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OPINION CLASSIFICATION OF ONLINE REVIEWS USING THE PROBABILISTIC NEURAL NETWORK AND PRINCIPAL COMPONENT ANALYSIS

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ABSTRACT

Sentiment analysis of product reviews is an attracting and increasing interest in the area of natural language processing and web text mining. Objective is to analyze the effect of ANN based method for opinion classification. In the research that has done so far on sentiment analysis, ANNs have been considered rarely. In this work, the probabilistic neural network (PNN) has been examined in sentiment classification. This work also examines neural network based sentiment classification methods for feature level sentiment classification on various levels of word granularity are used as features. Product reviews collected from the Amazon reviews website are used as dataset for evaluation. Our objective is to classify the product reviews into three classes: positive, negative and neutral. The results are empirically compared with SVM using various quality measures. The superiority of PNN with Principal Component Analysis (PCA) is also shown in terms of training time. PNN is found to perform better and yields higher accuracy in prediction. In general, statistical based approaches do not perform well as that of neural network based approaches. Compared with traditional techniques, the ANN based approach shows the performance improvement in quality measures and in training time. Through the experimental results it will be show that shortening of training time and increasing the classification accuracy can be achieved by hybrid combination of PNN with PCA.

Keywords: *Opinion Mining, Classification, Principal Component Analysis, Neural Networks, Sentiment Analysis*

1. INTRODUCTION

In general, buying habits of the customer in taking decision to buy a product is influenced by online reviews given by other customers. An automated online review mining system is required to provide decision support for the customer to help in decision making to buy a product. This automated system is an opinion mining system which extracts all the reviews of the product under consideration given by reviewers and mines out the information to provide decision support to the customer to take decision for buying the product. The automated mining system mines the attitude or judgment provided by the reviewers using NLP to extract features and classify them to provide decision support. The system could be developed as an application programming interface (API) and could be integrated to the ecommerce web portal to help the customers in buying a product. The objective of the automated opinion mining system is to reduce the misclassification rate.

2. LITERATURE REVIEW

In the paper, "Multi-facet rating of product reviews in Advances in Information Retrieval", the author Baccianella has stated that, a set of computational techniques for analyzing natural language texts that allows computers to understand human language is called Natural language processing (NLP). Sentiment analysis discipline places itself at the crisis of information retrieval and computational linguistics. From these two fields (information retrieval and computational linguistics) sentiment analysis collects and associates many concepts, design and methods. This technique was also quoted by Wilson.T, Hatzivassiloglou. V [27,32,34] . The primary unit

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of NLP is the language term and each language term has various linguistic features, such as grammatical category, meaning, sense, co-occurrence similarity and contextual relationships that are employed for term classification and subjectivity analysis. The NLP tasks require a knowledge base for information extraction and analysis. While some techniques are necessary for building a knowledge base, other techniques use existing knowledge bases to analyze documents. Research has presented greater contributions in this area and diverse approaches have been employed to accomplish the subjective analysis [10,13,16]. The subjective texts are often vast for people to make effective decisions. An automatic sentiment classification model is required to categorize text messages into various sentiment types. Many machine learning problems involve analyzing whether a particular text is explicitly stated to be positive or negative sentiment. It is also important to identify what every comment on the specific product expresses. Sometimes it may not be stated clearly whether the review is purely positive or negative sentiment. Many of the product review comments give us only objective facts and do not explicitly express any sentiments in their review. At time, some review comments give us conflicting sentiments. Most of the researchers have worked on identifying the sentiments based on binary perception, i.e., identifying whether the review is a negative sentiment or a positive sentiment [19,5,17,2,29,28]. Thus, it is essential to have more information to classify the sentiments for better performance results.

In the existing literatures, it has been found that less work based on neural network for text sentiment classification has been done. In our proposed work, neural network based sentiment analysis is employed for predicting the sentiment of the product reviews. Further the text sentiment classification are extended to consider neutral reviews along with positive and negative reviews for better results. Here product attributes are used as features for predicting the sentiments. The results obtained are correlated with baseline method such as SVM by computing various attributes. Three different data models (models I, II and III) are developed in order to analyze the relationship amongst the reviews. By using unigram feature, data model I is constructed. Data model II has been constructed by using unigram and bigram features. Similarly by using unigram, bigram and trigram features data model III is constructed. The major contributions of our work are (i) use of PNN for sentiment classification, and also (ii) use of hybrid combination of PCA and probabilistic neural networks. For evaluating the prediction methods, we have used multiclass classifications rather than binary classifications. To show the superiority of feature reduction with the neural network based approaches, training time is measured. In the subsections to follow, section 3 discusses the methodology used to construct the models. The data source used is reported in Section 4. The various techniques used to model the prediction system are introduced in Section 5. Section 6 summarizes the results.

3. METHODOLOGY

The following is the overview of the methodology that has been used for developing and validating the prediction models.

i. Preprocessing of data is done and the features are isolated.

ii. The word vector is developed for data model I using unigram attributes, similarly using product attributes as features, data model II is developed using unigram and bigram and data model III using unigram, bigram and trigram features.

iii. PCA is performed on the data model I, data model II and data model III to produce reduced feature sets.

iv. The prediction model is constructed using training data set that has dimension reduced feature set.

  a. SVM model is constructed.

  b. Using PNN the neural network model is designed.

v. Prediction of the class (positive, negative or neutral) for each review is done on the test data set.

vi. With actual values obtained, the prediction results are compared.

vii. The various quality parameters are evaluated and the prediction results are compared.

4. DATA SOURCE

For any consumer to make an effective decision on buying a product, online product reviews serve as excellent sources. The consumer can get product related information through online reviews. Star ratings of a product serves as an excellent cues for decision making as they provide a quick indication of a review.

4.1 Data preparation

The sentiment data set used in this work contains a set of product review sentences which were categorized as positive, negative or neutral class. The neutral class is important because not all sentences have sentiments. The neutral class is not only considered as a state between positive and negative classes, but also as a class that denotes the lack of sentiment. Also in binary classes, we force the words to be classified as either positive class or negative class leaving no room for neutrality. This leads to over fitting and becomes vulnerable to situations where due to randomness, a particular neutral word occurs more times in positive or negative class examples. For constructing the dataset, we collected customer reviews of a particular product from publicly available website www.amazonreviews.com. Digital camera reviews have been chosen to perform our proposed research. In a total of 2420 reviews, sentences are crawled using Amazon reviews downloader and parser. For the customized dataset used, a sample review crawled from the Amazon website is as given below in Figure 1. Then product ID is given as input to the downloader. The data format after downloading is shown in Figure 2.

Figure 1: Sample review from Amazon

product/productId: B003ZYF3LO

review/userId: A1RSDE90N6RSZF

review/profileName: Joseph M. Kotow

review/helpfulness: 9/9

review/score: 5.0

review/time: 1042502400

review/text:Good camera with quality pictures. Many features some of which never used. Holds battery life OK.

Figure 2: Data format of downloaded review

The text review contains written text to explain the star review. Since the reviews are provided by various individuals with ranging backgrounds, the meaning of a 5-star review changes from a person to person. Then the reviews are extracted and sentiment class is assigned based on the review score in the data format (sentiment class is positive if review score is >3, if review score is < 3 the class label is assigned negative or else the class label is assigned neutral). Amongst 2420 review sentences, 970 are positive reviews, 710 are negative reviews and 740 are neutral review sentences. Outliers analyses are also performed. When the outliers are implemented on the dataset, the results obtained are 950 positive reviews, 731 negative reviews and 680 neutral class review sentences. To overcome the skewed class distribution, we have chosen randomly 600 positive classes, 600 negative classes and 600 neutral classes as review sentences.

4.2. Feature Extraction

The product attributes in the review sentences are to be collected by part of speech (POS) tagging by considering each of positive, negative and neutral class reviews. The main aim is to extract the features about a particular product and to analyze the features which people like or dislike. It is also important to identify the product features that people are interested in discussing. These product features contribute to the crucial step. For example, consider a sentence from the reviews of a digital camera:

"The pictures are very clear."

In the above sentence, it is clear that the user is convinced with the quality of the picture of the camera. Here the user talks about *picture* which is considered as a feature. In certain product review sentences, features are explicitly stated whereas in some reviews, it is very hard to find the feature as they are implicit. In our research, we have focused only on the explicitly stated features and are identified by noun or noun phrases. The identification of implicit features are left for future work. Usually nouns or noun phrases in review sentences are considered as product features. For this research, we extracted only noun phrases from a document based on the consideration that the feature terms are nouns. The NLP Stanford parser has been used to parse each review and to split text into sentences and for each word POS tag is produced. Figure 3 shows the POS tagging for the given sample review sentence.

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"I recently purchased the Canon and I am extremely satisfied with the purchase. In POS tagging, the words Canon and purchase are identified as nouns (NN).

```
(ROOT
(S
(NP (PRP I))
(ADVP (RB recently))
(VP (VBD purchased)
(SBAR
(S
(NP
(NP (DT the) (NN canon))
(CC and)
(NP (FW I)))
(VP (VBP am)
(ADJP (RB extremely) (JJ satisfied)
(PP (IN with)
(NP (DT the) (NN purchase))))))))
(. .)))
```

Figure 3: POS tagging for a review sentence

Each sentence considered for review processing along with the POS tag information of each word in the sentence is stored in review database. The next step is the generation of frequent features. A transaction file is created for this purpose. The transaction file contains only pre-processed nouns/noun phrases of the sentence. All the frequent pattern item sets are identified by association mining. An item set is nothing but a set of words that occurs together in a paragraph. The need for using association mining in this process is to identify the frequent item sets that are likely to be product features. The infrequent noun or noun phrases are expected to be non-product features. Apriori algorithm is applied on the transaction set of nouns/noun phrases. Each resulting frequent item set is a possible feature, if minimum support of the product review sentences are more than 1%. All the candidate frequent features generated association mining are not genuine features. Compactness pruning and redundancy pruning are used to discard the unlikely features. For redundancy pruning a p-support lower than the minimum p-support of three is used. The sample product features identified for the dataset is given in Table 1.

Table 1: Sample Product features identified for the dataset

Unigram features	Camera, digital, price, battery, flash, quality, setting, lens, lcd, pixel, viewfinder, light, mode, zoom, use, software, optical, picture, canon, lag, mp, download, speed.
Bigram features	digital camera, lens quality, manual, optical zoom, mega pixel, metering option, movie mode, battery life, image download, compact flash, lag time, auto mode, raw format, exposure control, indoor picture, indoor image, manual function.
Trigram features	indoor image quality, light auto correction, gb memory card.

4.3. Data Pre Processing

The review sentences for a particular product need to be pre processed for creating the word vector list. From the literature review, it is clear that pre processing plays a major role in improving the performance of text retrieval, classification and summarization [6,35]. The steps involved in data preprocessing are tokenization, transformation (converting upper case letters into lower case letters) for reducing ambiguity. The stop words are filtered to remove common English words such as 'a' and 'the' etc. Stemming is done to reduce words to their respective stems. For the process of stemming, Porter stemmer algorithm is used. Porter stemming is used to remove common morphological endings from English words. After product feature identification, the preprocessed review sentences are transformed into a vector space representation. Comparing the influence of using different n-gram schemes is also important for this work. For this purpose, we have adopted several n-gram models which include unigrams, bigrams and trigrams. Three different vector models are created with various combinations of n-grams. Table 2 shows the detailed view of the data models used. Three models are constructed with varying levels of word granularity in order to know the influence of word size in prediction. Data model I is constructed with word vector containing only unigram attributes. Data model II is constructed with word vector containing unigram and bigram attributes. Data model III is constructed with word vector containing combination of unigram, bigram and trigram attributes.

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Table 2: Properties of Data source

Camera review	No. of Reviews	Feature	No. of features	Positive Reviews	Negative Reviews	Neutral Reviews
Data model I	1800	Unigrams only	185	600	600	600
Data model II	1800	Unigrams + Bigrams	185 + 52 =237	600	600	600
Data model III	1800	Unigrams + Bigrams +Trigrams	185+52 +24 =261	600	600	600

4.4 Feature Reduction

The statistical method widely used to reduce the dimension of feature set is PCA. The new principal component variables are referred to as new domain metrics. Assuming Z(a·b) matrix as the standardized word vector data with "a" reviews and "b" product attributes. The algorithm for carrying out PCA is :

i. Determine the covariance matrix *R* of Z.

ii. Determine Eigenvalues λ_k and Eigenvectors e_k.

iii. The dimensionality of the data is scaled down.

iv. Determine domain metrics for each product review using t_k

The identification of PCA with its respective features (185, 237 and 261 in our case) for each model is identified by Weka tool. 'Eigen value >1' is the stopping rule used for this process. As stopping rule has been imposed, the number of principal components for data model I, II and III are reduced to 4, 6 and 6. The percentage of variance becomes less as stopping rule has been implied. With the reduced principal components as features, the word vector models (I, II and III) are reconstructed. The principle components obtained for models I, II and III are shown in Table 3.

Table 3: Description of models (feature reduced)

Properties	Data model I	Data model II	Data model III
No.of Components	PC1–PC4	PC1–PC6	PC1–PC6
Variance	<56.7%	<57.9%	<61.4%
Standard Deviation	0.72	0.72	0.72
No. of Features (original)	185	237	261
No. of. principal components (Reduced)	4	6	6
No. of Reviews	1800	1800	1800
Positive Reviews	600	600	600
Negative Reviews	600	600	600
Neutral Reviews	600	600	600

5. METHODS

This section gives a brief discussion of the technique used for constructing the prediction system. For this research work, the statistical approach (SVM) is implemented using RapidMiner tool. We have also used neural network based PNN for constructing the prediction model. The neural network approach is employed using Neural Network Toolbox available in MATLAB package. The baseline methods are described in detail by the researchers Tao Li and Ziqiong Zhang [33,37]. Default values are used as parameters in the tools.

5.1 Probabilistic Neural Network (PNN)

A Probabilistic Neural Network is a technique which adopts on statistical Bayesian classification algorithm. In this technique, the functions are formulated into multilayered feed forward network with four layers. The input layer, pattern layer, summation layer and output layer are the four layers in multilayered feed forward network. The input layer has input nodes, which are the set of review measurements. The pattern layer for each pattern in training set is connected to the input layer. Depending on the class pattern the output from pattern layer is connected to summation units. PNN is a non linear classification technique based on Bayesian minimum risk criteria. From the previous studies, it is proved that SVM performs much better in sentiment classification but the disadvantage of SVM is its high computational cost for finding the best parameter combinations. The advantage of PNN is that it is simple and can be trained easily. PNN has only one parameter to be optimized and hence training is easy. For parameter optimization, PNN classifier is the best choice [3]. For a given unknown sample x, we can calculate its posterior probability $P(c_i|x)$ to obtain which class label the sample x belongs to. According to Bayesian rule, $P(c_i|x)$ is proportional to the multiplication of all prior probability π_i by probability density function $f_i(x)$. That can be represented as: $P(c_i|x) \alpha \pi_i f_i(x)$. Let *m* be the number of training samples, *n* the number of genes,

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x_{ij} the jth training sample for class i, and k_i the number of samples of class i. The Parzen estimate probability density function for class i can be written as (Eq. 1)

$$f_i(x) = \frac{1}{(2\pi)^{m/2}\sigma^m} \frac{1}{k_i} \sum_{j=1}^{k_i} \exp\left[-\frac{(x-x_{ij})^T(x-x_{ij})}{2\sigma^2}\right] \quad (1)$$

where σ is a smoothing parameter. The prior probability can be evaluated by the following formula (Eq . 2)

$$\pi_i = \frac{k_i}{\sum_{j=1}^{c} k_j} \quad (2)$$

where C denotes the number of subclasses in dataset. The datasets used in this work have only two sub classes positive and negative.

6. RESULTS AND DISCUSSIONS

The effectiveness of the prediction models varies greatly. Misclassification rate, correctness and compactness are used for evaluating the quality of the prediction models. The data models I, II and III are validated using 10-fold cross validation.

6.1 Misclassification Rate

Misclassification rate is the ratio of number of wrongly classified reviews to the total number of reviews classified by the prediction method. The wrong classifications fall into three categories. C1 represents number of negative and neutral reviews classified as positive. C2 represents number of positive and neutral reviews classified as negative. C3 represents number of positive and negative reviews classified as neutral.

$$\text{Type I error} = \frac{C1}{(\text{Total no of positive reviews})}$$

$$\text{Type II error} = \frac{C2}{(\text{Total no of negative reviews})}$$

$$\text{Type III error} = \frac{C3}{(\text{Total no of neutral reviews})}$$

$$\text{Misclassification rate} = \frac{C1 + C2 + C3}{(\text{Total no of reviews})}$$

Table 4: Predicted Confusion Matrices for SVM for all the three Models

	Data model I			Data model II			Data model III		
Actual	Positive	Negative	Neutral	Positive	Negative	Neutral	Positive	Negative	Neutral
Positive	458	78	64	464	75	61	471	68	61
Negative	87	439	74	82	460	58	73	465	62
Neutral	65	91	444	61	83	456	50	78	472
	Type I Error 25.3%	*Type II Error* 28.2%	*Type III Error* 23.0%	*Type I Error* 23.8%	*Type II Error* 26.3%	*Type III Error* 19.8%	*Type I Error* 20.5%	*Type II Error* 24.3%	*Type III Error* 20.5%
	Misclassification rate: 25.5%			Misclassification rate: 23.3%			Misclassification rate: 21.8 %		

Table 5:Predicted Confusion Matrices for PNN for all three Model

	Data model I			Data model II			Data model III		
Actual	Positive	Negative	Neutral	Positive	Negative	Neutral	Positive	Negative	Neutral
Positive	513	43	44	530	32	38	531	26	43
Negative	46	509	45	36	517	47	24	526	50
Neutral	42	37	521	32	44	524	27	39	534
	Type I Error 14.7%	*Type II Error* 13.3%	*Type III Error* 14.8%	*Type I Error* 11.3%	*Type II Error* 12.7%	*Type III Error* 14.2%	*Type I Error* 8.5%	*Type II Error* 10.8%	*Type III Error* 15.5%
	Misclassification rate: 14.3%			Misclassification rate: 12.7%			Misclassification rate: 11.6 %		

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Tables 4 and 5 summarize the misclassification results of all classification methods for the balanced dataset used. Table 4 gives the classification results in terms of error measures for SVM method. The type I, type II and type III errors are considerably higher. SVM method also predicts positive reviews more accurately (type II error is less than type I error) than negative and neutral reviews for data models I, II and III. It is evident from the results that, SVM performs much better for data model III than data models I and II.

PNN prediction results are presented in Table 6. The type I, II and III errors of the PNN models are lesser than the respective type of errors in SVM classification method. For PNN, the overall misclassification rate is less for data model III than the other two data models I and II. Thus the PNN method classifies considerably much better with unigrams, bigrams and trigrams combinations. The possible reason for better performance of PNN observed when compared to best individual classifier (SVM) could be due to the parametric model nature of PNN, while SVMs are non-parametric. The deep architectures of PNN with hidden layers represent intelligent behaviour more efficiently than shallow architectures like SVMs.

6.2 Correctness

Correctness is defined the number of reviews correctly classified as positive to the total number of reviews classified as positive.

The results from Table 6 show that the SVM based modes gives low correctness, which implies that a large number of sentences that are not positive would have been inspected. Data model III of PNN achieves 91.2% correctness in identifying positive review sentences, 89.0% correct in identifying negative review sentences and 85.2% correctness in identifying neutral review sentences. The prediction results of data model III are good when compared to data model I and data model II. The results suggest that the combined effect of unigram, bigram and trigram is the best option for review classification. Of all the prediction models, the reviews classified by PNN based models are more accurate.

6.3 Completeness

Completeness is defined as the ratio of number of positive reviews classified as positive to the total number of reviews. Completeness of the prediction model is given in Table 7. The results observed are as follows : When compared with other data model the maximum positive, negative and neutral reviews are identified by data model III of PNN. All the methods predict positive reviews more completely than negative and neutral reviews.

Table 6: Correctness of classifiers based on prediction using various models

Methods	Data model I (Predicted)			Data model II (Predicted)			Data model III (Predicted)		
	Positive	Negative	Neutral	Positive	Negative	Neutral	Positive	Negative	Neutral
SVM	75.1	72.2	76.3	76.4	74.4	79.3	79.3	76.1	79.3
PNN	85.4	86.4	85.4	88.6	87.2	86.0	91.2	89.0	85.2

Table 7: Completeness of classifiers based on prediction using various models

Methods	Data model I (Predicted)			Data model II (Predicted)			Data model III (Predicted)		
	Positive	Negative	Neutral	Positive	Negative	Neutral	Positive	Negative	Neutral
SVM	76.3	73.2	74.0	77.3	76.7	76.0	78.5	77.5	78.7
PNN	85.5	84.8	86.8	88.3	86.2	87.3	88.5	87.7	89.0

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Table 8: Summary of the training time using PCA and without using PCA

Method	Without PCA (in sec)			With PCA (in sec)		
	Data model I	Data model II	Data model III	Data model I	Data model II	Data model III
PNN	121.8	163.3	170.4	43.3	46.4	49.0
SVM	160.5	196.9	229.2	58.7	72.5	85.7

The results obtained clearly show that among the methods, PNN based prediction models perform well in all aspects. The high accuracy is achieved in data model III based prediction which concludes that including bigram, trigram in prediction provides better results when compared to results obtained using unigram only. From Table 8, we can observe the effect of feature reduction using PCA in terms of training time. Table 8 summarizes the average training time reduction using PCA prediction technique. From the analysis, it is predicted that huge data size and high dimensionality of text data will automatically reduce the performance of the classifier and hence leading to longer training time. From this table, it is proved that the neural network method reduces considerably the time taken for training.

7. CONCLUSION

This paper proposes opinion mining system for online reviews based on PNN and SVM to provide decision support for customers in taking a decision for a buying a product.. The System extractes unigram, bigram and trigram features from Amazon reviews on camera product and SVM and PNN methods are applied for prediction. From the results, it is observed that misclassification rate is lesser and correctness measure is higher for PNN when compared to SVM. This work, also identifies better performance in classification models based on the combination of unigram, bigram and trigram. It analyzes the effect of ANN based method for opinion classification. PNN performs better and yields higher accuracy in prediction. When compared to statistical approaches, neural network approach performs better than SVM approach. Compared with traditional techniques, the ANN based approach shows better performance both in quality measure and in training time.

In sentiment classification, the reduction of input attributes has now become an important issue for machine learning techniques. Our experimental results based on the hybrid combination of PNN and PCA could be a possible solution for increasing the performance of classification and shortening the training time. Future work can be an extension of this research using ensemble methods and various others feature selection methods. The general limitation of this work is that it cannot be implemented in other domains for example medical field. Since the results cannot be guaranteed as in case of product reviews.

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