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A CORRELATION ANALYSIS BETWEEN SENTIMENTAL COMMENT AND NUMERICAL RESPONSE IN STUDENTS' FEEDBACK

Phuripoj Kaewyong[1], Anupong Sukprasert[2], Naomie Salim[3] and Fatin Aliah Phang[4]
[1] Information Technology Department, Suan Dusit University, Thailand
[2]Mahasarakham Business School, Mahasarakham University, Thailand
[3]Faculty of Computing, Universiti Teknologi Malaysia, Malaysia
[4]Faculty of Education, Universiti Teknologi Malaysia, Malaysia
E-Mail: phuripoj@yahoo.com

ABSTRACT

This paper aims to study a qualitative measuring of students' comments using sentiment analysis to teacher evaluation and investigate its qualitative analysis. A small dataset of students' feedbacks was collected from the public website and was utilized in the experimental. We performed the lexicon based sentiment analysis to identify sentiment word and determine overall sentiment polarity of students' comment into positive and negative classes based on Opinion Lexicon automatically. A comparison between overall sentiment scores and numerical response scores of teacher evaluation aspects were evaluated and plotted into graphs in order to compare the relationship between each pair of two variables. Especially, we applied the statistical techniques using Pearson's correlation and Spearman's rank to confirm these visual correlation results. The experimental results suggested that there is a significant correlation between overall sentiment scores from its qualitative analysis and numerical response scores of teacher evaluation aspects. Based on this, it might be possible to convert from qualitative to quantitative type of teacher evaluation by performing lexicon based sentiment analysis.

Keywords: Sentiment analysis, teacher evaluation, students' comment, correlation analysis.

INTRODUCTION

Students' feedbacks are often used as a source to teacher evaluation in higher education. It is a common method for evaluate the teaching process quality and has been the most widely used in most colleges and universities. It is generally accepted that teaching evaluation from the student opinions is an important part of teaching practice. Additionally, this method continues to be the most frequently used for testing teacher's teaching performance and the course in higher education (Samian and Noor, 2012). Generally, students' feedbacks include numerical responses and freestyle textual comments. Most scholars focused on quantitative student responses but ignored qualitative student responses. Although, students' writing comments are usually consists of the opinions from students' perspective that can be helpful for teachers to identify problems in their teaching practice in order to reflect and improve teaching quality. 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. However, the results from quantitative analysis cannot answer the even query "What is the problem from the students' perspective" but the students' comments can answer that question 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). The traditional method to analyse the students' expressions from their comments is a manual tally. The lecturer can 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, the performing of this method may take extensive times to interpret a huge data of student comments. The automatic interpreter of unstructured text responses from the students' feedbacks is needed.

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). As mentioned above, those problems are similar to the teacher evaluation; the interpretation of qualitative data from a large volume of students' comments is a difficult task. We could not use those opinion resources for knowledge representation directly because of the traditional methods cannot be applied directly to these unstructured text of students' comment. However, 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). There is a few research have been applied to teacher evaluation.

"How to analyze students' feeling and opinion about particular teacher expressed by student in their comments"

Regarding customer feedbacks evaluation, the unstructured textual of customer comment is 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). The other example is 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 percentages 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 analyzing 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 analyze a large volume 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. To address this problem sentiment analysis comes to perform effective automated textual analysis method for enhancing teacher evaluation.

Therefore, the theme of this paper is to study a qualitative measuring of students' comments using sentiment analysis to teacher evaluation and investigate its qualitative analysis. 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 prove our concept that demonstrate the need for enhance teacher performance evaluation. The substances of this paper are organized as following: related work described the literature reviews. In addition, next section proposed methods and experimental design were described in methodology, results and discussions and the last section is conclusions of this study and gives a suggestion for future works.

RELATED WORK

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 opinion from the reviews and easily to understand. This knowledge will give a good reference resource to guarantee a decision making in various objectives.

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 discovered seven works that specified this idea.

First, El-Halees (2011) study feature-based sentiment analysis to course quality evaluation. They extracted the frequent features by WhatMatter System and defined those features as the course evaluation indicators. Three machine learning methods using Naïve bays, k-nearest and SVM were applied to classify opinion polarity as positive and negative classes. The result of this experimental indicates that Naïve Bays has the best accuracy. This study suggests the benefit of user-generated content to improve course performance. Second, Rashid (2013) study the frequency features and opinion words extraction from students' feedback dataset about faculty evaluation using two pattern mining algorithm; e.g., sequential pattern algorithms (Apriori) and Generalized Sequential Pattern (GSP). This study considered Noun and Adjective extraction. The experimental results indicated that GSP is more efficient than Apriori for frequent features and opinion word extraction. However, these study results were not compared with the other study. Furthermore, Jagtap and Dhotre (2014) introduced the idea of automated sentiment analysis from teacher feedback assessment using HMM and SVM base hybrid sentiment classification. The authors only discussed and demonstrated the effective method concept. There is not experiment result. In another study, Bharathisindhu and Brunda (2014) presented the concept of automated sentiment analysis in E-learning system to evaluate a topic or area which the users interested. This information can give the benefit for the developer and educator to know which area the learner

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concentrating. In this work, the authors only discussed their idea. On the other hand, Wen, Yang, and Rosé (2014) study the lexicon based sentiment analysis to study of the students drop out behavior in Massive Open Online Course (MOOC). They collected the students' feedback from Coursera.org using a screen scraping protocol. In this study, the authors applied this information to observe the correlation between the sentiment that students expressed in the course forum and the number of students drop out per course. The experimental results were visualized in a graph. However, this work has some limitation. The sentiment word polarity was predicted based on the lexicon recourse of product reviews. The construction of specific domain lexicon recourse could improve the system. In Ortigosa, Martín and Carro (2014) proposed other approach using a combined method between Spanish lexical based sentiment analysis and machine learning techniques to analyzed the students' feedback in Facebook. The experimental results suggested that it is possible to perform sentiment analysis to analyze the students' feedback in Facebook with high accuracy (83.27%). Furthermore, they point out to apply this method to extract information about the student's sentiments from the messages in the context of e-learning. However, this work still has some limitation, 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 to apply a finer-grained classification. Similar to Pong-inwong and Rungworawut (2014) proposed the construction of their teaching evaluation lexicon resource. In this work, the weight score of terms was defined by the experts with the ranged from -1.00 to 1.00. They employed SVM, ID3 and Naïve Bayes algorithms in their experimental in order to perform the sentiment classifications with a 97% highest accuracy of SVM. This proposed method can address the problem of automated sentiment orientation polarity definition in teaching evaluation in the previous works, but it was constructed in Thai language.

As mentioned above, the application of sentiment analysis in students' comment was used in various objectives; e.g., faculty evaluation, teaching evaluation, course-online evaluation and teacher evaluation. It is possible to perform sentiment analysis in students' comment. The target of automatic sentiment analysis is improving the better accuracy result of sentiment classification and summarization. Current researchers in this area focus to aspect-based sentiment analysis. Moreover, improving the effective Lexicon resources for a specific domain is one of the important issues. 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.

METHODOLOGY

Proposed Method

The following section describes the overview of our proposed method. We divided the automatic interpret of students' comments into three tasks as follows:

1. Preprocessing
2. Identifying Sentiment Word
3. Scoring Text Corpus

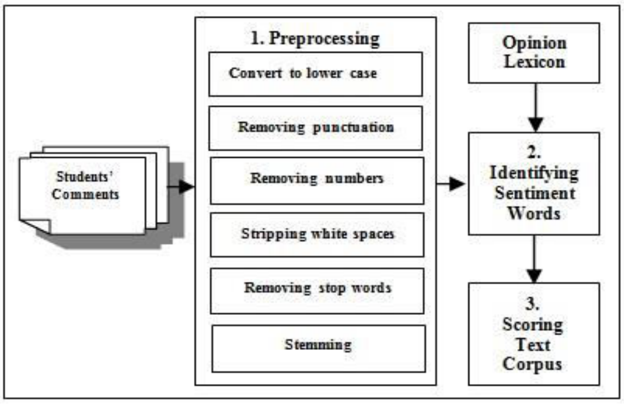

Figure-1. Proposed method.

Figure-1 illustrates the diagram of our proposed method. In the last step, after the performing of scoring text corpus we evaluated our technique by looked at the relationship between sentiment scores and the numerical response scores of teacher evaluation aspects from the original data source.

Experimental Design

In order to demonstrate our method, we set up the experiment by gathered the students' feedbacks from the public website RateMyProfessors.com. This section describes the detail of the experimental design include of datasets used in our experiment, preprocessing, identifying sentiment words, scoring text corpus and evaluation.

Datasets

In this experimental a small dataset contains 1,148 students' feedbacks from 30 teachers was used. We collected students' feedbacks from RateMyProfessors.com using multi-stage sampling as indicated in 4 stages below.

Stage 1: Select the University from RateMyProfessors.com using specified sampling technique.

Stage 2: Select the teacher who has a number of students' feedbacks of several courses greater than or equal to 30 using the purposive sampling technique. The students' feedbacks of several courses from 82 teachers were selected.

Stage 3: From sample unit select the teacher who has a number of students' feedbacks of particular course greater than or equal to 20 using the purposive sampling technique. The students' feedbacks of particular course from 36 teachers were selected.

Stage 4: Cutting duplicate students' feedback. The students 'feedbacks from 30 teachers were collected. A total number of students' feedbacks is 1,148.

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 indicators related to teacher evaluation aspects were Helpfulness and Clarity. For each teacher, the overall rating was computed from the average of these two quantitative indicators ratings. While Easiness rating represents course evaluation. Furthermore, this system provided a list of students' comments of each teacher. The student can check the teacher overall rating and read a list of comments from other students 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.

Preprocessing

In this section, we applied R programming and tm package (Feinerer and Hornik, 2014) to prepare students' comments corpus from a collection of students' comments and perform some data preprocessing to prepared text data for sentiment analysis.

Table-1. Preprocessing.

Preprocessing	Description
Converting to lower case	Converting characters to lower case.
Removing punctuation	Removing punctuation from the text.
Removing numbers	Removing numbers that do not relevant to our analysis.
Stripping white spaces	Stripping white spaces from the text.
Removing stop words	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	Removing word suffixes for English words, such as\'s", \es", and \ed".

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 the following processes as indicated in Table-1 (Feinerer, 2011).

Identifying Sentiment Words

We utilized a very simple algorithm to identify all sentiment words from the students' comment and returned the total number of "positive" and "negative" words occurrence. The "positivity" and "negativity" based on Opinion Lexicon published by Hu and Liu (2004). For the given document of students' comment, the number of positive words *(N_P)* is the total number of positive words occurrence in students' comment *(W_{Pi})* and the number of negative words *(N_N)* is the total number of negative words occurrence in students' comment *(W_{Ni})* as shown in Equation (1) and (2).

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

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

Scoring Text Corpus

In this stage, the students' comment text corpus score was determined. For the given document of students' comment, the polarity *(S)* is positive if the aggregate number of positive words *(N_P)* greater than or equivalent to the aggregate number of negative words *(N_N)* and contrarily students' comment polarity is negative as shown in Equation (3).

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

Then overall sentiment score of the teacher was aggregated. Overall sentiment score of each teacher *(S_C)* is the ratio of a summation of students' comments polarity *(S_i)* to a total number of students' comments *(n)* as shown in Equation (4).

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

Table 2 indicates the performing of scoring text corpus. For example, if the total number of students' comments of *Teacher X* is 5 and the total number of positive comments is 4 then the student comment text corpus score should be 0.8. We call this score is overall sentiment score of *Teacher X*.

Table-2 Scoring text corpus.

Students	Comments	Scoring Text Corpus		
		N_P	N_N	Score
Student 1	he often teach really complex thing	0	1	0
Student 2	he is more than willing to help if you need it	1	0	1
Student 3	very good teacher explain material well easy test which are usually scale	3	0	1
Student 4	take him if you are willing for a challenging but awesome class	2	1	1
Student 5	he is so helpful and really want his student to do well	2	0	1

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Evaluation

We designed the evaluation of our technique by looked at the correlation between Overall sentiment scores and numerical response scores of teacher evaluation aspects. In the first step, we evaluated the possibility of our technique by using the visual graph. Three pairs of two variables; e.g., 1) Overall sentiment scores and Helpfulness ratings, 2) Overall sentiment scores and Clarity ratings and 3) Overall sentiment scores and Overall ratings were analyzed and plotted into graphs in order to compare the relationship between each pair of two results from different methods. The second step, we applied the statistical techniques to confirm these visual correlation results and prove our concept using Pearson's correlation and Spearman's rank.

RESULTS

In order to evaluate the result of the qualitative measuring using lexicon based sentiment analysis to teacher evaluation. First of all, three pairs of two results from qualitative and quantitative analysis were analyzed and plotted into graphs in order to check the relationship between each pair of two variables. We compared the correlation between Overall sentiment scores and the numerical response score of two teacher evaluation aspects; e.g., Helpfulness ratings and Clarity ratings. Second, we compared the correlation between Overall sentiment scores and Overall ratings of teachers. Figure-2 illustrates the correlation between Helpfulness ratings and Overall sentiment scores from students' feedbacks. The graphs present the moving curves between these two variables are increasing in the same direction, Figure-3 illustrates the correlation between Clarity ratings and Overall sentiment scores from students' feedbacks. The graph presents the moving curves between these two variables are increasing in the same direction and Figure-4 illustrates the correlation between Overall ratings and Overall sentiment scores from students' feedbacks. The graphs present the moving curves between these two variables are increasing in the same direction. Then these visual correlation results were investigated by the statistical techniques. Pearson's correlation and Spearman's rank were used to determine correlations between the Overall sentiment scores of students' comments with the Overall ratings and the ratings of Helpfulness and Clarity. Table-3 indicates the strong correlation between the Overall sentiment scores and the numerical response scores of teacher evaluation aspects.

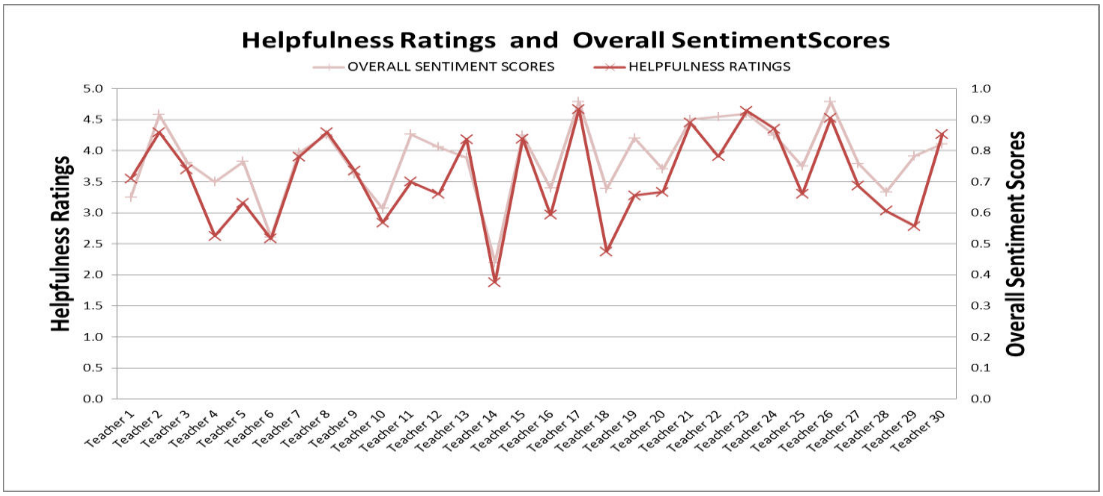

Figure-2. The correlation between Helpfulness ratings and Overall sentiment.

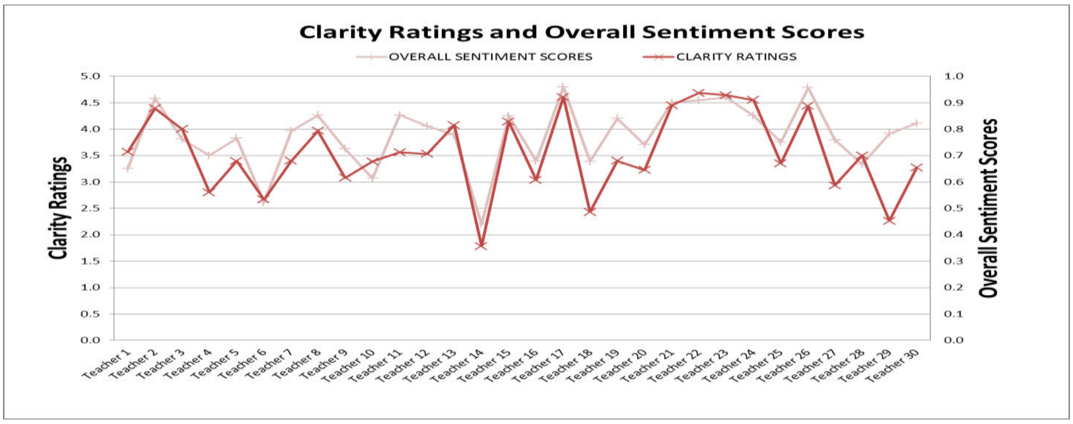

Figure-3. The correlation between Clarity ratings and Overall sentiment scores.

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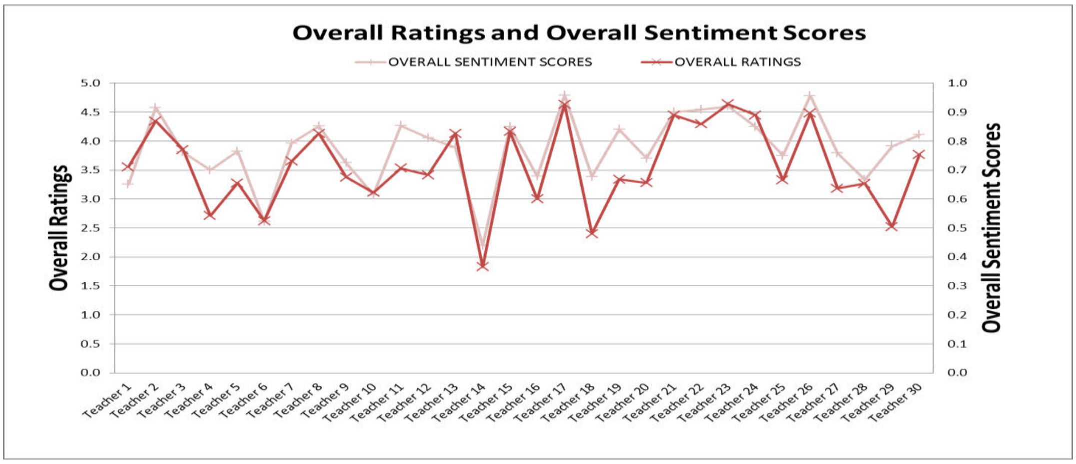

Figure-4. The correlation between Overall ratings and Overall sentiment scores.

Table-3. Correlation Table.

Teacher Evaluation Aspects	Overall Sentiment Scores			
	Pearson Correlation	Sig. (2-tailed)	Spearman's rho	Sig. (2-tailed)
Helpfulness	0.923**	0.000	0.875**	0.000
Clarity	0.894**	0.000	0.819**	0.000
Overall	0.922**	0.000	0.878**	0.000

*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

DISCUSSIONS

The results from the above graphs in Figures-2 to 4 illustrate the correlation between Overall sentiment scores and the numerical response scores of teacher evaluation aspects; e.g., Helpfulness ratings, Clarity ratings and Overall ratings. The graphs present that the moving curves between Overall sentiment scores and the numerical response scores of teacher evaluation aspects and Overall ratings are increasing in the same direction. Moreover, the statistical analysis results from Table-3 indicated a strong correlation between each pair of two variables above and support these visual correlation results. However, this work still has the limitation of the sentiment analysis, in this experimental the “positivity” and “negativity” of sentiment words based on Opinion Lexicon the lexicon resource of product reviews. Furthermore, there are some limitations of the identifying sentiment words process. The first issue is the limit to detect the nagation and return incorrect polarity; e.g., Not clear, Not helpful. The second issue is the limit to check the opinion target correctly. The specific domain lexicon resource for teacher evaluation, the improvement of nagation detection and opinion target checked for students’ comment are still needed.

CONCLUSIONS

In this study, we utilized a small dataset of students’ comments to evaluated teacher performance. The experimental results of this study suggested that there is a significant correlation between overall sentiment scores from its qualitative analysis and numerical response scores of teacher evaluation aspects. Based on this, it might be possible to convert from qualitative to quantitative type of evaluation by performing lexicon based sentiment analysis to teacher evaluation. Future exploration may need to consider aspect-based sentiment classification utilizing a large scale dataset and the specific domain lexicon resource in order to detect more hidden sentiment words related to all teacher evaluation indicators that students express in their comments. More particularly, we are going to identify and categorize the teacher evaluation aspects and sub-aspects into more teacher evaluation indicators and improve our algorithm to detect the nagation, check the opinion target and calculate the different degree between the different counting number of comments so that this would help to enhance the accuracy and efficiency result of teacher evaluation using sentiment analysis.

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