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SENTIMENTAL ANALYSIS USING TWIN EXTREME LEARNING MACHINE CLASSIFIER

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ABSTRACT

Sentiment Analysis is the process of determining whether a piece of writing is positive, negative or neutral. It's also known as opinion mining, deriving the opinion or attitude of a speaker. A common use case for this technology is to find out how people feel about a specific topic. Many methods and approaches were implemented for this sentiment analysis. This paper works with TELM for the better performance and accuracy of the sentimental analysis. Twin Extreme Learning Machines (TELM) are the extension of Extreme Learning Machines (ELM). This approach gives the good result when compared to other techniques. Here the comparison is made among TELM, ELM, SVM and TSVM also experiment shows that TELM has better accuracy than others.

KEYWORDS: *Sentimental Analysis, Comparison, TELM, ELM, SVM and TSVM*

I. INTRODUCTION

SENTIMENT Analysis (or opinion mining) is defined as the task of finding the thoughts of authors about particular entities. Sentiment analysis in reviews is the process of exploring product reviews on the internet to determine the overall opinion. This is treated as a classification task as it classifies the orientation of a text into either positive or negative.

Nowadays an increasing amount of investigation has been dedicated to recognizing favorable and unfavorable sentiments towards specific subjects within usual language texts. Areas of application for such analysis are several and varied, ranging from newsgroup flame filtering and informative augmentation of search engine responses to the analysis of public opinion trends and customer feedback. For many of these tasks, it is an important step to classify the tone of the communication as generally positive or negative. There are a number of challenging aspects of this task. Opinions in natural language are very often expressed in subtle and complex ways, presenting challenges which may not be easily addressed by simply text categorization approaches such as n-gram or keyword identification approaches.

Machine learning is one of the widely used approaches towards sentiment classification in addition to lexicon based methods and linguistic methods. Sentiment analysis has been applied to the broader area of research, including consumer product reviews and services.

This work presents experiment using Twin Extreme Learning Machines (TELM) for sentiment analysis.

The remainder of this paper is organized as follows. Section 2 contains the review of some related work. Section 3 presents the Sentimental analysis using Twin extreme learning machines and Section 4 contains Experiment and results. Finally, Section 5 concludes this paper.

II. RELATED WORKS

Zainuddin and Selamat (2014) have proposed a sentimental analysis using support vector machine. This work described experimental results that applied Support Vector Machine (SVM) on benchmark datasets to train a sentiment classifier. Pang Corpus and Taboada Corpus where the two datasets used here. N-grams and different weighting scheme were used as an input to the sentiment classifier. This paper also showed that the classification accuracy for both datasets considerably improved by using chi-square feature selection.

Xu et al (2012) has proposed an Improved Least Squares Twin Support Vector Machine. The empirical risk minimization principle was implemented by LS-TSVM instead of the structural risk minimization principle. To overcome this drawback, an improved LS-TSVM is proposed which enhances the classification accuracy of the classifier. This improved LS-TSVM algorithm implemented the structural risk minimization principle moderately than the empirical risk minimization principle. Here the feasibility and validity of the proposed algorithm were demonstrated by numerical experiments on seven benchmark datasets.

Huang et al (2014) have proposed Asymmetric least squares support vector machine (ALS-SVM) classifiers. In ALS-SVM, the expected value is used to measure the margin between two classes instead of the minimal value. ALS-SVM is made by the relation between the expectile value and the asymmetric squared loss.ALS-SVM showed that its insensitivity to noise around the boundary and its stability to re-sampling by theoretical analysis and numerical experiments.

Jadav and Vaghela (2016) have introduced sentiment analysis using support vector machine based on feature selection and semantic analysis. In this method first preprocessing is done by converting unstructured data into the structured form. Then lexicon-based approach is used to convert the structured review into numerical score value. After that SVM algorithm is applied to classify reviews where RBF kernel SVM is modified by its hyperparameters. This optimized SVM gives good results than SVM and naïve Bayes.

Mullen and Collier (2004) have proposed Sentiment analysis using support vector machines with diverse information sources. This paper introduced an approach to classifying texts as positive or negative using Support Vector Machines to bring together diverse sources of potentially relevant information. This method allowed several methods of assigning semantic values to phrases and words within a text to be exploited in a more useful way.

Ahmad et al (2018) has reviewed systematically sentiment analysis using SVM. This research has focused on the SVM technique of sentiment analysis and given a compact and detailed review of the latest research works. After a critical review of selected papers, it also provided the answers for identified research questions.

BholaneSavita and Gore (2016) have analyzed Twitter data using SVM. Here latent Dirichlet based approach used for sentiment variation tracking. Two tools were compared here with Support Vector Machine (SVM) are SentiStrength and Twitter Sentiment tools to analyze Twitter data. This work proved that SVM gives good results and its accuracy increased by 23.24% than the other two tools.

Ye and Xiong (2007) have compared SVM and least squares SVM. This paper explained the essential relationship between linear SVM and linear LS-SVM under a particular condition. The result showed that LS-SVM for binary class classifications is equivalent to the hard margin SVM based on the well-known Mahalanobis distance measure. This also explained the asymptotic of SVM when the data dimensionality tends to infinity with a fixed sample size.

Tomar and Agarwal (2015) have proposed Multiclass Least Squares Twin Support Vector Machine (MLSTSVM) for Pattern Classification. It is an extension of binary least squares twin support vector machine classifier. This classifier seeks M-non parallel hyper-planes for M-class classification problem, one for each class, by solving M-linear equations. Its experimental results showed that the MLSTSVM classifier yields the highest prediction accuracy and fast, as compared to the other classifiers.

Preety and Dahiya (2015) have proposed sentiment analysis using SVM and naïve Bayes algorithms. In this paper, the modified k-mean algorithm is introduced. The user interface, log pre-processing, Feature Clustering using Modified Kmeans and Naïve Bayes Classification, Training and testing using support vector machine are the four processes involved in this. This work resulted that a method using naïve Bayes and modified k means clustering has given more accuracy than by using naïve Bayes and support vector machine techniques individually.

III. SENTIMENTAL ANALYSIS USING TWIN EXTREME LEARNING MACHINE

A. Extreme Learning Machine

Extreme learning machine (ELM) has recently been proposed for Single-hidden Layer Feedforward Neural networks (SLFNs) with additive neurons to easily achieve good generalization performance at extremely fast learning speed. The extreme learning machine is an innovative learning algorithm for the single hidden layer feed-forward neural networks. Compared with the conventional neural network learning algorithm, it overcomes the slow training speed and over-fitting problems. ELM is based on empirical risk minimization theory and its learning process needs only a single iteration. The algorithm avoids multiple iterations and local minimization. It has been used in various fields and applications because of its better generalization ability, robustness, and controllability and fast learning rate.

B. Twin Support Vector Machine

Twin Support Vector Machine (TSVM) utilizes the concept of Generalized Eigenvalues Proximal Support Vector Machine (GEPSVM) and finds two non-parallel planes for each class by solving a pair of Quadratic Programming Problems. It enhances the computational speed as compared to the traditional Support Vector Machine (SVM). TSVM was initially constructed to solve binary classification problems; later researchers successfully extended it for the multi-class problem domain. TSVM always gives promising empirical results, due to which it has many attractive features which enhance its applicability. The Twin SVM generates two non-parallel hyper-planes by solving two smaller-sized QPPs such that each hyper-plane is closer to one class and as far as possible from the other. Many extensions of the Twin SVM have been proposed. The Twin SVM is insensitive to an imbalance in the class sizes. This is because it solves two smaller sized QPPs in order to find two non-parallel hyper-planes that pass through the respective classes. The first QPP tries to find a hyper-plane that passes through the points of class (+1) and is at least at a unit distance from the points of the other class.

Only samples of class (-1) contribute to the constraints of this problem. The second optimization problem tries to find a hyper-plane that passes through samples of class (-1) and is at a distance of at least one from samples of class (+1).

One solves for the two hyper-planes and then, for a test sample, determines which is the closer hyperplane and assigns the point to that class. The Twin SVM works very well on multiclass problems, which inherecently lead to unbalanced binary classification tasks in a one-versus-rest setting.

C. Twin Extreme Learning Machine

Twin Extreme Learning Machines (TELM) are the extension of ELM. TELM incorporates the idea of Twin Support Vector Machine (TSVM) into the basic framework of ELM, thus TELM could have the advantages of both the algorithms. TELM has less optimization, constraint variables, but has better classification performance when compared to TSVM. Twin extreme learning machine algorithm aims to learn two nonparallel separating hyperplanes in the ELM feature space for data classification. For each hyperplane, TELM minimizes its distance to one of the two classes and requires it to be far away from the other class. In order to alleviate over-fitting problems, TELM allows an acceptable training error by minimizing a regularization term jointly.Specifically, TELM tries to reduce both the training error and the sum of squares of the distance from one hyperplane to one of the two classes. Therefore, TELM simultaneously trains two ELMs based on the optimization method and has inherited the merits of ELM and TSVM.

1). Complete TELM Algorithm

Summarized TELM algorithm as follows:

Algorithm TELM: Given a training set$X = \{(x_i, t_i) | x_i \in \mathbb{R}^d, t_i = \{+1.-1\}, i = 1, \dots N\}$, activation function G (x), and the number of hidden node number L.

Step 1: Initiate an ELM network with L hidden nodes using the random input weight w_i and bias b_i.

Step 2: Construct input matrixes A and B. For linear TELM, then calculate their hidden layer output matrixes U and V, respectively; for nonlinear TELM, calculate matrixes R and S, respectively.

Step 3:

a)For Linear TELM, Construct Convex QPPs

$$\max_{\alpha} e_2^T \alpha - \frac{1}{2} \alpha^T V (U^T U + \epsilon 1)^{-1} V^T \alpha$$
$$s.t. 0 \le \alpha_i \le c_1, i = 1, \dots m_2.$$

$$\max_{\gamma} e_1^T \gamma - \frac{1}{2} \gamma^T U (V^T V + \epsilon 1)^{-1} U^T \gamma$$
$$s.t. 0 \le \gamma_i \le c_2, i = 1, \dots m_1,$$

b)For Nonlinear TELM, Construct Convex QPPs

$$\max_{\alpha} e_2^T \alpha - \frac{1}{2} \alpha^T S (R^T R + \epsilon 1)^{-1} S^T \alpha$$
$$s.t. 0 \le \alpha_i \le c_1, i = 1, \dots m_2.$$

$$\max_{\gamma} \begin{array}{c} e_1^T\gamma - \frac{1}{2}\gamma^T R(S^T S + \epsilon 1)^{-1} R^T \gamma \\ s.t. 0 \leq \gamma_i \leq c_2, i = 1, 2 \ldots m_1 \end{array}$$

Step 4: Obtain Lagrange multipliers α and γ by solving two QPPs.

Step 5:

a) For Linear TELM, Calculate the Output Weights β1 and β2 using

$\beta_1 = -(U^T U + \in I)^{-1} V^T \alpha, \beta_2 = -(V^T V + \in I)^{-1} U^T \gamma.$

b)For Nonlinear TELM, Calculate the Output Weights µ1 and µ2 using

$\mu_1 = -(R^T R + \in I)^{-1} S\alpha, \mu_2 = -(S^T S + \epsilon I)^{-1} R^T \gamma.$

Step 6: Calculate the perpendicular distance of data point x from the separating hyperplane using this equation,

$$f(x) = \arg\min_{r=1,2} d_r(x) = \arg\min_{r=1,2} |\beta_r^T h(x)|,$$

Then assign the x to class *i(i*= +1, −1).

IV. EXPERIMENTALRESULTS

This work is evaluated based on the performance measures parameters, accuracy, precision, and recall. The confusion matrix of movie dataset and Twitter dataset for TELM, ELM and TSVM were made. Using this dataset values accuracy, precision and recall were calculated and compared with each other.

Here the Polarity movie review dataset is used [5]. A separate text file is maintained for each review. The Twitter dataset is also taken to show the effect of the proposed method on a different dataset. The Twitter dataset is taken from Twitter API [5].

Table1: Confusion Matrix

	Positive	Negative
Positive	True Positive (TP)	False Positive (FP)
Negative	False Negative (FN)	True Negative (TN)

Accuracy: Accuracy is computed as "the total number of two correct predictions, the True Positive (TP) + True Negative (TN) divided by the total number of a dataset Positive (P) + Negative (N)".

Accuracy = (TP+TN) / (TP+TN+FN+FP)

Precision: Precision is computed as "the number of correct positive predictions (TP) divided by the total number of positive predictions (TP + FP)". Precision is also known as a positive predictive value.

Precision = TP/(TP+FP)

Recall: Recall is computed as "the number of correct positive predictions (TP) divided by the total number of positives (P)". The recall is also known as the true positive rate or sensitivity.

Recall = TP/P

Table 2 and 3 shows the confusion matrix for the small movie and twitter dataset after implementing the TSVM algorithm.

Table 2: Confusion Matrix for Movie Dataset

	Correct Labels	
	Positive	**Negative**
Positive	5236	0
Negative	1564	0

Table 3: Confusion Matrix for Twitter Dataset

	Correct Labels	
	Positive	**Negative**
Positive	3210	0
Negative	950	0

Table 4 and 5 shows the confusion matrix for the small movie and twitter dataset after implementing ELM algorithm.

Table 4: Confusion Matrix for Movie Dataset

	Correct Labels	
	Positive	**Negative**
Positive	5687	34
Negative	1745	16

Table 5: Confusion Matrix for Twitter Dataset

	Correct Labels	
	Positive	**Negative**
Positive	2897	45
Negative	876	36

Table 6 and 7 shows the confusion matrix for the small movie and twitter dataset after implementing the TELM algorithm.

Table 6: Confusion Matrix for Movie Dataset

	Correct Labels	
	Positive	**Negative**
Positive	5489	0
Negative	1765	0

Table 7: Confusion Matrix for Twitter Dataset

	Correct Labels	
	Positive	**Negative**
Positive	2574	26
Negative	879	76

A. Graphical Representation

This section represents the comparison of proposed TELM, ELM, and TSVM. Table 8 shows that TELM has good accuracy, precision, and recall than others.

Table 8: Comparison of TELM, ELM, and TSVM

Dataset	TELM			ELM			TSVM		
	Accuracy	Precision	Recall	Accuracy	Precision	Recall	Accuracy	Precision	Recall
Movie	79.87	84.56	83.37	77.33	79.44	78.12	76.68	78.27	77.65
Twitter	78.65	83.76	82.54	76.82	76.45	76.42	75.56	75.83	73.81

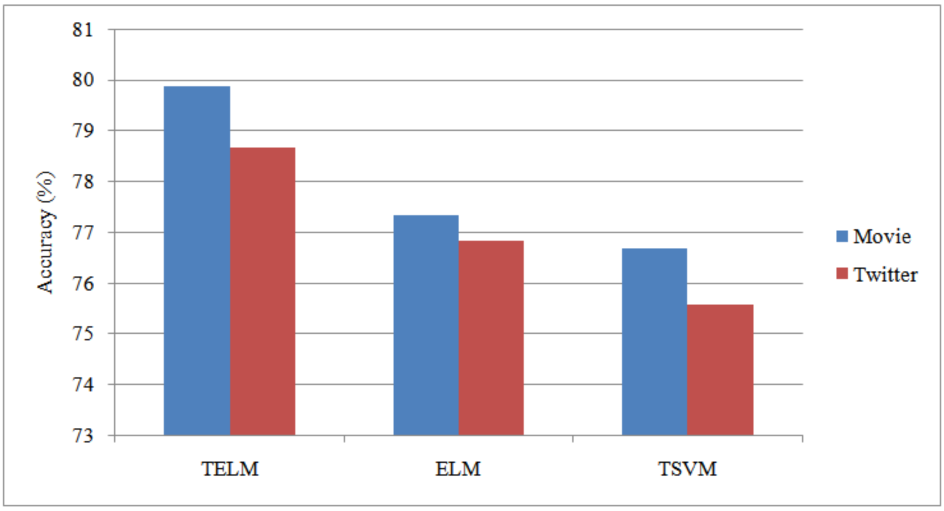

Figure 1: Accuracy Comparison

By using the confusion matrix, accuracy of TELM, ELM and TSVM were calculated for both movie and Twitter. The comparison of accuracy for TELM, ELM and TSVM are plotted in the chart. Above Fig.1 shows that TELM has the accuracy of 79.87% for the movie and 78.65% for Twitter whereas ELM has 77.33% for the movie and 76.82% for Twitter and TSVM has 76.68% for the movie and 75.56% for Twitter. Hence it is proved that TELM has good accuracy than others.

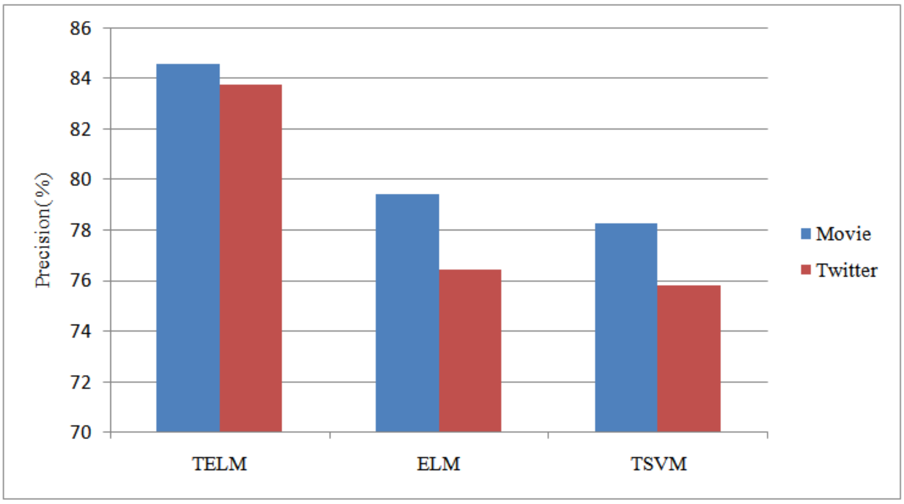

Figure 2: Precision Comparison

By using the confusion matrix, precision of TELM, ELM, and TSVM was calculated for both movie and twitter. The comparison of precision for TELM, ELM and TSVM are plotted in the chart. Above Fig.2 shows that TELM has the precision of 84.56% for the movie and 83.76% for Twitter whereas ELM has 79.44% for the movie and 76.45% for Twitter and TSVM has 78.27% for the movie and 75.83% for Twitter. Hence it is proved that TELM has better precision than others.

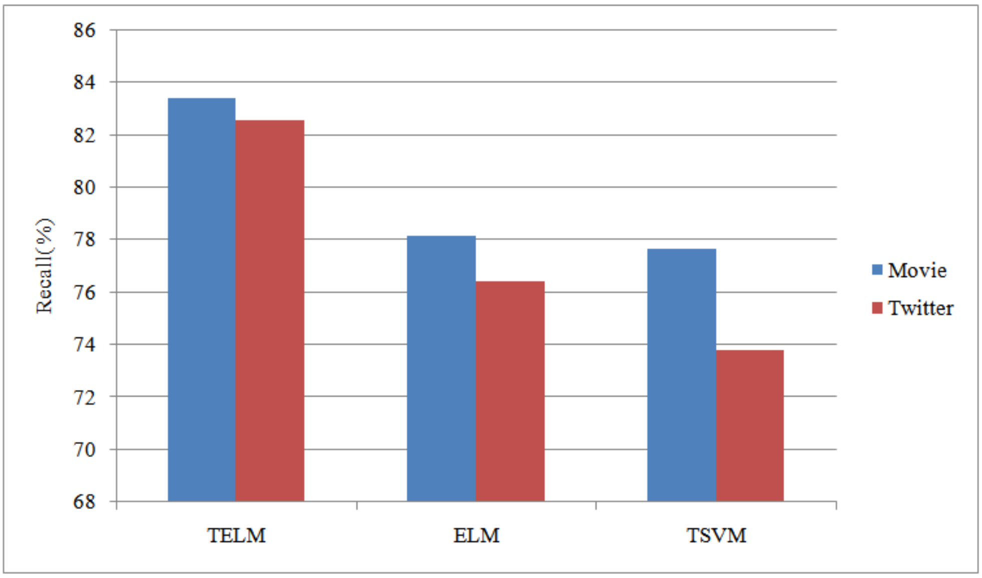

Figure 3: Recall Comparison

By using the confusion matrix, recall of TELM, ELM and TSVM were calculated for both movie and Twitter. The comparison of recall for TELM, ELM and TSVM are plotted in the chart. Above Fig.3 shows that TELM has the recall of 83.37% for the movie and 82.54% for Twitter whereas ELM has 78.12% for the movie and 76.42% for Twitter and TSVM has 77.65% for the movie and 73.81% for Twitter. Hence, it is proved that TELM has good recall than others.

CONCLUSIONS

This work deals with a new technique for sentimental analysis. Twin Extreme Learning Machines (TELM) is used here for the sentimental analysis. Due to the TELM incorporates the idea of Twin Support Vector Machine (TSVM) into the basic framework of ELM, so TELM could have the advantages of both algorithms. Here the datasets were made for movie and Twitter. Datasets were made with the help of a confusion matrix. Finally, accuracy, precision, and recall of TELM, ELM and TSVM are calculated using the confusion matrix and also compared. The result shows that TELM has good performance with better accuracy, precision, and recall than other techniques like TSVM and ELM. In Future, this technique will be implemented on sentimental analysis for industrial marketing.

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