THE POSSIBILITY OF STUDENTS' COMMENTS AUTOMATIC INTERPRET USING LEXICON BASED SENTIMENT ANALYSIS TO TEACHER EVALUATION

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ABSTRACT

This paper aims to investigate the possibility of the qualitative analysis of students' freestyle text comments using lexicon based sentiment analysis to predict teacher performance. The students' feedbacks from RateMyProfessors.com were collected for the experimental. We employ a qualitative measuring using lexicon based sentiment analysis to automatic interpret sentiment word and determine the overall polarity of one document in students' comment into positive and negative classes. A comparison between sentiment score and numerical response ratings of teacher evaluation aspects were analyzed and plotted into graphs in order to compare the relationship between each pair of two variables. Particularly, we investigate and elaborate these visual correlation results through the statistical techniques using Pearson's correlation and Spearman's rank. The initial results of the qualitative measuring using sentiment analysis are relative to enhance teacher performance evaluation using quantitative measuring. In order to gain additional insight into more teacher evaluation aspects from students' comments, aspect based sentiment analysis using a large scale dataset is recommended.

Keywords: *Sentiment Analysis, Teacher Evaluation, Students' comment, Correlation Analysis.*

1. Introduction

Teacher evaluation is a common method to evaluate the teaching process quality. It is generally accepted that teacher evaluation from the student opinions is an important part of teaching practice. In higher education, it has been the most widely used in most colleges and universities. Additionally, this method continues to be the most frequently used for testing teacher's teaching performance and course (Samian and Noor, 2012).

In generally, the questionnaire has been used as the instrument for data collection. The answers of student evaluation consist of quantitative and qualitative data collected by two question types; the quantitative data was collected by close-ended questions as multiple choices and the qualitative data was collected by open-ended questions as comments and suggestions from student opinions in textual form. It is easy to analyze quantitative data in numerical rating scale by statistical techniques, but it is difficult to interpret the qualitative data from the students' comments. Most researchers on teacher evaluation focused to quantitative data but ignored qualitative data. However, the personal answers from open-ended questions contain the sentences or phrases regarding teacher commented. These student comments can answer the question "*What has happened in the classroom after teaching from the students' perspective*" and give feedback to the teacher for improving their teaching. Therefore, the processing of qualitative data analysis is very importance and can enhance the teacher evaluation effectiveness (Pong-inwong and Rungworawut, 2012).

In order to analyze the students' expressions from their comments, the lecturer can employ a very basic traditional method by read all comments and make a list of characteristics that can encourage to effective teaching. Then mark negative comments with the minus sign (-) and positive with the plus sign (+). Finally, the lecturer can see the actual number of the most written comments. One of a study that performed this method is the work of Samian and Noor (2012) the authors marked positive and negative students' comments in order to categorized student's perception on the lecturers. However, it may take extensive times to employ this manual tally with a huge data of student comments. The problem is *"How to interpreter unstructured textual responses from the students' feedbacks automatically"*.

In past recent years, there are many scholars who have been studying opinions in the textual information described that opinions are subjective expression that describe people's sentiment, appraisal or feeling toward entity, event and their property. Opinions are a personal point of views to represent an idea, belief, assessment, judgment or evaluation about something. Opinions provide a great impact to human beings for making correct decisions in every such level individuals, organizations, social communities and government. Recently, the internet offers a rich source of public opinions like blogs, discussion forums, e-commerce and etc. which the individual users generated plenty amount of contents include the user feedbacks and reviews. However, the users could not use those opinion resources for knowledge representation directly because of the web data is usually unstructured text and impossible to manually processed a huge volume data. While human being needs fast, accurate and summarized information for quick and right decision making. It is complicated for a human to read, find relevant sources, extract related sentences with opinions, summarize and organize opinion in textual forms into usable forms. Therefore, automated discovery hidden opinion and summarized them are needed. Hence, efficient tools and potential techniques for extract and summarize people's opinions from all these online resources are needed. To deal with this problem a study of sentiment analysis or opinion mining was grew up (Liu, 2012; Liu, 2010). Sentiment analysis techniques have been extensively used in the evaluation of products, services, political and etc. (Vu et al., 2011; Mullen and Malouf, 2006; Zhuang et al., 2006). However, there is a few research have been applied to teacher evaluation.

Regarding customer feedbacks evaluation, these unstructured textual comments are very complex and the evaluation of a large volume of comment is a difficult task. Therefore, an automated textual analysis is required; sentiment analysis is applied to classify customer feeling and opinion about particular product expressed by the customer in their comments (Dalal and Zaveri, 2014). This problem is similar to teacher evaluation; the interpretation of qualitative data from a large volume of students' comment is a difficult task. To address this problem sentiment analysis comes to perform effective automated textual analysis method for enhancing teacher evaluation. For example in a study of Altrabsheh, Cocea and Fallahkhair (2014), the authors examined a scenario of one lecturer who applied their system to learn the sentiment from students' comments before move to the next part of his lecture. The system extracted the sentiment words and provided the visualization of positive, negative and neutral sentiment. When he saw the different proportions of the sentiment he found the frequent words with the negative polarity such as 'complicated', 'confused', 'example' and 'lost' with 60 percentages of negative feedback, 30 percentages of neutral feedback and 10 percentages of the positive feedback. The result presented that 60 percent of the class did not clear in this part. Then he decided to repeat a part in a different way.

It is clearly that sentiment analysis can improve teacher evaluation by saving time in analysing students' comments, the lecturer can change their teaching style after finding out students opinions over time periods or repeat a part that most students did not clear (Altrabsheh et al., 2014) In order to analyse large volumes of unstructured textual data generated by the evaluation of the students it is necessary to have an effective method to extract hidden knowledge of words from students' comments in a systematic and consistent. Therefore, the theme of this paper is to investigate the possibility of the qualitative analysis of students' comments to predict teacher performance. We focus to the development of automated textual analysis system from the students' comments using lexicon based sentiment analysis approach and compare a correlation between quantitative and qualitative data analysis in order to proof a concept that demonstrate the need for enhance teacher performance evaluation.

The contents of this paper are structured as follows: Literature reviews were discussed in related work. In addition, next section described proposed methods, results and discussions and the last section is the conclusion of this study and gives a recommendation for future works.

2. Related Work

2.1. Sentiment Analysis

Sentiment analysis or opinion mining was defined in Liu (2010) as the field of computational about opinions, sentiments and emotions expressed in text. The target of opinion mining is to extract evaluation information (called opinion) from subjective text automatically. It is a highly challenge problem in natural language processing (NLP) and text mining. It is also one of a popular research area in recent years (Liu, 2012; Pang and Lee, 2008). Previous researchers study the techniques that are used to find people's opinion on certain products, services, event and occasions. Sentiment analysis has been treated as a text classification problem. In this area, in order to respond the differential of user requirements several fields have emerged such as subjectivity classification, sentiment classification and opinion summarization. The goal of this field is to help the users to classify the various accessibility of opinions from the reviews and easily to understand. This knowledge will give a good reference resource for guaranteeing a decision making in various objectives.

2.2. Sentiment Analysis in Education

In educational domain, sentiment analysis is implemented in order to explore the hidden knowledge and the answers relevant to student opinion from open-ended questions in the evaluation process. Most scholars focused to quantitative data analysis. However, some works have been done on qualitative data using sentiment analysis, we found six related works that mentioned this idea.

First, El-Halees (2011) study feature opinion mining in educational data for course improvement. In this study, frequent features were extracted by WhatMatter System. Naïve bays classifier was used to classify opinion polarity. This study presents the usefulness of user- generated content to improve course performance. Second, Rashid (2013) applies two sequential pattern algorithms GSP and Apriori to extract the commented frequent features and opinion words from students' feedback dataset on a sentence level. However, this study only considers the effective technique to extracting Noun and Adjective. The experiment results show that GSP is 6% more efficient for frequent features and 2.03% for opinion word as compared to Apriori. This system was not compared with the other study.

In another study, Jagtap and Dhotre (2014) discussed the idea of effective method of automated sentiment analysis from teacher feedback assessment using HMM and SVM base hybrid sentiment classification model. There are no experiment results in this work, the authors only discussed and demonstrated the effective method for teacher feedback assessment. According to Bharathisindhu and Brunda (2014) proposed the idea of automated sentiment analysis in E-learning system to identify the sentiment of the users from the E-portal pages in which users generally browse on a topic or area they are interested. This information useful for the developer and educator to know where the learner concentrating on specified areas with any feedbacks from the user. In this work, the authors only discussed the idea of using sentiment analysis technique in E-learning.

On the other hand, Wen, Yang, and Rosé (2014) applied sentiment analysis using the lexicon recourse of product reviews in order to study the student drop out in Massive Open Online Course (MOOC), the result was visualized in a graph. This work has some limitation. The lexicon recourse of product reviews was utilized to predict the sentiment polarity. The construction of specific lexicon recourse for MOOC context could improve the system. In Ortigosa, Martín and Carro (2014) proposed other sentiment analysis approach in Facebook using a combined method of Spanish lexical based and machine learning techniques and showing the results to the users through an interactive interface. The results obtained through this approach show that it is possible to perform sentiment analysis in Facebook with high accuracy (83.27%). In the context of e-learning, it is possible to extract information about the student's sentiments from the messages they write in Facebook, the students' sentiments towards a course can serve as feedback for teachers, especially in the case of online learning. However, this work still has the limitation of the sentiment analysis, all the words tagged as the same polarity get the same score, all positive words get the score = 1, all negative words get the score = -1 and all neutral words get the score = 0. They did not assign different weights to different words. In order to enhance the efficiency of sentiment analysis, the authors discussed the opportunities and challenges to applying a fine-grained classification.

Similar to Pong-inwong and Rungworawut (2014) proposed the construction of their own sentiment lexicon for an automated sentiment orientation polarity definition in teaching evaluation. The experimented model employed SVM, ID3 and Naïve Bayes algorithms, which were implemented in order to analyze sentiment classifications with a 97% highest accuracy of SVM. In this work, the weight score of terms was defined by an expert. The sentiment weight was ranged from -1.00 to 1.00. This proposed method can address the problem in the previous works, but it was constructed in Thai language.

As mention above it is possible to perform sentiment analysis in students' textual feedback. The application of sentiment analysis in students' comment was used in various objectives; teaching evaluation, course-online evaluation and teacher evaluation. The target of automatic sentiment analysis is improving the better accuracy result of sentiment classification and summarization. However, current works considered the sentiment classification into binary classes; positive and negative. None of the methods above considered the degree of student's opinion.

3. Proposed Method

3.1. Data Gathering and Aggregation

In this paper, we designed the experimental by gathered 1,148 students' feedbacks of 30 teachers from RateMyProfessors.com using multi-stages sampling. Inside RateMyProfessors.com there are three quantitative indicators; e.g., Helpfulness, Clarity and Easiness were defined as Likert scale (on a scale of 1-5) to represented teacher characteristic in each course. However, only two attributes related to teacher evaluation aspects were Helpfulness and Clarity. For each teacher, the overall rating was computed from the average of these two quantitative attributes ratings. While Easiness rating represents course evaluation. Furthermore, RateMyProfessors.com provided a list of students' comments of each teacher. The student can check the teacher overall rating and read a list of other students' comments and make a decision for their own register. In this experiment, we able to gathered both quantitative and qualitative data of students' feedbacks from the same user.

3.2. Preparing Students' comments Corpus

From the previous stage after students' comments was gathered to achieve text analysis in a collection of students' comments. We applied R programming and tm package (Feinerer and Hornik, 2014) to prepared students' comments corpus and perform some data preprocessing to prepared text data in students' comments for sentiment analysis.

3.2.1 Data Pre-processing

With tm package, we can apply the transformations sequentially of data preprocessing to remove unwanted characters which do not support sentiment value from the students' comments included these following processes below (Feinerer, 2011).

Converting to lower case: For text analysis we often convert characters to lower case to not differentiate between words. This transformation is the process of converting characters to lower case.

Removing punctuation: For preliminary analyzes we often ignore the punctuation. This transformation is the process of removing punctuation from the text.

Removing numbers: This transformation is the process of removing numbers that do not relevant to our analyzes.

Stripping white spaces: This transformation is the process of stripping white spaces from the text.

Removing stop words : This transformation is the process of removing common words which do not support sentiment value from text, such as is, are, and, of, for, has, have, had, it, the, to, etc.

Stemming: This transformation is the process of removing word suffixes for English words, such as\'s", \es", and \ed".

3.3. Sentiment Analysis in Students'Comments

3.3.1 Identifying Opinion words and related feature

In this paper, the 2 attributes; e.g., Helpfulness and Clarity are handpicked as the teacher evaluation indicators based on RateMyProfessors.com. These attributes are considered as the seed list and are further use in generating teacher evaluation oriented words based on WordNet. For each attribute, the synonym is considered as a positive word while antronym is considered as a negative word. In this process, the positive and negative word lexicon related to Helpfulness and Clarity are constructed. The positive keyword lexicon contains 167 words and the negative keyword lexicon contains 108 words.

3.3.2 Identifying Sentiment Words

From a set of students' comments, the next task is identifying sentiment words. In this paper, we performed lexicon based sentiment classification using our positive and negative word lexicon resource. We used a very simple algorithm to detect all sentiment words that student expressed in the given document of student comment and returned the counting number of occurrences of “positive” and “negative” words as defined in definition 1. We considered to identifying the sentiment words related to Helpfulness, Clarity and Overall.

Definition 1: The number of positive words in students’ comment is the counting number of positive words and the number of negative words in students’ comment is the counting number of negative words occurrence in students’ comment.

$$N_P = \sum_{i=1}^{n} W_{P_i} \qquad (1)$$

$$N_N = \sum_{i=1}^{n} W_{N_i} \qquad (2)$$

where N_P is number of positive words in students’ comment, N_N is number of negative words in students’ comment, W_P is positive word in students’ comment, W_N is negative word in students’ comment, i is order of positive or negative words in students’ comment from 1 to n and n is total number of positive or negative words occurrence in students’ comment.

3.3.3 Scoring Text Corpus

In this stage, the student comment text corpus score was determined based on definition 2. Finally, the sentiment scores of Helpfulness, Clarity and Overall of each teacher were aggregated as indicated in definition 3.

Definition 2: Students’ comment polarity is positive if the counting number of positive words greater than or equal to counting number of negative words and inversely students’ comment polarity is negative.

$$S = \begin{cases} 1 if & N_P \geq N_N \\ 0, & N_P < N_N \end{cases} \qquad (3)$$

where S is students’ comment polarity, N_P is a number of positive words in students' comment and N_N is a number of negative words in students' comment**.**

Definition 3: The sentiment score of each teacher is the ratio of a summation of students’ comments polarity to a total number of students' comments.

$$S_C = \frac{\sum_{i=1}^{n} S_i}{n} \qquad (4)$$

where S_C is the sentiment score of the teacher, i is the order of students' comment from 1 to n and n is a total number of students’ comments. For example, if the gathering of students’ comments of *Teacher X* is 6 and the counting number of positive comments is 4, student comment text corpus score should be 0.67.

3.Results and Discussions

In order to investigate the possibility of an automated students 'comments analysis. We checked whether the results of qualitative analysis correlated with the results of the quantitative analysis. Three pairs of two variables; e.g., 1) Helpfulness ratings and Helpfulness sentiment scores, 2) Clarity ratings and Clarity sentiment scores and 3) Overall ratings and Overall sentiment scores were plotted into graphs in order to compare the relationship between each pair of two results from different methods as present in Figures 1 to 3.

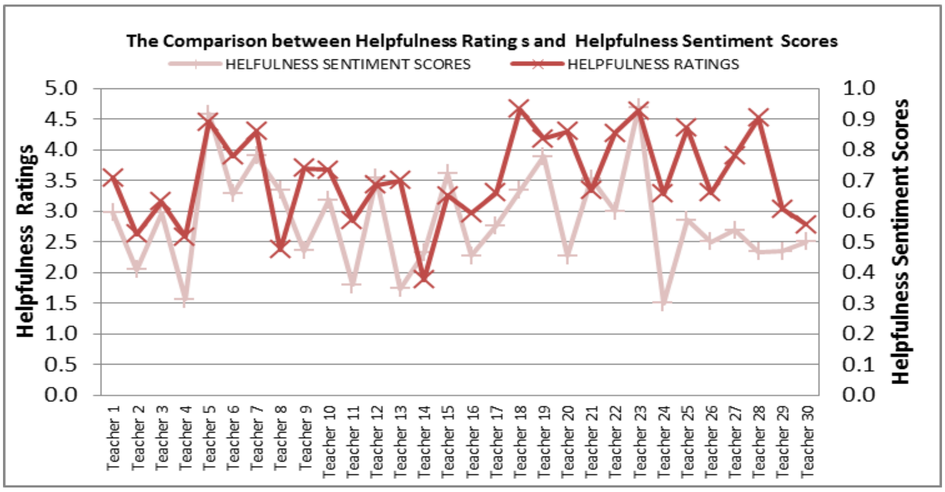

Figure 1: The comparison between Helpfulness ratings and Helpfulness sentiment scores

Figure 1 shows the graphs between Helpfulness rating and Helpfulness sentiment scores. The moving curves between these two variables from five samples e.g., Teacher 19, Teacher 20, Teacher 21, Teacher 28 and Teacher 30 are moving in the converse direction while the moving curves between Helpfulness rating and Helpfulness sentiment scores from the other twenty five samples are increasing in the same direction.

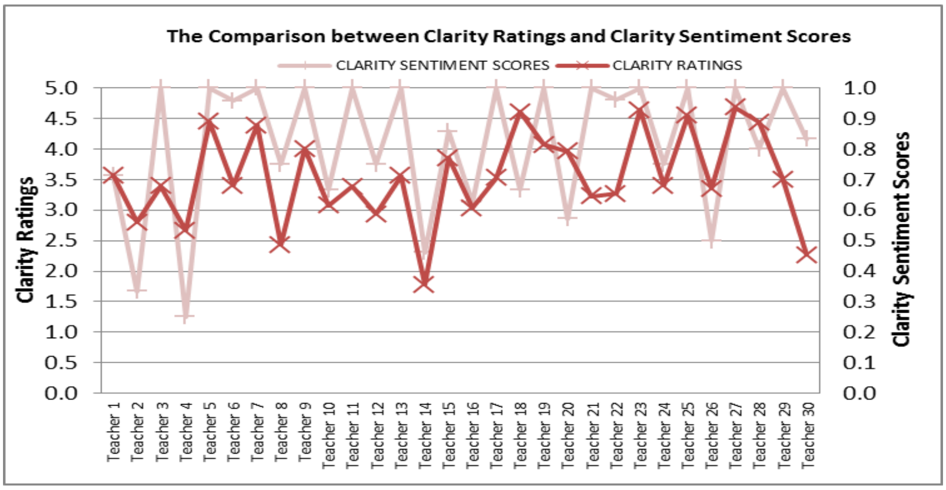

Figure 2: The comparison between Clarity ratings and Clarity sentiment scores

Figure 2 shows the graphs between Clarity rating and Clarity sentiment scores. The graphs present that Clarity ratings from seven samples e.g., Teacher 17, Teacher 18, Teacher 19, Teacher 20, Teacher 21, Teacher 22 and Teacher 29 is moving in the converse direction as Clarity sentiment scores while the moving curves between these two variables from the other thirteen samples are increasing in the same direction.

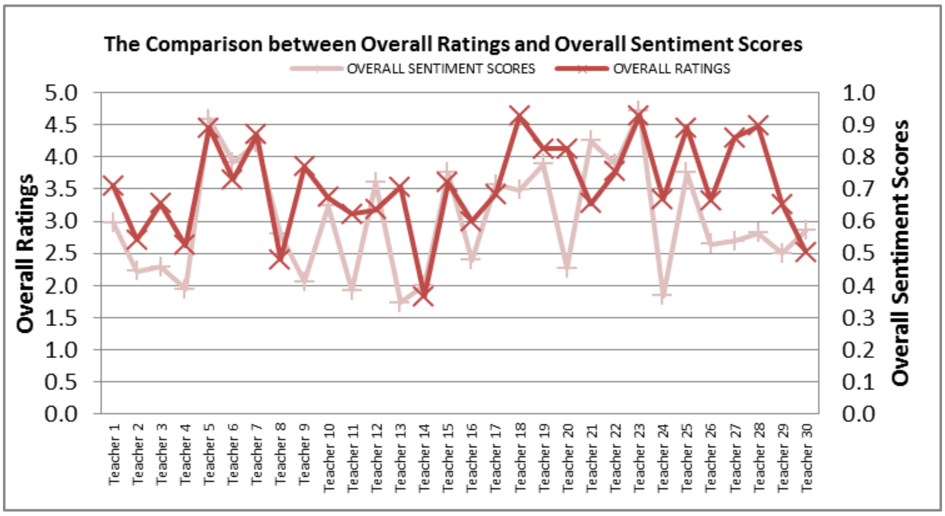

Figure 3: The comparison between Overall ratings and Overall sentiment scores

Figure 3 shows the graphs between Overall ratings and Overall sentiment scores. We can observe that Overall ratings from nineteen samples is relatively increasing in the same direction as Overall sentiment scores while the moving curves between these two variables from the other eleven samples e.g., Teacher 9, Teacher 10, Teacher 12, Teacher 13, Teacher 14, Teacher 17, Teacher 18, Teacher 19, Teacher 20, Teacher 21 and Teacher 30 are increasing in the converse direction.

The above line graphs in Figures 1 to 3 show the comparison between three pairs of the numerical response ratings and the sentiment score of teacher evaluation aspects. Figure 1 shows the comparison between Helpfulness ratings and Helpfulness sentiment scores, Figure 2 shows the comparison between Clarity ratings and Clarity sentiment scores and Figure 3 shows the comparison between Overall ratings and Overall sentiment scores. The visual correlation results above present that the moving curve between three pairs of those quantitative results and qualitative results of students' feedbacks are relatively moving in the same direction. In a final step, the statistical techniques using Pearson's correlation and Spearman's rank have been applied to confirm the relationship between each pair of those two variables and proof our concept as present in Table1.

Table 1: Correlation Table

Teacher Evaluation Aspect Ratings	Overall Sentimental Scores			
	Pearson Correlation	**Sig. (2-tailed)**	**Spearman's rho**	**Sig. (2-tailed)**
Helpfulness	0.507**	0.004	0.482**	0.007
Clarity	0.512**	0.004	0.529**	0.003
Overall	0.532**	0.002	0.521**	0.003

*.Correlation is significant at the 0.05 level (2-tailed).

**.Correlation is significant at the 0.0۱ level (2-tailed).

The results shown in Table 1 indicates a positive correlation between the quantitative results and the qualitative results of teacher evaluation using sentiment analysis considering Helpfulness, Clarity and Overall.

5. Conclusions and Future work

In this experimental a small data set of students' comments was utilized to teacher evaluation. This preliminary studies on the possibility of the qualitative analysis of students' free-style text comment using lexicon based sentiment analysis to teacher evaluation. The initial results of this study showed significance correlation between the sentiment scores from qualitative analysis and the numerical response ratings of teacher evaluation aspects from quantitative analysis and highlight the similarities of the moving curves between three pairs of two variables between Helpfulness ratings and Helpfulness sentiment scores, Clarity ratings and Clarity sentiment scores and Overall ratings and Overall sentiment scores. The existence of visual correlation shows that the analysis of students' comments using lexicon based sentiment analysis technique can potentially be applied to teacher evaluation. It is a promising technique to analyze the students' textual responses by saving time and more efficiency than manual tally. By performed sentiment classification using our positive and negative word lexicon we can convert qualitative students' responses to quantitative information as Helpfulness sentiment score, Clarity sentiment score and Overall sentiment score of each teacher. This technique can gain additional useful information to teacher performance evaluation from the students' perspective. Future research may need to consider the analysis of a large scale data set using aspect based sentiment classification in order to discover hidden aspects and sub-aspects related to teacher evaluation attributes that student likes or dislikes inside the students' comments. More especially, we are going to identify and categorize these teacher evaluation aspects and sub-aspects into more teacher evaluation attributes and improving the negation detection so that this would help to enhance the accuracy and efficiency result of teacher evaluation using sentiment analysis. Moreover, the specific lexical resource related to more teacher evaluation aspects is needed.

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