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Opinion mining technique for developing student feedback analysis system using lexicon-based approach (OMFeedback)

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Abstract

Online assessment systems are increasingly utilised as an evaluation tool for measuring the performance of lecturers in Institutions of Higher Learning (IHLs). These systems commonly have a set of questionnaires comprised of quantitative and qualitative questions. Most online lecturer teaching assessment systems are focused on the quantitative part of the questionnaire since it is easy to analyse. On the contrary, the qualitative part, which requires students' opinions, is often omitted and neglected, and the level of opinion results are excluded. This is because students' opinions are usually in the form of unstructured texts, which makes it hard to manually analyse all the feedback. To address this problem, a system that could automatically analyse students' feedback (known as OMFeedback) was developed. This system applies an opinion mining technique to reveal the teaching assessment results, which are underpinned by a lexicon-based approach. Lexicon-based is a common textual data quantification method that can analyse the sentiment tendency of a student's feedback. A database of English sentiment words, known as the Vader Lexicon, was utilised as a lexical source to determine the polarity of words. By analysing these sentiment words, which included intensifier words extracted from students' feedback, this system was able to determine the results for the lecturer teaching assessment by describing the level of positive, negative, or neutral opinions. This system was also able to process new features, such as capitalised words and emoji characters to enhance the opinion results. Ultimately, this newly developed system will provide useful information to IHLs for improving lecturers' teaching skills and course materials.

Keywords Opinion mining · Student feedback · Lexicon-based approach · Sentiment analysis · Teaching assessment

1 Introduction

Institutions of Higher Learning (IHLs) are always seeking mechanisms that can be used for enhancing teaching and learning processes. Such enhancements could be achieved by gathering feedback from students regarding their classes (Khan and Khan 2019). Feedback is crucial for understanding the patterns of students' opinions that could effectively improve teaching performance and for creating teaching plans (Dhanalakshmi et al. 2016). According to Aung and Myo (2017), feedback from students is vital for measuring the quality of teaching delivered by their lecturers. Feedback is also important for providing instant insight into the level of students' understanding during their learning process (Abdulla 2018). Thus, it is imperative that students' feedback is addressed by IHLs to successfully increase their academic achievements.

One approach to obtain students' feedback is through the teaching assessment system, which includes their perspective on teaching instructions, their learning environment, and the quality of the lessons they learned (Balachanran and Kirupananda 2017). Such system would include quantitative and qualitative questions. The quantitative part would be composed of closed-ended questions, such as multiple choices, while the qualitative part would include open-ended questions, such as comments and suggestions from students in textual form. Previous studies had focused on quantitative questions that rely on fixed rubric rules compared to analysing feedback through qualitative questions (Balahadia et al. 2016). Although faculties often face difficulties in making sense of the feedback from qualitative questions, such feedback is rich with personal opinions, feelings, beliefs, and desires (Aung and Myo 2017; Balahadia et al. 2016).

Despite a variety of methods and techniques are available, this study applied the opinion mining technique for its ability to track textual reviews (Aung and Myo 2017). Previous studies have also reported that the lexicon-based approach is the most appropriate approach for analysing students' feedback (Aung and Myo 2017; Nasim et al. 2017; Nitin et al. 2015). Therefore, this study aims to develop a new student feedback analysis system (hereafter known as the OMFeedback system) using lexicon-based approach. This system will also incorporate the capitalisation of words (Hutto and Gilbert 2014) and emojis (Shiha and Ayvaz 2017), which are actively used in most web-based systems.

2 Literature review

Opinion mining, also known as sentiment analysis, is an advancement in the area of text mining, which is primarily utilised to determine the opinions of people from big datasets involving unstructured texts (Dhanalakshmi et al. 2016). It is a common textual data quantification method that can analyse the sentiment tendency of a textual feedback. According to Song et al. (2019), human opinions are usually based on emotion, which can be classified as positive (e.g., joy and trust), negative (e.g., anger, fear, sadness, and disgust), and neutral (e.g., surprise and anticipation).

In the educational context, positive emotion is believed to have significant effect on students' behaviour, while negative emotion could impact their learning behaviour (Binali et al. 2009). Several studies have discussed the application of opinion mining for analysing students' emotion. For instance, Binali et al. (2009) proposed a conceptual emotion detection system, which uses GATE's visual environment for developing, implementing, and testing language processing modules. Opinion mining was also used by Aung and Myo (2017), Balahadia et al. (2016), Barron-Estrada et al. (2017), Dhanalakshmi et al. (2016), and Nasim et al. (2017) for detecting emotion through students' feedback on lecturers and courses.

The remarkable use of opinion mining for analysing feedback from students has led to the development of a plethora of techniques. Basically, opinion mining can be classified into machine learning and lexicon-based. Machine learning focuses on building models with the aid of large training datasets to determine text orientation (Soong et al. 2019). Meanwhile, the lexicon-based approach uses sentiment dictionary with opinion words and matches them with data to determine polarity (Aung and Myo 2017). This approach will assign sentiment scores to the opinion words describing how positive, negative, or neutral the words are, as found in the Vader Lexicon dictionary. Positive opinion words are used to express necessary things, negative opinion words are used to describe unnecessary things, and neutral opinion words are used for a better distinction between positive and negative words.

Various machine learning techniques have been utilised to analyse students' feedback, such as Naïve Bayes, support vector machine, neural network, and k-nearest neighbour. According to Dhanalakshmi et al. (2016), Naïve Bayes is the most commonly used technique to calculate the possibility of a given text belonging to a particular feature. Support vector machine works best for classifying sparse text data. Neural network employs multiple layers of neurons for text classification and k-nearest neighbour uses Euclidean distance to calculate the similarity of text data. Several studies found that neural network is the perfect technique for opinion mining as it is capable of analysing a large number of text data (Balahadia et al. 2016; Dhanalakshmi et al. 2016; Pong-Inwong and Kaewmak 2016; Tseng et al. 2018). However, this study has identified that the neural network technique often requires high computation power to train the dataset to generate accurate results.

Meanwhile, Aung and Myo (2017), and Nasim et al. (2017) found that the lexicon-based approach neither needs a large number of text data nor high computation power for producing accurate results. This is because lexicon determines the polarity of a word by using the constructed dictionaries. These dictionaries would contain sentiment scores that will be assigned to the opinion text to form the final expression of emotion (positive, negative or neutral). Previous studies on opinion mining have also shown that the capitalisation of words is crucial to emphasise the user's intent (Hutto and Gilbert 2014), while the use of emoji characters may enhance the expressivity of the feedback (Shiha and Ayvaz 2017). However, only a small number of studies have utilised these features to enrich the ability of the opinion mining technique for analysing students' feedback. Based on the above reasons, this study has developed the OMFeedback system, and incorporated the capitalisation of words and emoji characters to the lexicon-based approach to analyse students' feedback.

3 System architecture

This study has designed the OMFeedback system through the Unified Modelling Language (UML), as depicted in Fig. 1. This system comprises of two main users, namely, the students and the admin. Both sets of users need to log in to the system using their username and password. Students must select a lecturer's name before writing their feedback for the teaching assessment in the space provided. The completed feedback is stored in the database and can only be viewed by the admin. This system uses the Vader Sentiment Intensity Analyser to analyse each word in the feedback and it

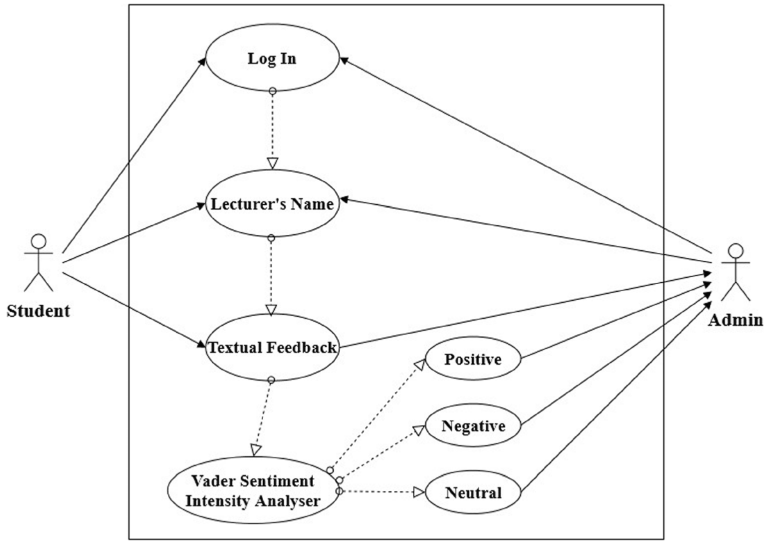

Fig. 1 OMFeedback system architecture

will calculate the score based on the value assigned in the Vader Lexicon. The scores are categorised as positive, negative, and neutral to represent the overall opinion of the students towards their lecturer's teaching performance. Finally, the results of these scores can be viewed by the admin for further actions.

4 System development

The OMFeedback system has been developed through the *Python 3.7*, while the *WxPython* package was used to develop the interface of the system. Algorithm 1 and Algorithm 2 are the login algorithms used by students and administrators, respectively, to access the OMFeedback system. Students would only need to enter their matrix number and password. Data entered to the login space will be stored in the database as a student entry record. Administrators would need to enter their username and password to access this system to view students' feedback on a lecturer's teaching performance.

Algorithm 1. Student's login algorithm for the OMFeedback system.

Input:
Matric Number *matric;*
Password *password*;
Output
Run next process

START
1. GET *matric*;
2. GET *password*;
3. IF *matric* AND *password* == TRUE
4. Run next process
5. ELSE
6. Show error message

Algorithm 2. Admin's login algorithm for the OMFeedback system.

Input:
User name *username;*
Password *password*;
Output
Run next process

START
1. GET *username*;
2. GET *password*;
3. IF *username* AND *password* == TRUE
4. Run next process
5. ELSE
6. Show error message

Algorithm 3 shows the process of entering a lecturer's information and feedback in the form of opinion texts by students regarding the lecturer's teaching performance. Students would need to choose the name of the lecturer from a list and type their feedback in the space provided. This feedback text will be analysed by the Vader Sentiment Intensity Analyser, which will assign positive, negative, and neutral scores. The lecturer's name, the feedback text, and the score will then be stored in the database

Algorithm 3. Student's textual feedback analysis through the Vader Sentiment Intensity Analyser.

Input:
Lecturer's name *name*;
Feedback *feedback*;
Output:
Sentiment score *score*;

START
1. GET *name*;
2. GET *feedback*;
3. def sentiment_analyzer_scores(*feedback*):
score = analyser.polarity_scores*(feedback)*
print("{:-<40} {}".format(*feedback,* str(*score*)))
4. Send variable *[name, subject, group, feedback,score]* to database
5. END

Algorithm 4 shows the algorithm used by the administrator to view the results of the lecturer's teaching evaluation. Once an administrator logs into the OMFeedback system, the administrator must choose the name of the lecturer to read students' opinion texts on the selected lecturer. Based on the name of the selected lecturer, the OMFeedback system will perform a search in the lecturer database. Next, the sentiment score (positive, negative, and neutral), as analysed by the Vader Sentiment Intensity Analyser, will be displayed to the administrator in the form of pie charts for better comprehension

Algorithm 4. Lecturer's performance result.

Input:
Lecturer's name *name;*
Output:
Lecturer's performance *performance*

START

1. GET *name*
2. GET *group*
3. Search in database data that containing variable [*name, group*]
4. Present score analysis in pie chart
5. END

5 Experiment

This study collected feedback from 120 third-year students in the Computer Science course during Semester I of the 2019/2020 session at the National Defence University of Malaysia. The following Fig. 2 shows the feedback form that the students need to complete at the end of the semester.

This paper presents an example of students' feedback on a selected lecturer. As shown in Table 1, the students' feedback shows different scores for positive, negative, and neutral polarities. These scores were analysed using the Vader Sentiment Intensity Analyser and each of the textual feedback has its own fixed values, which are stored in the Vader Lexicon. As previously mentioned, this study is introducing two new features, namely, the capitalised words and emoji characters in the OMFeedback system. Based on 120 third-year students, 15 of

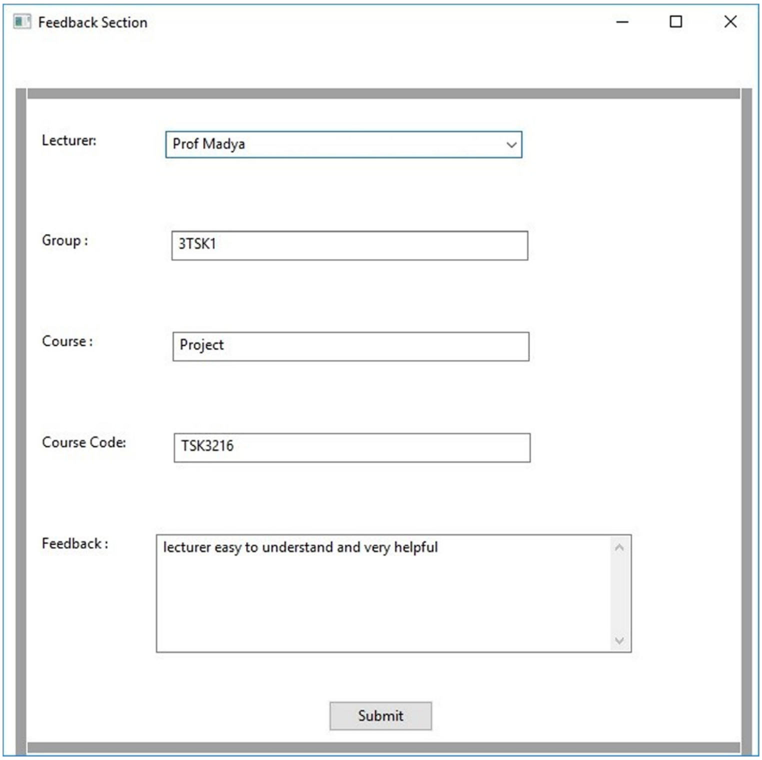

Fig. 2 The feedback form in the OMFeedback system

Table 1 List of students' textual feedback

No.	Textual Feedback	Positive	Neutral	Negative
1.	schedule well organized and strict rules implement...	0.357	0.643	0
2.	Sir has a good managing skils	0.42	0.58	0
3.	Everything is okay and arrangable but student alwa...	0.153	0.847	0
4.	cool lecturer with great attitude	0.681	0.319	0
5.	lecturer with good performance of lecture	0.367	0.633	0
6.	Very flexible and so determined and very punctual	0.449	0.551	0
7.	i do not understand about what he talking	0	1	0
8.	he has a good example for me	0.367	0.633	0
9.	His course is a very good course and need to be co...	0.242	0.758	0
10.	Helping student to learn more about developing sys...	0.239	0.761	0
11.	ths course is very helpful to the student, unlike ...	0.402	0.598	0
12.	sometime the lecturer had emergency leave and had ...	0	0.615	0.385
13.	Making the class much more interesting have been a...	0.394	0.606	0
14.	A very strict but still a kind person. he will hel...	0.36	0.53	0.111
15.	Has a very good teaching skills and punctual	0.347	0.653	0
16.	good man but has a very bad joking sense	0.316	0.335	0.348
17.	he is a good lecturer ;)	0.615	0.385	0
18.	very BAD lecturer :(	0	0.206	0.794
19.	he is very very very good	0.428	0.572	0
20.	good good good	1	0	0
21.	The Best	0.808	0.192	0
22.	he is the best	0.583	0.417	0
23.	very strict lecturer but very nice	0.453	0.547	0
24.	he is very nice but strict	0.29	0.71	0
25.	the BEST	0.831	0.169	0
26.	very good at giving lecturer	0.661	0.339	0
27.	he is very smart and respected lecturer	0.56	0.44	0
28.	he is very strict, nice and smart lecturer:)	0.491	0.509	0
29.	respected lecturer	0.756	0.244	0
30.	nice lecturer:)	0.737	0.263	0
31.	he is a good lecturer and very respected by the st...	0.44	0.56	0
32.	very good lecturer	0.615	0.385	0
33.	very good and nice lecturer	0.676	0.324	0
34.	he is the Best	0.583	0.417	0
35.	lecturer always try to give the best in his lectur...	0.318	0.682	0
36.	his class is very interesting	0.428	0.572	0
37.	very respected lecturer	0.629	0.371	0
38.	his class is very interesting	0.428	0.572	0
38.	very respected lecturer	0.629	0.371	0
40.	his teaching is understandable	0	1	0
41.	very good:)	0	1	0
42.	the best lecturer ever	0.583	0.417	0

Table 1 (continued)

No.	Textual Feedback	Positive	Neutral	Negative
43.	he is respected by student	0.437	0.563	0
44.	his lecture never boring	0.395	0.605	0
45.	very nice lecturer	0.607	0.393	0
46.	good lecturer	0.744	0.256	0
47.	strict but very very good lecturer	0.485	0.515	0
48.	good lecturer	0.744	0.256	0
49.	he is very respected by student	0.404	0.596	0
50.	very smart but strict	0.4	0.6	0
51.	he is very respected, strict and smart	0.549	0.451	0
52.	GOOD lecturer	0.784	0.216	0
53.	good but strict lecturer	0.394	0.606	0
54.	he is very nice, good but sometimes strict	0.408	0.592	0
55.	I like the topic and how it is taught	0.263	0.737	0
56.	clear explanation by lecturer	0.464	0.536	0
57.	best lecturer	0.808	0.192	0
58.	the module is very useful	0.444	0.556	0
59.	the teacher is very interesting	0.428	0.572	0
60.	interesting lecturer	0.73	0.27	0
61.	flexible teaching style	0.487	0.513	0
62.	enjoy the lectures	0.615	0.385	0
63.	the lecture attract my attention:)	0.385	0.615	0
64.	THE BEST	0.808	0.192	0
65.	the lecturer makes the class interesting and fun	0.5	0.5	0
66.	the teaching is clear and accessible	0.342	0.658	0
67.	lecturer easy to understand and very helpful	0.545	0.455	0
68.	flexible teaching style	0.487	0.513	0
69.	good lecturer explains things well	0.625	0.375	0
70.	good explaination by lecturer	0.492	0.508	0
71.	very BEST lecturer	0.723	0.277	0
72.	lecturer are very clear and useful to understand d...	0.389	0.45	0.161
73.	lecturer is interesting and relevant	0.403	0.597	0
74.	lecturer makes the subject interesting	0.403	0.597	0
75.	lecturers light hearted	0	1	0
76.	lecturer does explain things well	0.344	0.656	0
77.	GOOD LECTURER	0.744	0.256	0
78.	lecturer explains the slide nicely	0.42	0.58	0
79.	best lecturer	0.808	0.192	0
80.	very good lecturer	0.615	0.385	0
81.	good interaction with student	0.492	0.508	0
82.	interesting,taught well	0.677	0.323	0
83.	flexible teaching style	0.487	0.513	0
84.	strict but good lecturer	0.562	0.438	0

Table 1 (continued)

No.	Textual Feedback	Positive	Neutral	Negative
85.	good lecturer	0.744	0.256	0
86.	punctual lecturer	0	1	0
87.	the best:)	0	1	0
88.	strict but nice	0.649	0.351	0
89.	very good lecturer	0.615	0.385	0
90.	nice lecturer	0.737	0.263	0
91.	THE LECTURER IS VERY EXCELLENT	0.5	0.5	0
92.	best lecturer	0.808	0.192	0
93.	the lecture are very interesting	0.428	0.572	0
94.	the lecture is very clear and uptodate	0.325	0.675	0
95.	interesting lecturer but sometimes strict	0.316	0.684	0
96.	many useful practices	0.592	0.408	0
97.	good lecturer	0.744	0.256	0
98.	topic includes in the module is interesting	0.31	0.69	0
99.	good communication with student	0.492	0.508	0
100.	good lectures and good lecturer	0.659	0.341	0
101.	good lecture notes	0.592	0.408	0
102.	lecture style is great	0.577	0.423	0
103.	easy to understand the lecture	0.42	0.58	0
104.	not bored with the lecture	0.312	0.688	0
105.	interesting lecturer	0.73	0.27	0
106.	good in explaining	0.592	0.408	0
107.	very understandable lecturer	0	1	0
108.	good interaction with student	0.492	0.508	0
109.	good slide provided	0.592	0.408	0
110.	good lecturer:)	0.744	0.256	0
111.	nice lecturer	0.737	0.263	0
112.	he is very respected:)	0	1	0
113.	the lecture is interesting and never boring	0.483	0.517	0
114.	useful content and slide	0.492	0.508	0
115.	strict but good	0.658	0.342	0
116.	interesting lecturer	0.73	0.27	0
117.	very nice	0.756	0.244	0
118.	nice lecturer	0.737	0.263	0
119.	smart but strict	0.481	0.519	0
120.	strict but very respected	0.605	0.395	0

them used these new features to emphasise and better express their text feedback, while other students used the common textual style for expressing their opinion. It was interesting to find that when both the capitalisation of words and emojis were used simultaneously in a sentence, a high negative score (79.4%) was obtained.

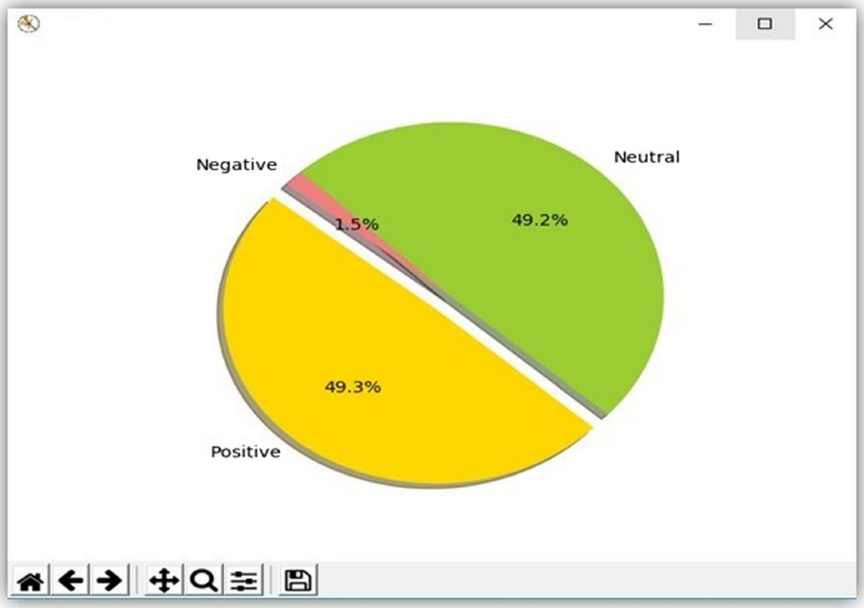

Fig. 3 Results of students' feedback on a lecturer

Figure 3 shows a pie chart representation of the students' feedback according to the aforementioned polarities. Based on the feedback from 120 students, 49.3% have positive opinions towards their lecturer's teaching performance. Neutral opinions were at 49.2% and only 1.5% were for negative opinions. These results indicated that most of these students have positive and neutral opinions about their lecturer's teaching.

6 Conclusion

This study has developed the OMFeedback system that incorporates the opinion mining technique for analysing students' feedback in the textual format. While most opinion mining studies rely on machine learning techniques, particularly the neural network, the lexicon-based approach, with capitalisation of words and emoji characters to improve the textual feedback, is often ignored. By utilising the lexicon-based approach, with the aforementioned new features, lecturers' teaching performance could be better analysed. This improved lexicon-based approach could shed some light into the text mining research area, thus, opening up a new avenue for other research directions.

Although this study has provided significant evidence that qualitative analysis (textual feedback) will complement the quantitative analysis (fixed-rubric rules) of students' feedback, the OMfeedback system still needs improvements to better understand the complexities of students' opinions. Therefore, future studies are encouraged to add more words in the lexicon dictionary to enhance the classification accuracy. This system should also be added with a spelling and grammar checker for verifying each feedback. In addition, IHLs are recommended to facilitate the study of this type of system to increase the effectiveness of the lecturer teaching assessment system.

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