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Sentiment Analysis Using FFBP Neural Network for Profit of Commercial Products in Industry

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***Abstract* -** From its inception in the early 2000s to the present, sentiment analysis and opinion mining have taken several twists and turns. People are increasingly using social media sites to voice their opinions and communicate with others who share common ideas, thanks to advancements in technology, smartphone and internet networks, and ease of access to these services. As a result, a vast volume of data has been generated on the internet, necessitating the need to analyse it Sentiment research aids various organisations in determining how customers perceive their goods and services, as well as what improvements are needed to enhance them. The paper uses an inbuilt python library called Text Blob to perform sentiment analysis, which is the classification of tweets into positive, negative, and neutral on views on a certain product, for three platforms: twitter, Facebook, and news websites. It also discusses how Artificial Neural Networks (ANN) provide a platform to perform sentiment analysis in a much easier and therefore less time consuming process.In this article, feed-forward back propagation neural networks (FFBPNN) were used to split the task into training data, and a min-max method has been used to measure the information and analysing the sentiment accuracy rate with ANN. To have a quantitative approach to the findings and quantify the success of ANN, precision, memory, and accuracy were measured. We discovered that this kind of neural network is very effective at accurately predicting the outcome.
Index Terms -ANN, Sentiment analysis, Text classification, Opinion mining, FFBPNN

I .INTRODUCTION

Sentiment analysis is the method of analysing consumer sentiment using natural language processing, text analysis, and statistics. The best companies are aware of their consumers' feelings—what they're doing, how they're doing it, and what they think. Tweets, mentions, ratings, and other areas where customers mention your brand will reveal customer opinion. Sentiment Analysis is the domain of using apps to grasp certain feelings, and it's a must-know for developers and corporate executives in today's workplace. Advances in deep learning, like many other disciplines, have pushed emotion analysis to the forefront of slicing algorithms. To derive and categorise the sentiment of words into positive, negative, or neutral types, we now use natural language processing, statistics, and text analysis. Natural Language Processing (NLP) approaches and algorithms are used in sentiment analysis, including:

- Rules-Based Systems: focus on a series of manually designed rules to learn from data
- Automated Systems: rely on machine learning strategies to learn from data
- Hybrid Systems: mix rule-based and automatic methods to learn from data

Machine learning methods, such as sorting, are used instead of manually designed rules in these applications. Sentiment analysis uses classification, which is an automated mechanism that requires sample text before returning a form, such as positive, negative, or neutral. Automatic systems are divided into two levels:

- Training

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- Prediction

A sentiment analysis algorithm learns to accurately tag a text as negative, neutral, or positive using sample data during the training stage. The feature extractor converts the text into a feature vector, resulting in pairs of feature vectors and tags (such as positive, negative, or neutral) that are fed into the machine learning algorithm to produce a pattern.

The feature extractor is used in the prediction process to convert unseen text into feature vectors, which are then fed to the model, allowing it to render emotion forecasts.

II LITERATURE REVIEW

The author of [1] wrote about hot product views using the hotel comments dataset as the key analysis. They filtered the data based on comment length and feature selection by evaluating the features of consumer feedback. They created a statistical model for preprocessing and used the clustering algorithm to retrieve the ultimate viewpoints. They compared it with the original comments, the experiment results were more accurate. In [2] 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. Cluster analysis is the process of grouping a collection of objects such that objects in the same cluster are often more related with each other than artifacts in other clusters. D. Tang et al. [4] used a supervised learning system to train continuous word representation for Twitter emotion classification. The sentiment information is integrated into the loss functions of three neural networks to learn word embedding. Current neural models are outperformed by sentiment-specific word embeddings by a massive margin. The disadvantage of this model is that it learns sentiment-specific word embedding from scratch, which takes a long time to process.

SVM and naive bayes have been extensively used for classification of online feedback among the several studies performed on emotion classification using machine learning algorithms (Pang et al., 2002,Wilson et al., 2005,Wang et al., 2007,Tan and Zhang, 2008,Prabowo and Thelwall, 2009), SVM outperformed other classifiers such as naive bayes, centroid classifier, K-nearest neighbour, and winnow classifier in comparative analyses in the literature (Tan and Zhang, 2008).

Challenges Of Sentiment Analysis :

1. Sarcasm and exaggeration
2. Different types of agreements
3. The use of ambiguous words
4. The definition of multipolarity

III PROPOSED PROCESS OF SENTIMENT ANALYSIS WITH FFBPNNMETHOLOGY

This paper proposes an approach for sentiment analysis wenblog based on ANNsFFBPNN

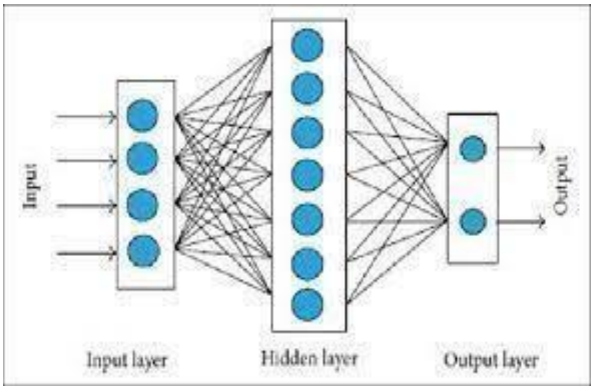

Figure 1: Structure of FFBPNN

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The use of a feed-forward back propagation neural network (FBBPNN) with training feature gradient descent, learning rule of momentum, and adaptive learning has improved the speed, reliability, and recognition rate. Classifying the polarity of a given text at the document, sentence, or feature/aspect level—whether the conveyed viewpoint in a document, a sentence, or an object feature/aspect is positive, negative, or neutral—is a fundamental role in sentiment analysis.

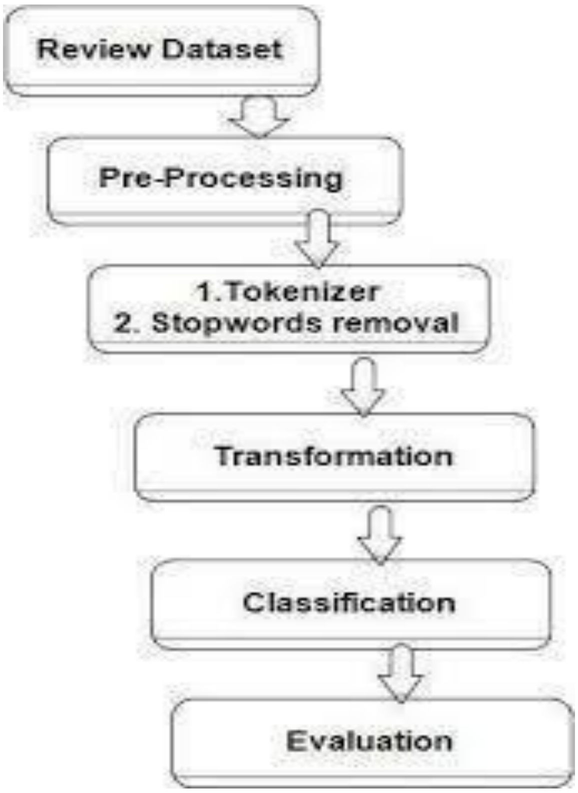

Figure 2: process of sentiment analysis

Advanced "beyond polarity" sentiment description examines emotional states such as pleasure, frustration, disappointment, sorrow, anxiety, and uncertainty, to name a few. The General Inquirer[2], which gave pointers toward quantifying trends in text, and, separately, psychological studies that analysed a person's psychological status based on examination of their verbal actions, were forerunners to sentimental psychology.[3] Following that, Volcani and Fogel outlined a process in a patent[4] that looked directly at sentiment and classified individual colloquial expressions in text in relation to various cognitive measures. As seen in Figure 1, a current scheme based on their work, called EffectCheck, provides synonyms that can be used to raise or reduce the amount of conjured emotions inside each measure.In the training dataset, the number of observed tokens N is proportional to the number of neurons in the input layer. An N-element vector of zeros if the token does not appear in the tweet and the number of token occurrences otherwise is used in each input vector. Each output vector is made up of C elements, with C denoting the number of target groups. The number of neurons in the secret layer is denoted by X. The statement of the transfer function ai is calculated by each neuron in the hidden layer in the following manner:

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

where ,xj - jth input element, wi;j - weight coefficients between ith hidden and jth input element bi - bias coefficient.

The ith neuron produces output:

yi = f(ai) = f Xn j=1 (2)

xjwi;j + bi (3)

Hidden and output neurons have either hyperbolic tangent sigmoid transferfunction:

y = tansig(a) =2 (4)

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1 + e^2a (5)

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

y = logsig(a) =1 (6)

1 + e^a (7)

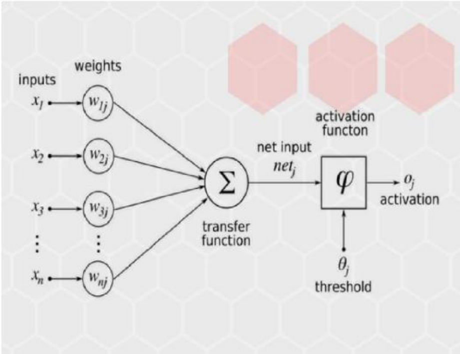

Figure 3 Structure of the proposed Artificial Neural Network

This output represents an input to the neurons of another layer, or an elementof 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 shouldbe very careful with increasing the number of hidden layers, since it also increasestraining time and the danger of over fitting, which can lead to poor generalization forthe test dataset. The use of two opaque layers exacerbates the issue of local minima, which can result in severe spikes even though the number of weights is much less than the subset of the training events. To speed up convergence, the network was trained using the scaled conjugate gradient (SCG) back-propagation algorithm instead of the conventional gradient descent approach. The derivatives of performance with respect to the weight and bias variables are calculated using backpropagation.While this routine takes more iterations to converge than other conjugate gradient algorithms, the number of computations per iteration is substantially lower since no line search is done. SCG prevents a time-consuming line search per learning iteration by using a phase size scaling function, making it quicker than other second-order algorithms (e.g., conjugate gradient with linesearch, Broyden-FletcherGoldfarb-Shanno quasi-Newtonal algorithm) [23].When the full number of epochs is reached, or the network output on the validation set fails to increase for a predetermined number of epochs, training comes to an end.

IV RESULTS AND DISCUSSION

Natural language processing (NLP) approaches, such as emotion interpretation, can be useful in a number of cognitive science specialties. The effect of NLP methods, various sentiment functions, and sentiment lexicon generation approaches on linear discriminant analysis of Persian language internet feedback is investigated in this article. A Persian sentiment lexicon was developed using FerdowsNet and a created corpus of feedback, with I mapping to the SentiWordNet and (ii) a semi-supervised learning process, and the results of both methods were compared. A selection of different characteristics, in addition to sentiment terms, were extracted and added to the sentiment classification. Then, using a variety of well-known function selection techniques. The emotion classification for Persian text feedback was then carried out using a combination of well-known feature collection techniques and cutting-edge machine learning methods. The findings show that sentiment lexicon consistency plays a critical role in improving sentiment classification quality in the Persian language.

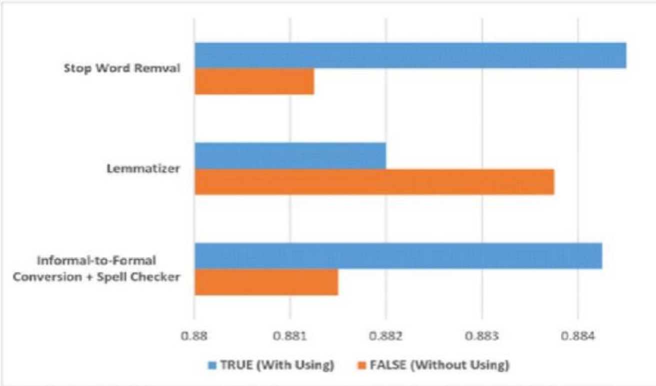

Figure 4: Sentiment Polarity Classification in Persian Reviews

V CONCLUSION

This paper concludes that it is not possible to make a straight choice of the best machine learning method for the task of sentiment analysis of weblog. Indeed, the choice will depend on the underlying learning problem. ANNs have shown to be very robust to noisy input data, making them a good choice when manual annotations are not available (as in STS corpus). MaxEnt are, on the other hand, sensitive to noisy data, but perform better when training data are highly unbalanced (as in SemEval 2014 task 9 corpus), and probably are the best trade-of between performance and computational complexity. SVMs are competitive in terms of performance in all our experiments, but large number of support vectors makes them computationally slow in both training and test phase, which is especially important for realtime applications. MNB is a good candidate only in the presence of very large training datasets, due to computational efficiency

Two mathematical methods are related to the performance of neural network-based approaches. The homogeneous ensemble approach outperforms the conventional method .

PNN was the most stable of the individual neural network methods used. The proposed method of integrating a neural network into PCA outperforms the competition not only in terms of consistency, but also in terms of training time. This suggests that feature reduction is a critical problem for emotion classification learning methods. According to our findings, a mixture of PNN and PCA may be a better approach for reducing training time and improving classification efficiency. In nearly all of the prediction models, the combination mixture of unigram, bigram, and trigram performs well, according to our findings.The combined impact of computational capacity and stability, while maintaining its simplicity, may be the reason for PNNs' superior efficiency. The ensemble method's estimation accuracy can also be improved by increasing the number of classifier combinations. Future studies may use various data domains and classification methods to assess the shortcomings of the proposed process, most likely using a much broader data collection of ratings.

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