Journal of Theoretical and Applied Information Technology
10th November 2014. Vol. 69 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

TWITTER SENTIMENT MINING (TSM) FRAMEWORK BASED LEARNERS EMOTIONAL STATE CLASSIFICATION AND VISUALIZATION FOR E-LEARNING SYSTEM

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ABSTRACT

E-learning is becoming the most influential and well-liked standard for learning through web based education. It is very important to categorize the online feedback of the learners emotion in e-learning system. Learning usually refers to teaching skills propagated with the help of computers to communicate knowledge in a web based classroom environment. It is very difficult to identify the learner's emotional state whether they are satisfied with the online courses. The twitter sentiment mining framework helps to find about the learners who are frequently interacting with the e-learning environment. Twitter has become the most popular micro-blogging area recently. Millions of users frequently share their opinion on the blogs. Twitter is referred as a right source of information to perform sentiment mining. This research presents a new method for sentiment mining in twitter based messages written by learners, initially helps to extract information about learners sentiment polarity (negative, positive), and to model the learners sentiment polarity to identify the change in their emotions. A model has been constructed from the training data of the sentimental behaviors of the e-learners using Naïve Bayesian approach. The model constructed has been tested through the test data during the prediction process of discovering the emotional states of e-learner. The results were compared against the other famous classification algorithms like support vector machines and maxentropy techniques. This information can be effectively used by e-learning system, by considering the learners' emotional state when recommending learner's the most appropriate activity each time. The learner's sentiment, emotional state towards the online course can provide feedback for e-learning systems. The experimental outcome show that our proposed research work outperforms recent supervised machine learning algorithms on accuracy findings of learner's emotional state classification.

Keywords: *e-learning, sentiment analysis, classification, visualization,*

1. INTRODUCTION

The technology enhanced E-learning systems have recorded a fast growth in the last decade. The E-learning systems are helpful to learners. The use of computers in education has meant a great contribution for students and teachers. The incorporation of adaptation methods and techniques allows the development of adaptive elearning systems, where each learner receives personalized guidance during the learning process (1). In order to provide personalized e-learning system, it is necessary to store information about each learner in the model (2). The exact information to be stored depends on the goals of the e-learning system (e.g., learning styles, emotional state, user preference, various actions and so on). In specific, emotional factors, among other aspects, appear to change the learner motivation and, in general, the learning process outcome (3).Therefore, in learning environment, being able to identify and manage learners emotion at a certain time can make us know their possible needs at that time. On one hand, adaptive e-learning systems can make use of this information to accomplish those needs dynamically at runtime: they can provide the user with content recommendations about activities based on the emotional state of the user at that time. On the other hand, information about the learner emotions can act as feedback for the teacher. This is particularly useful mechanical for online courses get feedback from the learners. With more than 190 million online users and more than 65 million message postings per day, Twitter is the most well-known micro-blogging service available on the Web.

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People post short tweets about their daily activities on Twitter and recently many researchers investigate possibility of real time applications such as trend analysis (4) or Twitter-based timely caution systems (5). Usually, sentiment analysis can be categorized into three tasks: informative text detection, information extraction and sentiment interestingness classification (emotional, polarity identification). This paper addresses the third issue - sentiment classification. Sentiment classification (e.g., negative or positive) plan to predict the sentiment polarity based on the users' sentiment data (e.g., blogs, reviews) (15). There has been a huge amount of study in the area of supervised sentiment classification. Traditionally, most of the study has primarily focused on categorizing larger pieces of text (reviews) (6). Tweets differ from reviews primarily because of their function: while tweets are sending message they are restricted to maximum of 140 characters length, reviews are summarized the opinion of the authors. There has been some investigation by researchers in the area of sentence level sentiment classification recently (7). Linguistic search sets of seed words were used. The results obtained in those works served as the basis for document classification, considering that the word's semantic orientation is an indicator of whether the text is negative or positive (11).(19) Defined that real time social media messages are categorized into three groups; informative, transformative and persuasive. The tweet data is collected (65 music bands) where each tweet was class labelled by humans. The authors do not explain if there was any checking process performed to reach a good set of judgments. The results show that the proposed method is effective for the 'informative' category only. Sentiment Classification methods can be categorized into the lexicon based machine learning technique (18). Machine learning approaches are applicable to opinion mining, mostly belongs to supervised classification (8). One major difficulty of the text opinion classification problem is the high dimensionality of the features used to describe texts. The aim of feature selection methods is to obtain a reduction of the original feature set by removing some features that are considered irrelevant for text opinion classification to yield an improved classification accuracy of learning algorithms (9)(10). In e-learning systems, it is useful to have information about the user's sentiments. User's sentiment information can be effectively used by e-learning systems to maintain modified learning, by considering the user's sentiment when recommending him/her the most appropriate activities to be tackled at each time. The students' sentiments towards a particular subject can supply necessary feedback for users, especially in the case of web based learning environment, where face-to-face contact is very less frequent. The effectiveness of this work in the e-learning context, both for users and for adaptive systems (20).Working with various noisy labels (12), by creating, for example, emoticon vocabularies for representing sentiment and for training supervised sentiment classifiers, such as Naïve Bayes (NB), Maximum Entropy (MaxEnt) and Support Vector Machines (SVMs) (13)(14). In general, document can be divided into extractive summarization and abstractive reducing documents. Now a day's tag clouds have become very popular on the web. They allow the graph representation of entire websites in a compact way, through a set of tags whose color or size reacts their frequency of use (16). Tag cloud visualization in R an in-depth description of the modern text mining area offered by tm package and word cloud (17).

2. METHODOLOGY

Twitter has evolved to become a source of collection of rich and heterogeneous information. The users upload and post opinions on various contents, discussion about various issues, and express interestingness. In fact, companies manufacturing such products have started to poll these tweets to get a sense of general sentiment for their product. Many times these companies study user reactions and reply to users on twitter. However, the hugeness of information analysis is very difficult. Therefore, it is necessary to analyze the twitter data based on emotional state. In order to complete the analysis task, there is a vast require classifying and visualizing the twitters various emotional states.

The main contributions of this paper can be summarized as follows:

- We present a novel method to collect various learners twitter messages through API streaming using query string.
- We perform dataset preprocessing for sentiment analysis of the collected twitter messages corpus. This involves various intermediate operations remove retweet entities, remove at people, remove punctuation, remove numbers, remove html links, remove unnecessary spaces, tolower error handling, remove NA's.

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- We use the preprocessed dataset to build a learner's emotional state classification for e-learning systems.
- We conduct experiments on a collection of learners twitter posts to prove that our classifier technique is more efficient than the previously proposed method.

3. GENERAL ARCHITECTURE OF THE PROPOSED SYSTEM

The research application presented show a twitter sentiment mining based learner's emotional state classification and comparison cloud generation of learning systems. This information can be used by e-learning system, by considering the learners' emotional state when recommending learner's the most appropriate activity each time. The learner's sentiment emotional state towards the course can provide feedback message for e-learning systems. The general proposed architecture is presented in Fig 1. Give a learners twitter data input, a number of steps followed by the learners emotional state classification and visualization. The first step is the learners' twitter data acquisition. Dataset preprocessing for sentiment analysis represents the second step. At this stage twitter data cleaning methods can be applied to the twitter messages such as removal of retweet entities, removal at people, remove punctuation, remove numbers, remove html links, remove unnecessary spaces, tolower error handling, remove NA's. The next step is to perform learners' emotional state based classification and emotion comparison cloud generation. The last stage is to represent the test's precision, recall accuracy of classified sentiment on the database.

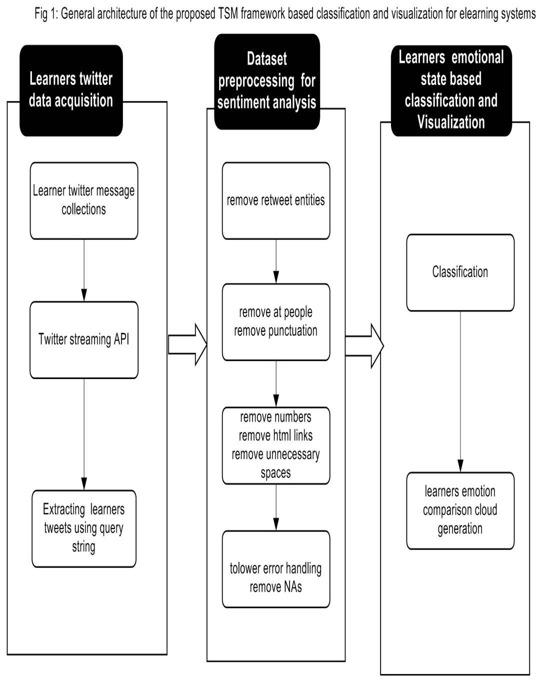

Fig 1: General architecture of the proposed TSM framework based learner's emotional state classification and visualization

4. LEARNER'S TWITTER DATA ACQUISITION

The fundamental purpose of learners twitter data acquisition layer is to collect the Twitter messages with various sparse parameters. The Twitter streaming API allows real time access to publicly available data on OSN. The learner's tweets supply as input to dataset preprocessing for sentiment analysis.

5. DATASET PRE-PROCESSING STEPS FOR SENTIMENT ANALYSIS

The dataset pre-processing involves performing intensive processing steps at each tweet separately, then they separated and well developed tweet passes to the classifier. This consists of subsequent steps: remove retweet entities, remove at people, remove punctuation, remove numbers, remove html links, remove unnecessary spaces, tolower error handling, remove NA's.

6. PROPOSED EMOTIONAL STATE CLASSIFICATION AND VISUALIZATION ALGORITHM AND EVALUATION PROCEDURE

Methods to mining sentiments from the twitter preprocessed documents can be categorized into supervised and unsupervised learning

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

approaches. Supervised techniques are those that make use of labeled data. Lexicon-based twitter sentiment mining classification is perhaps the technique for measuring the polarity of the sentiment of a collection of documents. Lexicon-based sentiment measurement requires a dictionary of words and each word's associated sentiment polarity score.

6.1 Naïve Bayes Classifier

Naive Bayes supervised classifier method involves a training dataset of twitter documents that have already been scored as having negative or positive sentiment; a statistical approach based on these forms the basis of scoring further documents.

To train Naïve Bayes classifier to be ableSu to differentiate documents featuring positive sentiment from those featuring negative sentiment.To do so, we supply the algorithm a preprocessed documents that are already labeled as containing positive or negative sentiments about a particular twitter message. Then, if all goes as planned, we can pass new documents to the model and have it predict the direction of their sentiment. The Naive Bayes classifier is fast, thus allowing us to use huge training sets to train a model and to generate output quickly.

Naïve Bayes supervised classification algorithm works well on the text document classification. We used Naïve Bayes multinomial model. Class A* is assigned to tweet t, where f represent feature.

$A^*=\arg\max P_{NB}(A|t)$

$$P_{NB}(A|t)=(P(A)\sum_{i=1}^{n} P(f\mid A)^{m_i(t)})/P(t) \qquad (1)$$

$m_i(t)$ represents the count of features f_i found in tweet t. Total number of features is n.P(A) and P(f|A) are obtained through maximum likelihood estimation.

6.2 Maximum Entropy classifier

Maximum Entropy is a general-purpose machine learning method that provides the least biased estimate possible based on the given document information. MaxEnt models are feature-based models.. MaxEnt makes no independence assumptions for its features, unlike Naive Bayes. This means we can add features like bigrams and phrases to MaxEnt without disturbing about features overlapping The model is represented as follows

$$P_{ME}(A|t)=\exp([\sum_i \lambda_i f_i(A,t)])/\sum_{A'}\exp[\sum_i \lambda_i f_i(A,t)] \qquad (2)$$

Where A is a class, t is the tweet, is a weight vector. The weight vectors present in the formula decides the significance of a feature of classification. The weight vector is used for optimization of the lambdas in order to maximize the conditional probability.

6.3 Support Vector Machines (SVM) classifier

Support vector machines is the another standard supervised classification technique. SVM generates non-overlapping partitions that employs to all the features. SVMs are based on max margin linear discriminant probabilistic approach. A supervised classification task usually involves training documents and test datasets. Every instance, in the training document set contains one target class label and several parameters. The main objective of the classifier is to build a model able to predict target values of information instances in the testing set, for which only the known parameters.

6.4 Visualization

The generation of the learner's emotion comparison cloud is performed using a R package.. The emotion cloud simply visualizes the most applicable and frequent sentiment terms present in the twitter document. The comparison cloud algorithm shows the terms with a font size proportional to the term weight. Words are set in decreasing order of weight. Each word is located randomly near the center of the cloud image. If a word intersects occurs, then it is simply moved one step advance in an ever-increasing spiral until is placed right location. The tag cloud generation algorithm also assigns colors randomly to the weight of the word. For low term frequencies one can state font sizes directly, from one to whatever the highest font size. For higher values, a suitable scaling transformation should be applied.

7. EXPERIMENTS AND RESULTS

Moreover, the behaviors of the twitter users have been collected from the twitter

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

application using twitter streaming API. In this paper, we have used publicly available standard twitter dataset of 180 tweets. Various cleaning processes were applied to the collected dataset for the purpose of remove retweet entities, remove at people, remove punctuation, remove numbers, remove html links, remove unnecessary spaces, tolower error handling, and remove NA's. Then Naive Bayes classifier was applied to classify the tweet. This process ensures that a set of good judgments are available for testing the classifier performance. Confusion matrices, precision, recall, F-measure and accuracy are used for evaluation of the proposed framework and comparison with other techniques. The confusion matrix of Naïve Bayes classifier is shown in Table I as the accuracy level of the classifier is 0.5.In order to compare this accuracy level with other standard machine learning approaches ,we have used the container mechanism to represent the training and testing set of the dataset. The generated container has been used for separately in other classifiers named SVM and MAXENTROPY. While observing the outcome of all such classifier, it has been predicted that the SVM and MAXENTROPY performs well and its accuracy is 0.95 as shown in the Table II..The evaluation results of learner's emotional categories histogram are shown in Fig 2. The learner's emotions comparison cloud is shown in Fig 3. The precision, recall graph of SVM is graphically presented in Fig 4. The precision, recall graph of MAXENTROPY is graphically shown in fig 5.

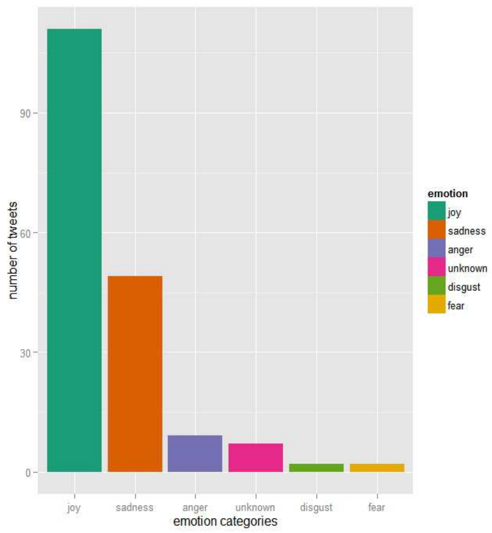

Fig 2: Learner's emotion categories histogram

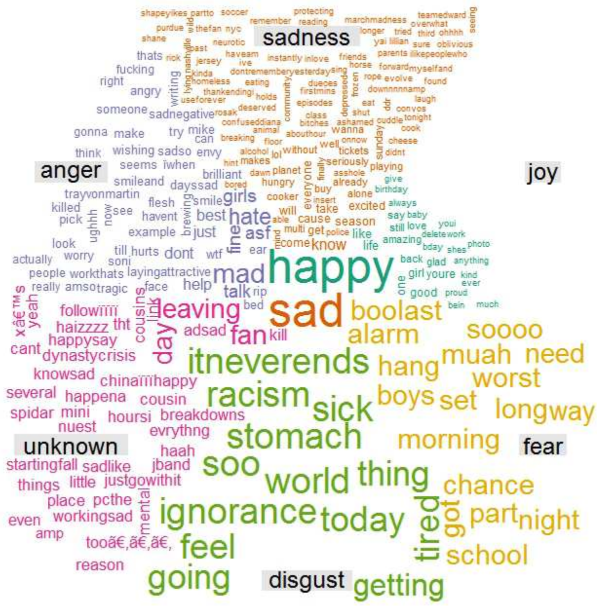

Fig 3: Learner's emotion comparison cloud

Table 1: Confusion matrix of naïve bayes classifier accuracy:0.5

Predicted emotion	Happy	Sad
Happy	10	0
Sad	10	0

Table 2: Algorithm performance

	PRECISION	RECALL	F-SCORE
SVM	0.955	0.95	0.95
MAXENTROPY	0.948	0.95	0.95

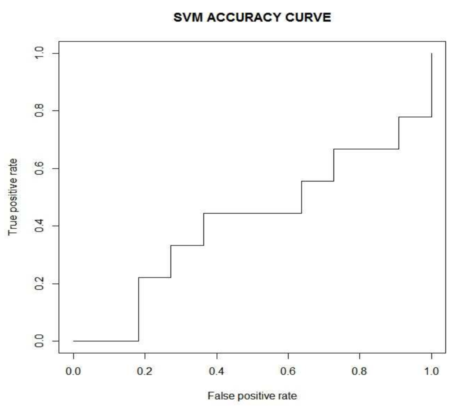

Fig 4: SVM accuracy curve

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

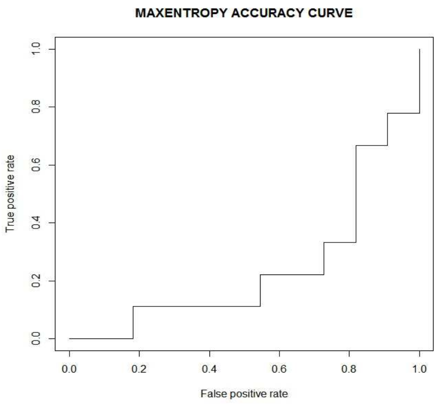

Fig 5: MAXENTROPY accuracy curve

8. CONCLUSIONS AND FUTURE WORK

The research work described in this paper demonstrates that it is viable to extract necessary information about the learner's sentiments from the messages they write on twitter. We have presented a novel method for twitter sentiment mining framework based learner's emotional state classification and visualization for Elearning systems. It mainly supports to retrieve information about the learners sentiment polarity (negative, neutral and positive) according to the messages they write and on the other hand, to model the learners regular sentiment polarity and to identify significant emotional state changes. The supervised classification technique implemented in TSM framework follows a lexicon based and machine learning approach. Our classifier is able to determine and visualize joy, fear, anger, sadness, and unknown emotional state of tweet documents. This can be considered as input for e-learning systems to provide learners emotional state based activity recommendation. When we are conducting experiments on the selected data set, it has been observed that the model SVM and MAXENTROPY are comparatively good by its average f-score is 0.95.We have formed machine learning classifier to improve the accuracy and performance of the learner's twitter messages. As the future work, we plan to classify twitter data with different native languages.

REFERENCES:

[1] Brusilovsky, P. (2001). Adaptive hypermedia. User Modeling and User-Adapted Interaction, 11(1/2), 87–110.

[2] Kobsa, A. (2007). Generic user modeling systems. The adaptive web: Methods and strategies of web personalization. Lecture notes in computer science (Vol. 4321, pp. 136–154). Springer.

[3] Shen, L., Wang, M., & Shen, R. (2012). Affective e-learning: Using ''Emotional'' data to improve learning in pervasive learning environment. Educational Technology & Society, 2, 176–189.

[4] Lerman, K., Ghosh, R.: Information contagion: an empirical study of spread of news on Digg and Twitter social networks. In: Proc. of 4th Int. Conf. on Weblogs and Social Media (ICWSM), AAAI Press (2010).

[5] Sakaki, T., Okazaki, M., Matsuo, Y.: Earthquake shakes Twitter users: real-time event detection by social sensors. In: Proc. of 19th Int. Conf. on World Wide Web (WWW), ACM (2010) .

[6] B. Pang, L. Lee, and S. Vaithyanathan. Thumbs up? Sentiment classi¯cation using machine learning techniques. In Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 79{86, 2002.

[7] T. Wilson, J. Wiebe, and P. Ho®mann. Recognizing contextual polarity in phrase-level sentiment analysis. In Proceedings of Human Language Technologies Conference/Conference on Empirical Methods in Natural Language Processing (HLT/EMNLP 2005), Vancouver, CA, 2005.

[8] H. Chen, Intelligence and security informatics: information systems perspective, Decis. Support Syst. 41 (3) (2006).

[9] A. Abbasi, S. France, Z. Zhang, H. Chen, Selecting attributes for sentiment classification using feature relation networks, IEEE Trans. Knowledge Data Eng. 23 (2011) 447–462.

[10] T. O'Keefe, I. Koprinska, Feature selection and weighting methods in sentiment analysis, in: Proceedings of the Australasian Document Computing Symposium, 2009, pp. 67–74.

[11] Turney, P. (2002). Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews. In Proceedings of the Association for Computational Linguistics (ACL) (pp. 417–424).

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[12] Read, J. (2005). Using emoticons to reduce dependency in machine learning techniques for sentiment classification. In Proceedings of the ACL-05, 43nd meeting of the association for computational linguistics. Association for Computational Linguistics.

[13] Barbosa, L., & Feng, J. (2010). Robust sentiment detection on twitter from biased and noisy data. In Proceedings of the 23rd international conference on computational linguistics: Posters (COLING '10) (pp. 36–44). Stroudsburg, PA, USA: Association for Computational Linguistics.

[14] Pak, A., & Paroubek, P. (2010). Twitter as a corpus for sentiment analysis and opinion mining. In Proceedings of the 7th international conference language resources and evaluation (LREC '10). European Language Resources Association ELRA.

[15] Pan S J, Ni X, Sun J T, et al. Cross-domain sentiment classification via spectral feature alignment.Proceedings of WWW,2010:751-760.

[16] F.B. Viegas, M. Wattenberg. Tag Clouds and the Case for Vernacular Visual- ization. ACM Interactions, 15(4), p. 49-52, 2008.

[17] Feinerer. An introduction to text mining in R. R News, 8(2):19{22, Oct. 2008. URL http://CRAN.R-project.org/doc/Rnews/

[18] Diana Maynard, Adam Funk. Automatic detection of political opinions in tweets. In: Proceedings of the 8th international conference on the semantic web, ESWC'11; 2011. p. 88–99.

[19] R. Machedon, W. Rand, Y. Joshi, Automatic Classification of Social Media Messaging using Multi-Dimensional Sentiment Analysis and Crowdsourcing, 2013, 2013. http://dx.doi.org/10.2139/ssrn.2244353 (Available at SSRN: http://ssrn.com/ abstract=2244353).

[20] Alvaro Ortigosa, José M. Martín, Rosa M. Carro. Sentiment analysis in Facebook and its application to e-learning.Computers in Human Behavior 31 (2014) 527–541.