SENTIMENT ANALYSIS USING FFBP NEURAL NETWORK FOR PROFIT OF COMMERCIAL PRODUCTS IN INDUSTRY

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ABSTRACT - *Sentiment analysis or opinion mining is a natural language processing technique Which is often used to predict the type of data is positive, negative or neutral. Sentiment analysis is broadly applied on textual data to promote and monitor the business products .sentiment analysis of customer feedback details collected from various social media where the people involves in online services like Facebook, Twitter etc., such huge amount of data have to analyzed on different parameter to understand customer needs in order to satisfy customer requirement on time.,. The sentiment analysis helps different organization to know how people look to their products and services and what changes are required to improve them. The paper performs sentiment analysis i.e. classification of tweets into positive, negative and neutral on views of a particular product using an inbuilt python library called Text Blob for three platforms Sentiment Analysis is the process is applied on the platform of Artificial Neural Network is easier and faster in time.. In this paper Feed-Forward Back propagation neural networks(FFBPNN) are used to split the data into train and test data and a min-max approach was applied to the data to reduce the size of data and analyse the accuracy of the sentiment using ANN. In order to measure the performance of ANN accuracy have been calculated to provide the quantitative approach to the results. It is found that such type of neural network is very efficient in predicting the result with a high accuracy.*

Key Words **ANN, Sentiment analysis, Text classification, Opinion mining, FFBPNN**

INTRODUCTION

Sentiment analysis is that the process of using tongue processing, text analysis, and statistics to investigate customer sentiment. the simplest businesses understand the sentiment of their customers—what people are saying, how they're saying it, and what they mean. Customer sentiment will be found in tweets, comments, reviews, or other places where people mention your brand. Sentiment Analysis is that the domain of understanding these emotions with software, and it's a must-understand for developers and business leaders in an exceedingly modern workplace.

As with many other fields, advances in deep learning have brought sentiment analysis into the foreground of cutting-edge algorithms. Today we use tongue processing, statistics, and text analysis to extract, and identify the sentiment of words into positive, negative, or neutral categories morphological chunking method that binds semantically related concatenations of morphemes. This helps to define boundaries of semantic scopes of opinionated terms and is faster, simpler and more efficient on sentiment analysis than a general full parser. These systems don't depend on manually crafted rules, but on machine learning techniques[25], like classification. Classification, which is employed for sentiment analysis, is an automatic system that has to be fed sample text before returning a category, e.g. positive, negative, or neutral.

There are two stages automatic systems:

- Training
- Prediction

In the training stage, a sentiment analysis model learns to correctly tag a text as negative, neutral or positive using sample data. The feature extractor then transforms the text into a feature vector, creating pairs of feature vectors and tags (e.g. positive, negative, or neutral) that are fed into the machine learning algorithm to generate a model.

In the prediction process, the feature extractor is used to transform unseen text into feature vectors, which are fed to the model, enabling it to make sentiment predictions.

LITERATURE REVIEW

In [1] the author wrote about hot opinions of the products comments using hotel comments dataset as the main research. They filtered the data from the length of the comments and the feature selection aspect by analyzing the characteristics of customer's reviews they have built a mathematical model for the preprocessing and adopt the clustering algorithm to extract the final opinions. They compared it with the original comments, the experiment results were more accurate. In [2] in this paper the author categorized the descriptive and the predictive and separated them using data mining techniques. The statistical summary he made was mostly for the descriptive mining of the online reviews. In [3] the main objective in this research is to extract useful information in case of a big data. Clustering: Cluster analysis is the task of grouping a set of objects in in a way that objects in the same group that you call cluster are more similar to each other than to those in other groups .In [4] D. Tang et al. Did a learning continuous word representation for Twitter sentiment classification for a supervised learning framework. They learn word embedding by integrating the sentiment information into the loss functions of three neural networks. Sentiment-specific word embedding's outperform existing neural models by large margins. The drawback of this model this author used is that it learns sentiment-specific word embedding from scratch, which uses a long processing time .Among the many studies conducted on sentiment classification using machine learning algorithms, SVM and naive bayes have been used widely for classification of online reviews (Pang et al.,2002, Wilson et al., 2005, Wang et al., 2007, Tan and Zhang, 2008, Prabowo and Thelwall, 2009), The comparative studies in the literature also showed that SVM outperformed other classifiers such as naive bayes, centroid classifier, K-nearest neighbor, winnow classifier (Tan and Zhang,2008).

Challenges Of Sentiment Analysis :

1. Irony and sarcasm
2. Types of negations
3. Wordambiguity
4. Multipolarity

PROPOSED PROCESS OF SENTIMENT ANALYSIS WITH FFBPNN METHOLOGY

This paper proposes an approach for sentiment analysis wenblog based on ANNsFFBPNN Speed of execution, efficiency and recognition rate have been enhanced by utilizing feed-forward back propagation neural network (FBBPNN) with training function gradient descent and learning rule of momentum and adaptive learning. A basic task in sentiment analysis is classifying the polarity of a given text at the document, sentence, or feature/aspect level whether the expressed opinion in a document, a sentence or an entity feature/aspect is positive, negative, orneutral.

Advanced, "beyond polarity" sentiment classification looks, for instance, at emotional states such as enjoyment, anger, disgust, sadness, fear, and surprise. Precursors to sentimental analysis include the General Inquirer,[2] which provided hints toward quantifying patterns in text and, separately, psychological research that examined a person's psychological state based on analysis of their verbal behavior.[3] Subsequently, the method described in a patent by Volcani and Fogel,[4] looked specifically at sentiment and identified individual words and phrases in text with respect to different emotional scales. A current system based on their work, called Effect Check, presents synonyms that can be used to increase or decrease the level of evoked emotion in each scale.

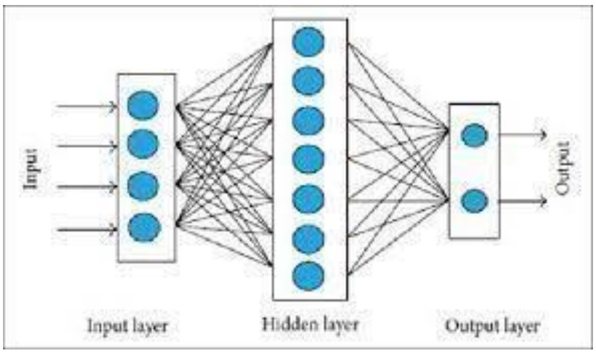

Figure 1: Struture of FFBPNN

As shown in Figure 1. The number of neurons in the input layer is equal to the number of detected tokens N in the training dataset. In each input vector is an N-element vector with zeros if the token does not appear in the tweet and the number of token occurrences otherwise. Each output vector is a C-element vector,

where C represents the number of target classes. X is thenumber of neurons in the hidden layer. Each neuron of the hidden layer calculatesthe argument of the transfer function ai, in the following way:

$$ai = x1wi;1 + x2wi;2 + : : : + xnwi;n + bi \quad (1)$$

where,

xj - jth inputelement,

wi;j - weight coefficients between ith hidden and jth input element

bi - biascoefficient.

The ith neuron produces output: yi = f(ai) = f Xn

j=1

xjwi;j + bi

Hidden and output neurons have either hyperbolic tangent sigmoid transfer function:

y = tansig(a) =2 1 + e^2a

Sentiment Analysis of Microblogs Using ANN 1131 or log-sigmoid transfer function:

y = logsig(a) =1 1 + e^a

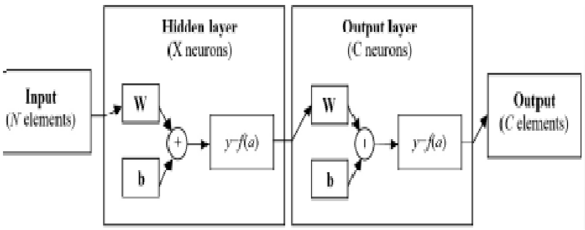

Figure 2 Structure of the proposed Artificial Neural Network

This output represents an input to the neurons of another layer, or an element of the neural network's output vector. We also experiment with three-layer feed-forward neural networks, by introducing a second hidden layer with sigmoid transfer function. However, one should be very careful with increasing the number of hidden layers, since it also increases training time and the danger of over fitting, which can lead to poor generalization for the test dataset. Using two hidden layers exacerbates the problem of local minima, which can have extreme spikes even when the number of weights is much smaller than the number of training cases. Instead of adopting the traditional gradient descent method, the network is trained using the scaled conjugate gradient (SCG) back-propagation algorithm, to speed up the convergence. Back- propagation is used to calculate derivatives of performance with respect to the weight and bias variables. Although this routine usually requires more iterations to converge compared to other conjugategradient algorithms, the number of computations ineach iteration is significantly reduced because no line search is performed. By using a step size scaling mechanism, SCG avoids a time consuming line search per learning iteration, which makes the algorithm faster than other second-order algorithms (e.g.conjugate gradient with line search, Broyden-Fletcher-Goldfarb-Shanno quasi-Newton algorithm) [26].Trainings tops either when the maximum number of epochs is reached or the network performance on the validation set fails to improve for predefined number of epochs.

RESULTS AND DISCUSSION

Natural language processing (NLP) techniques can prove relevant to a variety of specialties in the field cognitive science, including sentiment analysis. This paper investigates the impact of NLP tools, various sentiment features, and sentiment lexicon generation approaches to sentiment polarity classification of internet reviews written in Persian language. For this purpose, a comprehensive Persian WordNet (FerdowsNet), with high recall and proper precision (based on Princeton WordNet), was developed. Using FerdowsNet and a generated corpus of reviews, a Persian sentiment lexicon was developed using (i) mapping to the SentiWordNet and (ii) a semi-supervised learning method, after which the results of both methods werecompared. In addition to sentiment words, a set of various features were extracted and applied to the sentiment classification. Then, by employing various well-known feature selection approaches and state-of-the art machine learning methods, a sentiment classification for Persian text reviews was carried out. The obtained results demonstrate the critical role of sentiment lexicon quality in improving the quality of sentiment classification in Persian language.

Figure 5: The Impact of Sentiment Features on the Sentiment Polarity Classification in Persian Reviews

CONCLUSION

This paper conclude that it is not possible to make a straight choice of the best machine learning method for the task of sentiment analysis of weblog MNB is a good candidate only in the presence of very large training datasets, due to computational efficiency Performances of **neural network** based approaches are compared with two statistical approaches. The homogeneous **ensemble method** performs better than other classification methods used. Among the individual **neural network approaches** used, PNN was highly robust.. The proposed approach of combining the neural network with PCA shows its superiority not only in quality measures, but also in training time. This indicates that feature reduction is an essential issue for learning methods in sentiment classification The possible reason for the better performance of PNNs is because of the combined effect of the computational capability and flexibility, by retaining its simplicity. The prediction accuracy of the ensemble method can still be increased by increasing the number of classifier combinations.

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