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PRODUCT REVIEW CLASSIFICATION USING DEEP LEARNING

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Abstract: Product reviews are valuable for upcoming buyers in helping them to require decisions. Different opinion mining techniques are proposed to evaluate a review sentence's orientation. We propose a very unique deep learning framework for product review classification. The framework consists of two steps: 1. Embedding space which captures the sentiment distribution of sentences through rating information. 2.Upon adding Classification Layer on Embedding Layer make Supervised Learning much easier and more accurate. during this paper we used a preferred supervised learning algorithms they're 1.support vector machine Or svm. it's used for classification moreover as Regression problems. The goal of svm algorithm is to make the most effective line Or decision boundary. 2.Random forest which is employed for both classification moreover as regression. It creates decision trees on data samples so gets the prediction from each of them and eventually selects the most effective solution by means of voting.

Keywords: sentiment analysis, classification, embedding space.

I.INTRODUCTION

With the booming of e-commerce, people are becoming wont to consuming online and writing comments about their purchase experiences on merchant/review Websites. These opinionated contents are valuable resources both to future customers for decision-making and to merchants for improving their products and/or service. However, because the volume of reviews grows rapidly, people should face a severe information overload problem. To alleviate this problem, many opinion mining techniques are proposed, e.g. opinion summarization opinion polling, and comparative analysis . The key challenge is a way to accurately predict the sentiment orientation of review sentences. Popular sentiment classification methods generally fall under two categories: (1) lexicon-based methods and (2) machine learning methods. Lexicon-based methods typically take the tack of first constructing a sentiment lexicon of opinion words . Despite effectiveness, this sort of methods require substantial efforts in lexicon construction and rule design. Furthermore, lexicon-based methods cannot well handle implicit opinions. As known during this is additionally a very important sort of opinions. Factual information is sometimes more helpful than subjective feelings. Lexicon-based methods can only pander to implicit opinions in an ad-hoc way . After that, most research during this direction revolved around feature engineering for better classification performance. Different varieties of features are explored, e.g. n-grams, Part-of-speech (POS) information and syntactic relations , etc. Feature engineering also costs plenty of human efforts, and a feature set suitable for one domain might not generate good performance for other domains.

II. ALGORITHMS

Support Vector Machine Algorithm:

Support Vector Machine or SVM is one of the most popular Supervised Learningalgorithms, which is used for Classification as well as Regression problems. However,primarily, it is used for Classification problems in Machine Learning.

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The goal of the SVM algorithm is to create the best line or decision boundary that cansegregate n-dimensional space into classes so that we can easily put the new data point inthe correct category in the future. This best decision boundary is called a hyperplane.

SVM chooses the extreme points/vectors that help in creating the hyperplane. Theseextreme cases are called as support vectors, and hence algorithm is termed as SupportVector Machine. Consider the below diagram in which there are two different categoriesthat are classified using a decision boundary or hyperplane:

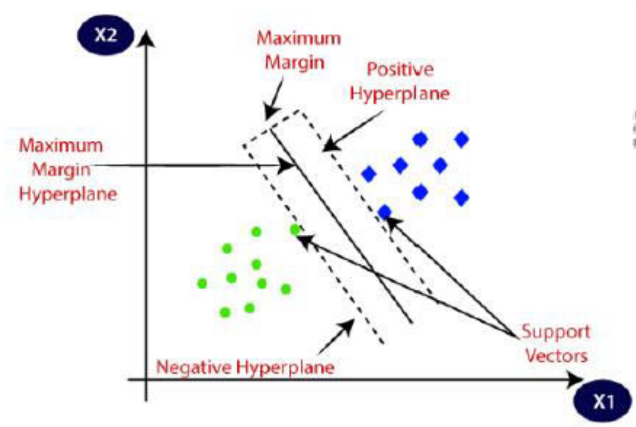

Fig1:SVMDiagram

Random forest Classifier:

Random forest is a supervised learning algorithm which is used for bothclassification as well as regression. But however, it is mainly used for classificationproblems. As we know that a forest is made up of trees and more trees means more robustforest.

Similarly, random forest algorithm creates decision trees on data samples and thengets the prediction from each of them and finally selects the best solution by means ofvoting. It is an ensemble method which is better than a single decision tree because introduces the over-fitting by averaging the result.

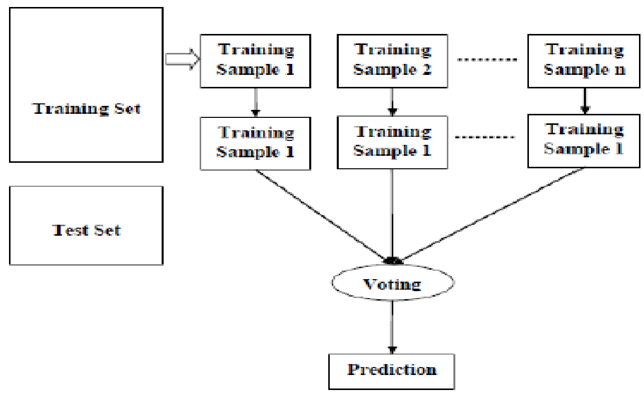

Fig 2: Random Forest Classifier

III. RESULTS

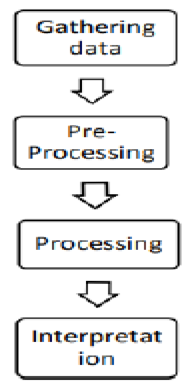

Fig 3:ProcessDagram

The Difference in their validation and accuracy on the data which is given shown below:

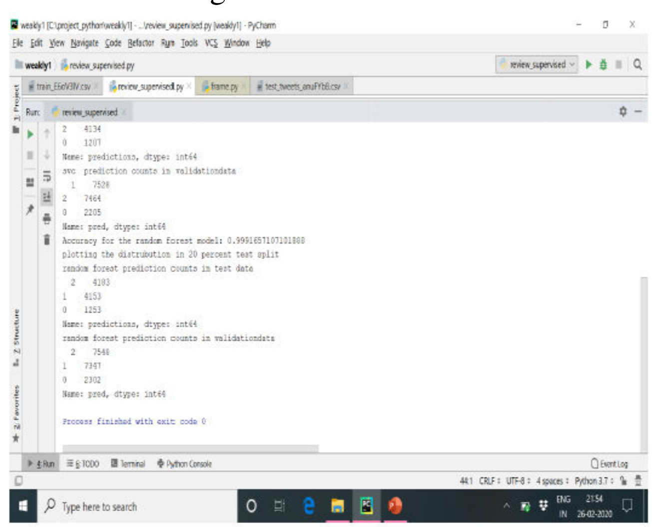

Fig 9.1 : Accuracy of SVC

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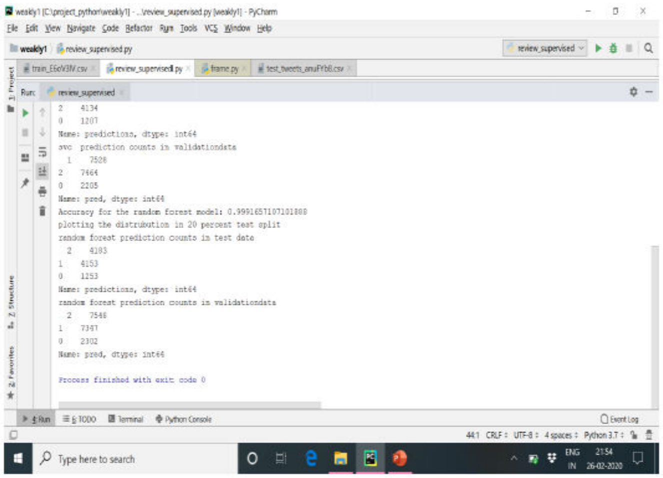

Fig 4: Accuracy of Random Forest model

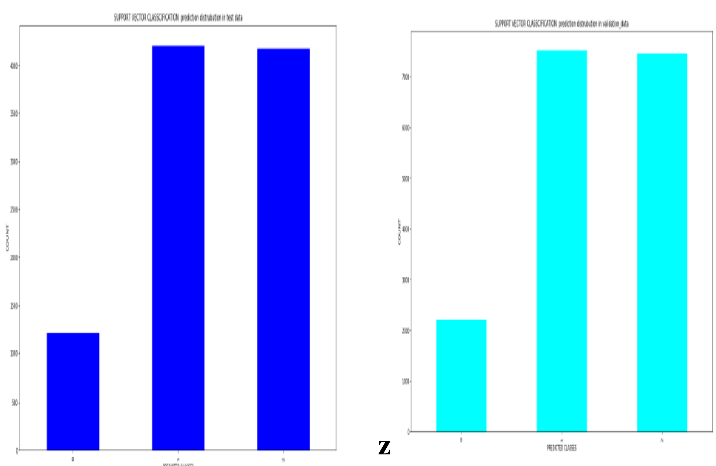

Fig 5:SVM Test and Validation Graphs

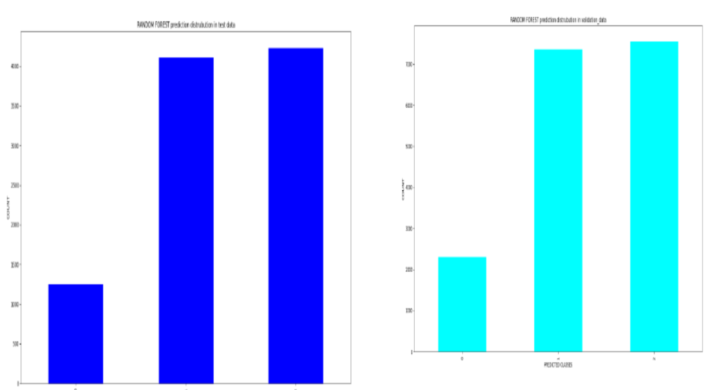

Fig 6:Random Forest Test and Validation Graaphs

IV. CONCLUSION

In this work we proposed a novel deep learning framework named Weakly-supervised Deep Embedding for review sentence sentiment classification. WDE trains deep neural networks by exploiting rating information of reviews which is prevalently available on many merchant/review Websites.

The training is a2-step procedure: first we learn an embedding space which tries to capture the sentiment distribution of sentences by penalizing relative distances among sentences according to weak labels inferred from ratings; then a soft-max classifier is added on top of the embedding layer nd we fine-tune the network by labeled data.

Experiments on reviews collected from mazon.com show that WDE is effective and utperforms baseline methods. Two specific nstantiations of the framework, WDE-CNN and /DE-LSTM, are proposed. Compared to WDE-STM, WDE CNN has fewer model parameters, nd its computation is more easily parallelized on PUs. Nevertheless, WDE-CNN cannot well andle long-term dependencies in sentences. WDE-STM is more capable of modeling the long-term dependencies in sentences, but it is less efficient than WDE-CNN and needs more training data.

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