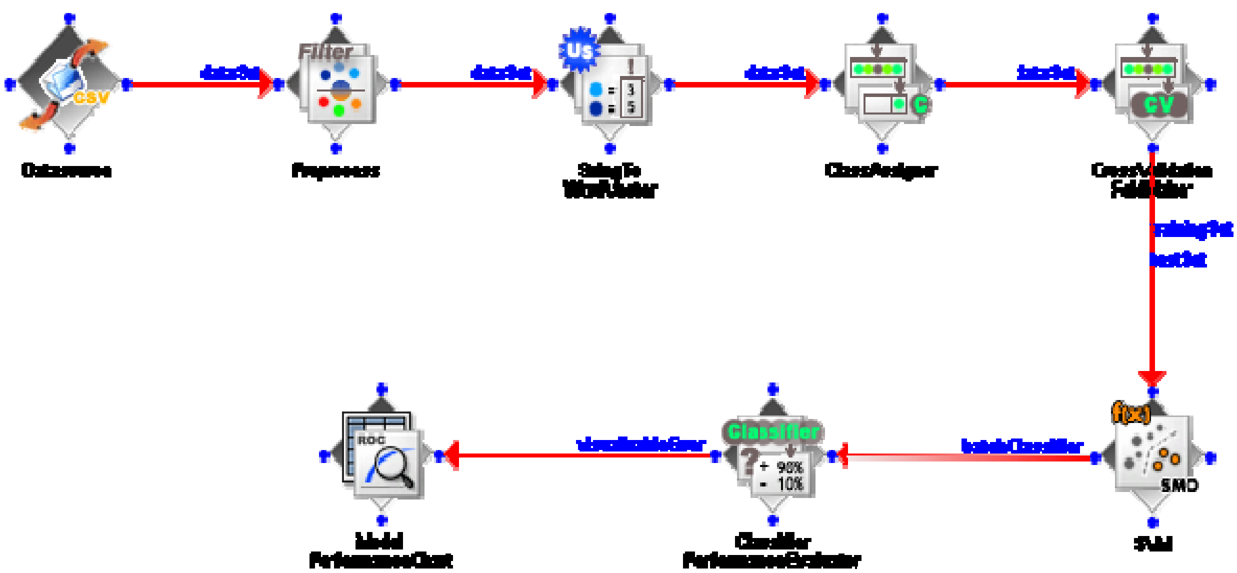

Fig 4. Knowledge flow of SVM.

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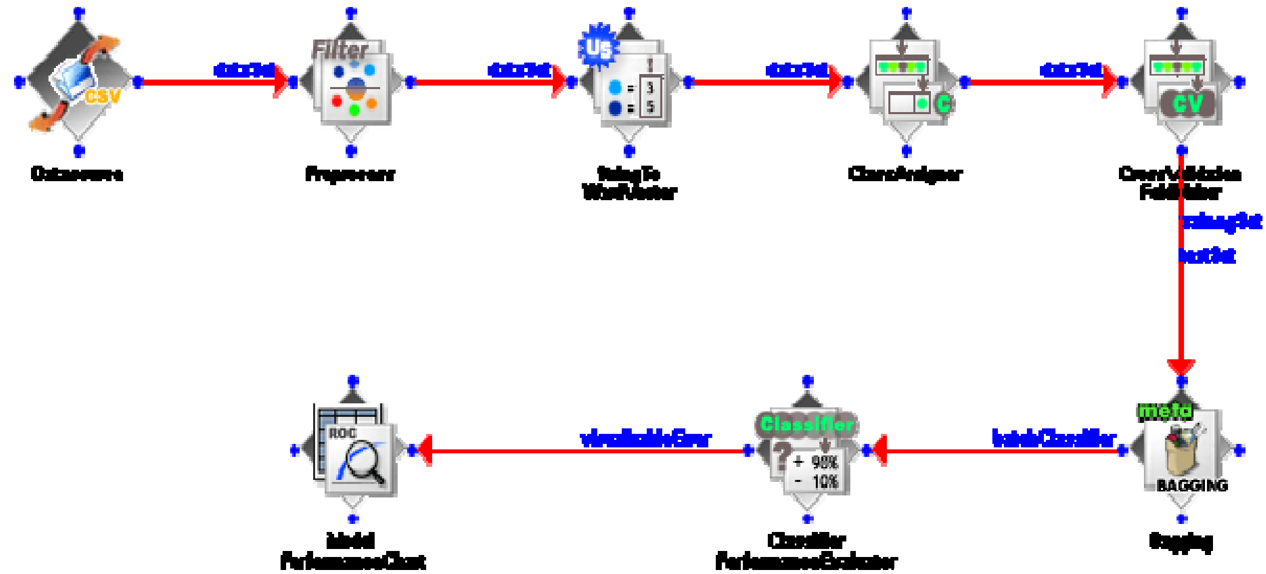

Fig 5. Knowledge flow of Bagged SVM.

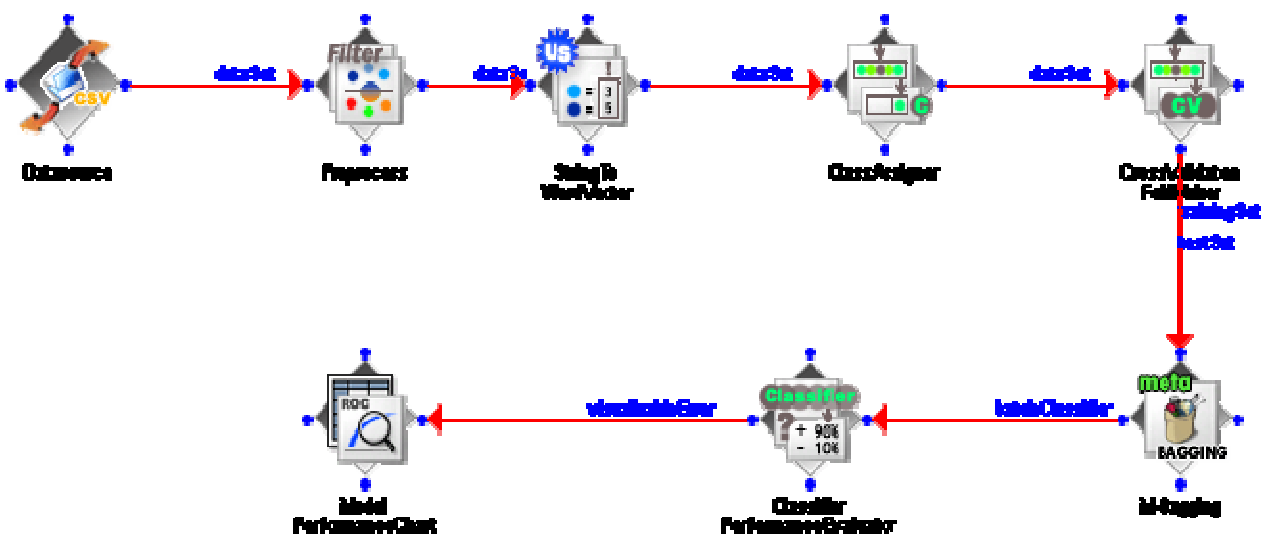

Fig 6. Knowledge flow of Modified bagged SVM.

6. RESULTS & DISCUSSION

To determine the efficiency and performance of the classification models used in this work, tenfold cross validation is used. In 10-fold cross validation, the original sample is randomly partitioned into 10 subsamples. Of the 10 subsamples, a single subsample is retained as the validation data for testing the

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model, and the remaining 9 subsamples are used as training data. The cross validation process is then repeated 10 times (the folds), with each of the 10 subsamples used exactly once as the validation data. The 10 results from the folds then can be averaged to produce a single estimation. Various traditional measures are used to measure the performance of classifiers in balanced dataset empirically (Tang et al, 2009; Songbo et al., 2008). However, in the framework of imbalanced datasets, traditional measures such as precision, recall, f-measure and accuracy does not discriminate between the numbers of correctly classified samples of different classes. For imbalanced domains, more suitable metrics are to be considered. A confusion matrix provides results for four metrics i.e. True positive rate (TPrate), True negative rate (TNrate), False positive rate (FPrate) & False negative rate (FNrate). As these measures predict results for each class independently, these measures are combined to achieve good quality results for both classes. ROC curve allows the visualization of the tradeoff between the benefits (TPrate) and costs (FPrate). Thus, it's evident that a classifier cannot increase the number of true positives without the increment of the false positives. Points in (0, 0) and (1, 1) are insignificant classifiers where the predicted class is always the negative and positive, respectively. On the contrary, (0, 1) point represents the perfect classification. The area under the ROC curve (AUC) provides a single measure of a classifier performance for the evaluation that which model is better on average. The AUC measure is computed just by obtaining the area of the ROC curve as follows:

$$AUC = (1 + TP_{rate} - FP_{rate})/2 \, . \qquad (1)$$

The classification systems are developed using methods discussed in Section 4 for the models I, II and III. The predicted classification results are compared to the actual sentiment of the reviews. Fig 7- 9 compares the performance of SVM, bagging and modified bagging classifiers with various datasets using ROC curves. ROC space point of modified bagging is closer to prefect point (0,1) for all data models (models I, II &III). Table 3 presents the results obtained for AUC by tenfold cross validation of the classifier model.

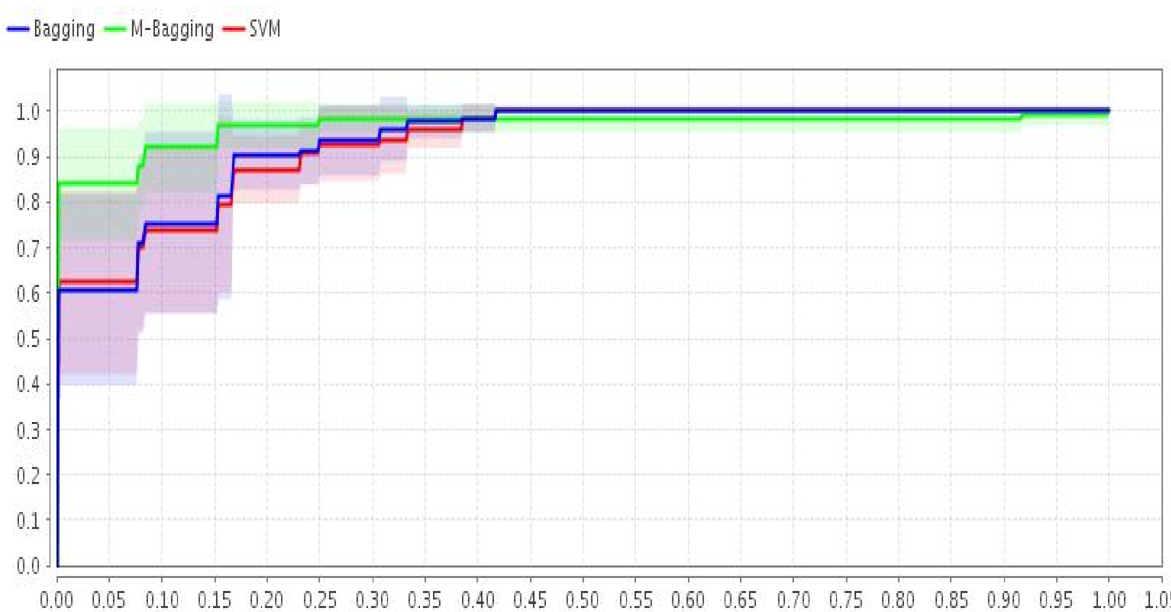

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Fig 7. ROC for classifiers (Model I).

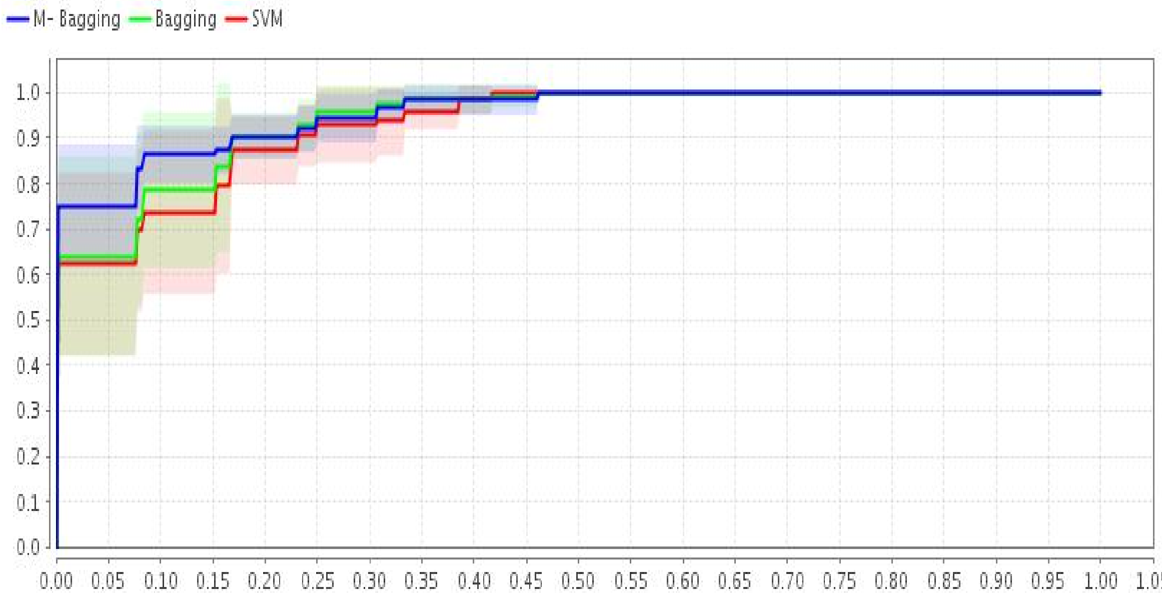

Fig 8. ROC for classifiers (Model II).

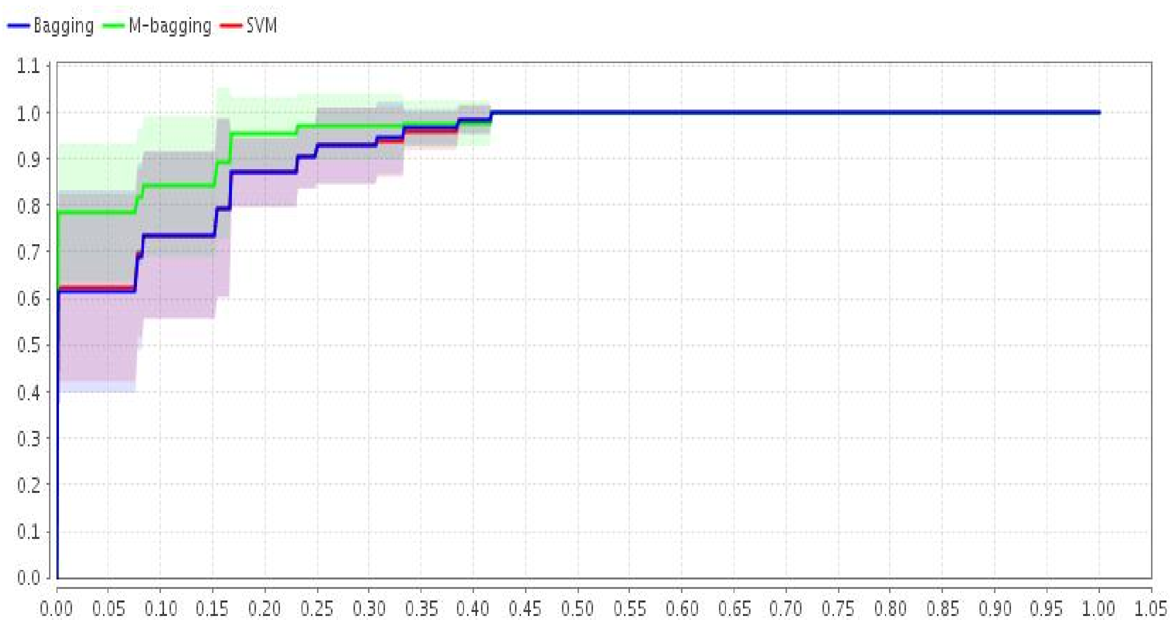

Fig 9. ROC for classifiers (Model III).

We observe that all classification methods used have different behaviours in terms of AUC. Modified bagging has better performance with imbalanced condition, whereas bagging is slightly better than SVM. The modified bagging approach obtains a high AUC value (close to 1).With respect to data models used, model I performance clearly outstands others. Though modified bagging provides better performance for all classifiers used, the variation in the AUC value indicates that sentiment analysis is very domain

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specific. Among models, model III exhibits very low AUC. This may be due to the high class imbalance ratio of model III compared to other models. Thus the modification done in the algorithm and data level of bagged SVM clearly dominates for imbalances datasets. However, the performance of the modified classifier depends on domain selected and the class imbalance ratio.

Table 3. Results of 10-fold Cross validation.

S.No	Method	**AUC-ROC (Model I)**	**AUC-ROC (Model II)**	**AUC-ROC (Model III)**
1	SVM	0.72	0.675	0.65
2	Bagging	0.785	0.74	0.715
3	Modified bagging	0.83	0.795	0.77

6.1. Threats for Validity

Although this investigation is based on a large review sample, there are a number of threats to its validity. This work does not consider neutral reviews for classification i.e. Multi class classification. Further, we restricted our analysis with product features of maximum word size to 3 (trigram). Rare possibilities may exist with words describing the product attribute of word size greater than 3. Though most of the sentiment mining work on product reviews has been carried out using reviews collected from Amazon reviews, very few benchmark dataset are also available for product, movie, and restaurant reviews. Further investigation is to be carried out using benchmark datasets available. As machine learning techniques are used to establish a domain specific model from a large corpus of labeled reviews, it is hard to create a domain independent classifier. Various other classification methods like fuzzy, genetic algorithm and ant colony based optimization techniques need to be analyzed (De Falco et al., 2007; Tomescu et al.,2007; El Sehiemy et al., 2013).

7. CONCLUSION

In the development of machine learning models to classify the reviews, reliable approaches are essential to reduce the rate of misclassifications of both classes. In this paper, SVM based modified bagging classifier that performs better than the classical bagging and SVM is introduced. Among the classification methods used, the modified bagging classifier method was more accurate, which is inferred through the AUC measures and ROC curves for the positively skewed data set. Further the AUC classifier methods can be increased by increasing the number of classifier combination. Further work needs to be done to include higher n-gram attributes. Finally, we conclude that ensemble based algorithms are worthwhile, improving the results that are obtained with the usage of data preprocessing techniques and training a single classifier. The use of more classifiers makes them more complex, but this growth is justified by the better results that can be assessed. The work done in this research relates to binary classification

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(positive class and negative class). In the future development, a multiclass of sentiment classification such as positive, negative, neutral and so on might be taken into consideration.

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