A Machine Learning Approach for Classification of Sentence Polarity

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Abstract—Opinion Mining is the process used to determine the attitude/opinion/emotion expressed by a person about a particular topic. Analyzing opinions is an integral part for making decisions. In the era of web, if a person wants to buy a product, he will look into the reviews and comments given by the experienced users in web. But it seems to be a tedious task to read the entire reviews available in the web. Hence people are interested in checking whether the review recommends to buy a product or not. If lot of reviews recommends to buy the product, user reach at a conclusion to buy the product, otherwise not to buy the product. In this study, Machine Learning approach is applied to the TripAdvisor dataset in order to develop an efficient review classification. For this work to be carried out, style markers are applied to each of the reviews. In the next stage, significant style markers are recognized with the help of some suitable feature selection method. Thus the reviews can be identified by developing a classifier using the style markers that help to characterize nature of reviews as positive or negative.

Keywords—Opinion Mining; machine learning; Classification; PoS tags; Aspects; ensemble model; Sentiment Classification

I. INTRODUCTION

Mining is the process of extracting relevant information from enormous amount of data. The World Wide Web contains a huge volume of documents containing comments, feedback, critiques, reviews related to wide documents. Processing of natural language is a herculean task for humans to understand, analyze and to extract useful information from enormous amount of data. Thus the work which helps to automatically determine the sentiment (positive or negative) of online texts is significant. The task of developing such a technique is often called sentiment analysis or opinion mining. Opinion mining or sentiment analysis [20] aim to extract the features upon which the reviewers express their opinions and help to determine whether the opinions are positive, negative or neutral.

In our day to day lives, analyzing the reviews/opinions has become an integral part for decision making. For example, if a person wishes to purchase a product online, he/she will refer to the prior reviews and comments given by the experienced users in web. In order to enhance the sales of a product and to improve the satisfaction of customer, most of the on-line shopping sites provide the opportunity for customers to write reviews about product .But it seems to be a cumbersome task to read the entire reviews available in the web for purchasing a specific product. Hence the user's interest is in checking whether the reviews influences/ recommends buying a product or not. If lot of reviews recommends buying the product, user will reach at a conclusion to buy, otherwise not to buy [11].

Basically, opinion mining has been studied by researchers at three levels namely, document level, sentence level, and feature/aspect level. Sentiment classification at document level classifies an opinionated document as expressing an overall positive or negative opinion. Sentiment classification at sentence level is applied to individual sentences in a document

Although opinion mining at the sentence level and document level appears to be beneficial in many cases, it still seems to be inefficient. In order to obtain more detailed opinion analysis, we need to delve into the aspect/feature level. This idea leads to the concept of aspect based opinion mining [6][7][15] [16].

In the proposed study, supervised machine learning approach [12] is used for sentiment classification. Supervised learning is the machine learning task of inferring a function from labeled training data. During the training phase, a feature extractor converts each input value to a feature set. Model is generated when a pair of feature sets and labels is fed to machine learning algorithm. During testing phase the same feature extractor is used to convert the given input to feature sets. The extracted feature sets are given as input to the model for generating predicted labels.

II. MOTIVATION

The growth of internet has changed the lifestyle of common people and their decision making. People will often read online reviews and suggestions regarding the product, a movie or a book before actually putting money on it. These methods could be employed to analyze the feedback of the users. For example, consumers can use sentiment analysis to research about services or products before making a purchase. Marketers can use this strategy to research public opinion of

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their company and products, or to analyze the customer satisfaction.

III. RELATED WORKS

In [1], sentence level sentiment classification is performed on the basis of syntax tree pruning and convolution tree kernel approach. Firstly, convolution kernel of SVM is applied to obtain the information that are usually structured and then apply syntax tree pruning strategy in sentiment classification. The authors in [2], proposed a verb oriented sentiment classification approach for social domains and this approach performs the classification 10% better than the bag of words approach. Experimental results depict the fact that when verbs are taken into account, it improves the performance of sentiment classification. The paper [3] focus on subjectivity analysis of social issues at sentence level and the proposed lexical-syntactic approach depicts the role of different opinion terms on opinions especially verbs regarding social issues. The paper [4] describes a method to apply opinion mining on the texts that are usually unstructured thereby extracting the polarity and finally performing the classification within a document at sentence level. The proposed solution was the development of a system called Sentiment Miner that provides features to process and then classifies text files (reviews and appraisals) for sentence level opinion mining using Opinion Mining algorithms and NLP techniques. A notable approach in [5] makes use of sentiment analysis at sentence level in which lexical contextual information and machine learning are used to classify and analyze the sentiment from reviews. The paper mainly focuses on sentence level to verify whether the sentences are subjective or objective and then to classify the polarity of the sentences to either positive or negative.

The paper [9] investigated author gender identification for short length, multi-genre, Text mining content-free text. Gender-related features include character-based (2) word-based (3) syntactic (4) structure based and (5) function words. Experimental results show that function words, word-based features and structural features are significant gender discriminators.

The authors in [6] proposed a novel optimization framework that focuses on the problem of constructing the sentiment lexicon which is domain specific and aspect dependent in the specific context. Samaneh, Martin et al [7] proposed methods of extracting aspects and/or estimating aspect ratings in which they introduce the problem of identifying aspects and estimating their ratings for cold start items. Moreover, Factorized LDA (FLDA) model has been proposed and the underlying assumption of this model is that the aspects and corresponding ratings of reviews are influenced not only by the items but also by the reviewers. Autors in [8] suggested a feature-opinion based method to perform sentiment classification on a review using the product features mentioned in the review and the relevant options to the corresponding features.

A novel deterministic approach was proposed by the authors in [16] in order to apply to the tourism domain which is considered as an extension of aspect-based opinion mining approach proposed by Bing Liu. As a result of the new and more complex Natural Language Processing based rules that has been developed for both subjective and sentiment classification, the new approach is able to perform better than the model proposed by Liu, improving Recall as well as Accuracy.

Moreover, researches has been carried out on aspect-based attributes in sentence level analysis, the results were not satisfactory. In this paper we will introduce an ensemble model to improve the accuracy as well as F-measure of aspects in hotel domain.

IV. METHODOLOGY

The dataset that has been taken into account is the TripAdvisor dataset [6] [16] [18] [22] [23]. The dataset is divided into 60 % as train and 40 % as test set. The first step is data preprocessing. The main aim of data pre-processing is to prepare raw data for further processing. The next step is selecting prominent features using a feature selection method. Finally, a classification model to identify review as positive or negative is to be built. These steps are portrayed in the Fig. 1 depicted below.

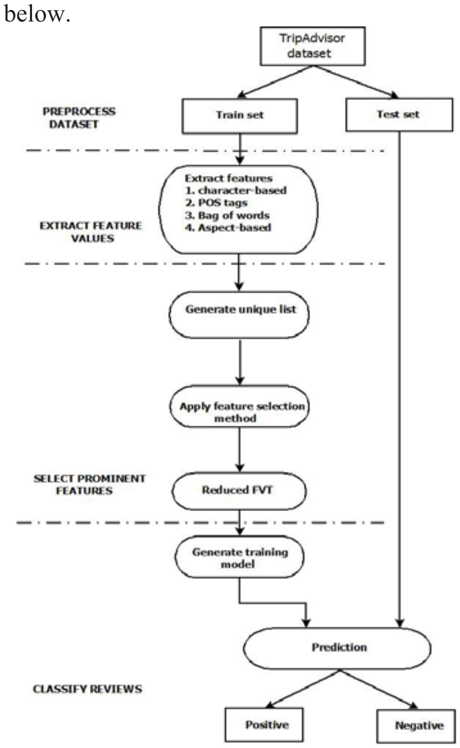

Fig. 1. Proposed Architecture

A. TripAdvisor Dataset

TripAdvisor, Inc is an american travel website company providing reviews regarding travel related content. It also includes interactive travel forums. To classify reviews as positive and negative, a benchmark dataset called TripAdvisor

Dataset [6] [16] [18] [22] [23] consisting of 12,773 files is used. The original dataset includes 12,773 JSON (Java Script Object Notation) files comprising of hotel reviews from various hotels. Each JSON file consists of various hotel attributes such as ratings, service, cleanliness, overall, value, sleep quality, rooms, location etc. The hotel reviews written by the author's from different parts of the world is also included in each JSON file.

B. Pre-process Dataset

Data pre-processing involves transforming raw data into an understandable format. Real world data is often incomplete, inconsistent, and is likely to contain many errors. The main aim of data pre-processing is to prepare raw data for further processing. The data pre-processing step involves tokenization, removal of stop words, unwanted punctuation, symbols, etc. The initial step in our study is to extract the reviews (contents) from each TripAdvisor file based on the overall rating score. The overall rating ranges from 1 to 5. The reviews with overall rating less than 3 falls into category of negative reviews and reviews greater than or equal to 3 falls into the positive category. During the pre processing step, positive reviews comprising of 9977 files and negative reviews comprising of 9260 files have been extracted.

TripAdvisor dataset is divided randomly into train and test sets based on a ratio of 60:40 for both positive and negative review files. Train set as well as test set should contain samples from positive class and negative class.

TABLE I. Train and test set

Dataset	Positive Reviews		Negative Reviews	
	Train	Test	Train	Test
TripAdvisor	5987	3990	5556	3704

C. Feature Set Selection

Finding good linguistic features (i.e. style markers) for correctly classifying reviews into positive and negative category is an open research problem. There are many style markers selected for the purpose of identifying the reviews in this study. The various style markers used as features are:

1) **Character-based features** : Character-based features include 29 stylometric features such as number of white space characters, number of special characters (e.g., percentage), etc.

2) **Bag-of-Words based features**: In Bag-of-Words, all sentences in each TripAdvisor file is tokenized into a set of words and frequency of every term is counted within each file (called as term frequency). Numbers, special symbols (!, =, ; etc) and stop words were removed from every tokenized file as they are irrelevant attributes. Later two unique lists were created (i.e, positive-unique list and negative-unique list). Using 5987 train positive files (containing the word count value) as an input, a BoW positive unique list, was created. It contains 4,61711 features, obtained from 5987 files. Using 5556 negative train files (containing the word count value) as an input, a negative-unique list, was created. It contains 1,53924 features, obtained from 5556 files. Initial pruning is conducted since there were too many features for positive files and negative files. A weight value is computed for every feature in this unique list to identify and eliminate sparse features. Top 50000 features are taken from both positive and negative unique lists, which were sorted in descending order of attribute's weight score. These attributes are utilized to generate a (single) combined unique list of positive and negative features. Combined unique list resulted 65421 features in total, which are fed into FVT generator as an input.

3) **PoS tag based features** : Part-of-Speech tagging (PoS tagging) [9] [18], also called grammatical tagging is the task of making every word in a sentence with parts of speech. Common part of speech in English includes noun, verb, adjective, adverb etc. In order to find out the tag based features, TripAdvisor dataset is given to NLTK (Natural Language Tool Kit) [21] in python and Part-of-Speech tagging is done. The default tagger named Penn Treebank Tagset [21] is used in this study.

TABLE II. Unique list for PoS tags : Positive Reviews

Feature	Positive_DocFreq	Positive_TotalFreq
DT	5971	6226224
JJ	5948	2353461
NN	5970	15462996

4) **Aspect based features** : Aspects[7][15][16] can influence sentiment polarity within a single domain. An aspect may be viewed as a set of terms characterizing a subtopic or a theme in a given domain, which can be the features of products or attributes of services. An aspect- annotated set comprising of 1849 files is included in the TripAdvisor dataset. Finally, 12828 aspect words has been extracted successfully from aspect annotated set and unique list has been created. Out of 461711 features present in 5987 positive train files, 11708 positive aspects has been extracted and out of 153924 features present in 5556 negative train files, 11360 negative aspects have been extracted. Later a combined unique list is created, which were fed to FVT generator as an input.

D. Select Prominent Features using Pearson's Chi-Square

Because in documents, there are tens of thousands of words, if all of them are chosen as features, then it will be infeasible to do the classification, as the computer can't process such huge amount of data. So it is important to select the features that are meaningful and representative for the purpose of classification. Dimensionality reduction or feature selection techniques [12] [14] [24] [26] are applied in order to handle this issue. Feature selection helps to determine optimal attributes from a huge feature space without changing physical meaning of the attribute. Moreover, feature reduction method results in high classification accuracy and lower computation cost of machine learning algorithms [26].

The feature selection is generally applied to the FVT (Feature Vector Table) obtained from the previous step. An

FVT consists of columns representing features from combined unique list and rows representing both positive and negative review files. Last column of FVT is denoted by class label (P:Positive and N:Negative). Later, a score is computed for each feature based on the feature selection method and irrelevant attributes are removed using the hypothesis test. Features are sorted in non-increasing order of score. Accordingly, features with high scores are selected from the obtained feature sets. Different feature lengths are selected from the list and model is constructed. Finally evaluation metrics (confusion matrix) is determined.

A weighting method named Pearson's Chi-Square [12] [25] is applied in this study. Chi-square is commonly used statistical test for comparing observed data with data that we would expect to obtain according to a specific hypothesis. The equation for Chi-Square is depicted below.

$$\chi^2 = \sum_{k=1}^{n} \frac{\left(O_k - E_k\right)^2}{E_k} \tag{1}$$

where χ^2 is the Pearson's cumulative test statistic, O_k is the number of observations of type k, E_k is the expected frequency of type k and n is the number of cells in the table.

E. Training Model and Evaluation

The models are created and classification is done using WEKA [19] tool. The feature vector tables constructed from the selected feature sets are given to classifier for classification. Classifiers used in our study includes: Multinomial Naïve Bayes[10][17] and Support Vector Machine (Linear, Polynomial, Radial, Sigmoid) [11].

The Multinomial Naïve Bayes (MNB) model [10] [17] has a number of attractive features for most text classification works. Multinomial Naïve Bayes is preferred classifier for many text classification tasks, due to simplicity and trivial scaling to large scale tasks. Being a probabilistic model, it is easy to extend for structured modeling tasks, such as multi-label classes. Naïve Bayes classifiers are probabilistic classifiers based on applying Baye's theorem.

Support Vector Machine (SVM) [11] [25] analyze the data and map them into a multidimensional space. It is capable of effectively handling large dimensional input data. SVM identifies a hyper plane that separates the instances of classes in the multidimensional space. New instances are evaluated by mapping them to this region and observing to which side of the hyper plane it lie.

When a positive review is classified as positive review, a true positive (TP) occurs. When a positive review is misclassified as negative review, a false negative (FN) occurs. When a negative review is classified as a negative review, a true negative (TN) occurs. When a negative review is misclassified as positive review a false positive (FP) occurs. Sensitivity (also called the True Positive Rate) measures the ratio of actual positives that are identified correctly as positive and is complementary to FNR. Specificity (sometimes called the True Negative Rate) measures the ratio of actual negatives which are identified correctly as negative itself and is complementary to FPR (False Positive Rate).
The equation for precision is as follows:

$$\text{Precision} = TP / (TP+FP) \tag{2}$$

Recall or sensitivity is calculated by dividing True Positive with True Positive and False Negative.

$$\text{Recall}=\text{Sensitivity}=TP / (TP+FN) \tag{3}$$

False Positive Rate is given by the equation:

$$FPR= FP / (FP+TN) \tag{4}$$

Accuracy is given by the equation:

$$\text{Accuracy}=TP+TN/TP+TN+FP+FN \tag{5}$$

The F-measure (F-score) can be interpreted as a weighted average of the recall and precision where an F1 score reaches the value at its best for 1 and worst score at 0.

$$\text{F-measure}= 2TP / (2TP+FP+FN) \tag{6}$$

V. EXPERIMENTS AND RESULTS

A. Train Results

In this section, we compared the evaluation parameters like Accuracy, F-measure, FPR (False Positive Rate) using the classifiers Multinomial Naïve Bayes and Support Vector Machine with kernels LibSVM K0 (Linear), LibSVM K1 (Polynomial), LibSVM K2 (Radial), LibSVM K3 (Sigmoid).

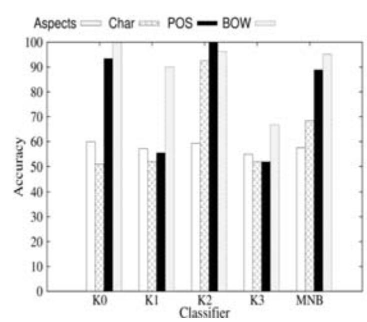

Fig. 2. Accuray Vs Classifier

From the Fig. 2, it has been analyzed that highest accuracy of 57.54% is obtained for aspect based features in MNB classifier, 92.60% for character-based features in LibSVM K2, 99.96% for PoS tag based features in LibSVM K2 and 99.87% for Bag of Words in libSVM K0. Hence we can say that PoS tag based features and Bag of Words based features provide good results on preview of accuracy which helps helps in efficient review classification.

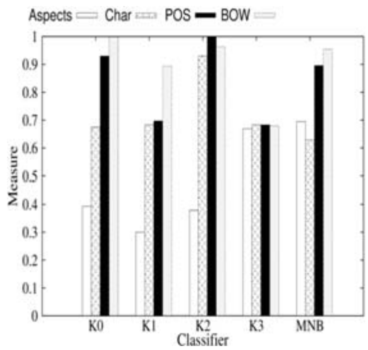

Fig. 3. F-measure Vs Classifier

From Fig. 3, it has been analyzed that highest F-measure of 0.69 is obtained for aspects in MNB classifier, 0.92 for character-based features in LibSVM K2, 0.999 for PoS tag based features in LibSVM K2 and 0.998 for Bag of Words in LibSVM K0.

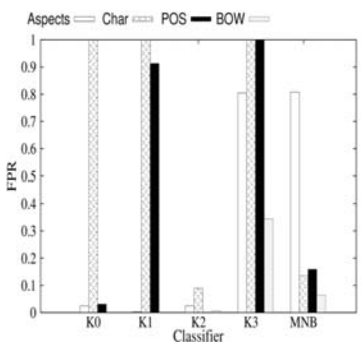

Fig. 4. FPR Vs Classifier

From the Fig. 4, it has been observed that lowest FPR of 0.8077 is obtained for aspects in MNB classifier , 0.089 for character-based features in LibSVM K2 classifier, 0 for PoS tag based features in LibSVM K2 and 0 for Bag of Words in LibSVM K0. For ideal classification, FPR should be very low. PoS tags and Bag of Words based features provides excellent results on preview of FPR.

Now let us examine the role of aspect based attributes in review classification. From the graphs plotted above, it has been noted that highest F-measure of 0.6943 and lowest FPR of 0.8070 was obtained for aspects in MNB classifier. This results show that aspect based feature doesn't contribute much for TripAdvisor review classification. In order to improve the results, we merged the top results (Top 20 PoS tags + Top 180 aspects) so as to build an ensemble model. Experimental results show that F-measure of 0.9875, accuracy of 98.7185 and FPR of 0.001 was achieved in ensemble model. For ideal classification, F-measure and accuracy should be high whereas FPR should be as low as possible. Hence we can say that the ensemble model provides better result for aspect-based attribute.

B. Test Results

TABLE III. Test of TripAdvisor-Bag of Words

Classifier	Attributes	Time(sec)	FPR	Accuracy	F1
K0	7500	123.62	0.0001	99.9133	0.9991
K1	3750	88.940	0.0498	89.8033	0.8963
K2	6000	81.250	0.0131	96.8119	0.9686
K3	8500	760.53	1.0000	51.7889	0.6823
MNB	7500	409.30	0.0106	95.5297	0.9554

TABLE IV. Test of TripAdvisor – PoS tag (unigram)

Classifier	Attributes	Time (sec)	FPR	Accuracy	F1
K0	38	92.250	0.0327	93.0780	0.9307
K1	30	341.98	0.0264	74.7639	0.6886
K2	20	115.73	0.0000	99.8787	0.9988
K3	5	769.36	1.0000	51.8669	0.6830
MNB	15	172.52	0.0309	90.6523	0.9039

TABLE V. Test of TripAdvisor-Aspects

Classifier	Attributes	Time(sec)	FPR	Accuracy	F1
K0	190	4.310	0.0251	59.8717	0.3922
K1	70	21.38	0.0325	56.0512	0.3015
K2	120	4.220	0.0246	59.9324	0.3932
K3	192	0.120	0.8468	54.6131	0.6755
MNB	180	0.060	0.8070	57.5327	0.6943

TABLE VI. Test of TripAdvisor-Ensemble (PoS Tags + Aspects)

Classifier	Attributes	Time(sec)	FPR	Accuracy	F1
K0	Ensemble	296.61	0.2163	87.8856	0.8922
K1	Ensemble	643.94	0.0001	55.2600	0.2419
K2	Ensemble	170.87	0.0012	98.7185	0.9875
K3	Ensemble	39.23	1.0000	51.8664	0.6830
MNB	Ensemble	0.32	0.1773	88.1954	0.8900

From TABLE III, it has been observed that highest F-measure of 0.991 and lowest FPR of 0.0001 was obtained for Bag of Words in K0 classifier. From TABLE IV, it has been observed that highest F-measure of 0.9988 and lowest FPR of 0 was obtained for PoS tags in K2 classifier. From TABLE V, it has been analyzed that highest F-measure of 0.6943 and lowest FPR of 0.8070 was obtained for Aspects in MNB classifier. From TABLE VI, it has been analyzed that highest F-measure of 0.9875, lowest FPR of 0.001 and highest accuracy of 98.7185 was obtained in ensemble model (PoS tags + Aspects) which is a significant achievement over aspect based attributes as they attain low F-measure when treated as an independent feature. Hence it is proved that ensemble model improves F-measure, accuracy as well as robustness over single model methods.

VI. CONCLUSION AND FUTURE WORK

Different style markers are employed on a benchmark dataset named TripAdvisor [6] [16] [22] [23]. Mainly features from four categories namely Character, PoS tag, Bag of Words and Aspects were extracted. It has been noticed that performance is improved when stop words are removed from text before model construction. Dimensionality reduction was applied subsequently using Pearson's Chi-Square [12] in order to choose the prominent features from a huge feature space. A vector space model for relevant features was constructed and given to the classifier using WEKA [19] tool. As the aspect based features procure less F-measure (0.6946), the meta feature space (ensemble model) was generated producing an FPR of 0.001 with highest F-measure of 0.9875 in radial kernel. Experimental results show that PoS tag, Bag of Words and ensemble model of features [13] significantly contributes for efficient sentence review classification.

Future work focus to extract as many features as possible for performing a comparative study so as to procure fine-grained results. Ensemble of features and feature selection methods can also be taken into account for obtaining better results. Classifiers other than MNB and SVM can also be employed for making a comparison.

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