A Conceptual Framework for Analyzing Students' Feedback

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***Abstract*—In academic institutions it is normal practice that at the end of each term, students are required to complete a questionnaire that is designed to gather students' perceptions of the instructor and their learning experience in the course. This questionnaire comprises of Likert-scale questions and qualitative questions. One of the important goals of this exercise is to enable the instructor and the senior management to examine the feedback and then enhance students' learning experience. In most universities, including our own, a lot of attention is paid to the quantitative feedback, which is summarized and statistical comparisons are computed, analysed and presented. However, the qualitative comments given by the students are not fully tapped. Capturing and analysing the qualitative feedback data, at the individual course, school and university-level, can provide valuable insights on teaching practices and curriculum. In this paper, we propose a conceptual framework for student feedback analysis that provides the necessary structure for implementing a prototype tool for mining student comments. We then discuss the application of the tool to analyse feedback from selected courses.**

Keywords—Student feedback analysis, framework, learning analytics, topics, sentiments, text analytics, clustering

I. INTRODUCTION

Learning analytics involves computer-aided analysis and transformation of large-scale data to provide meaningful insights in order to design appropriate interventions for improved teaching practices and learning processes [1]. The ultimate goal is to enhance students' learning. For the same purpose, all universities collect various forms of feedback from students [2, 3, 6]. The feedback from students helps instructors take note of their strengths and weaknesses to make appropriate changes to their teaching and curriculum so as to enhance student learning. The feedback is also important for curriculum design, and management decisions on faculty promotions [7]. While institutions have the right intent in collecting voluminous amount of data, the question is "what do universities do with the large collection of data?" Based on literature review we understand that institutional educational data such as student feedback are yet to be fully tapped and mined for gaining insights that help to improve teaching and learning.

In our university, the student feedback questionnaire is administered online using our in-house "FACETS" system. Students are to complete a questionnaire for each course they have taken. The collected data is analysed at an individual instructor level, and a summary of the quantitative data as well as compilation of qualitative comments in raw form are made available to the respective instructors as individual reports. This report is generated through the FACETS system. Schools may also retrieve school-level data from the FACETS system - but this is only the quantitative data. In addition to this, the Centre for Teaching Excellence (CTE) tabulates and presents quantitative data at school and university-level in the form of a stakeholder's report. However, the qualitative data is not included in the report. Thus, the qualitative data is largely untapped. Interestingly, this situation is not unique to our university.

Capturing and analysing the qualitative feedback data, at the individual course, school and university-level, can provide valuable insights on teaching practices and curriculum [16, 17] At the same time, the correlations between the quantitative and qualitative feedback can also provide additional insights. For example, in our preliminary analysis we noticed that in some instances the comments from the students are generally positive in nature but the numerical scores are quite low. So the faculty should not be judged using the numerical scores alone and there is a need to quantify the qualitative comments. Therefore study on correlations between the quantitative and qualitative scores is another aspect of feedback analysis.

In this paper, we propose a conceptual framework for student feedback analysis that provides a starting point for the community of stakeholders to consider how qualitative and quantitative feedback can help in making informed decisions with respect to teaching, learning, and curriculum improvements. It elaborates on the main components of a student feedback analysis model and the interactions between these components. It also illustrates the main aspects to be taken into account when implementing feedback analysis tools. Furthermore, in this paper, we present a case study where the framework is applied to a selection of courses within one school. In our preliminary study, we observed that the framework is useful in analysing the students' feedback in terms of topics of interest and sentiments on these topics. The results show that applying text analytics algorithms and summarization techniques are useful in discovering insights from qualitative feedback.

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The paper will be structured as follows. Section II will be devoted to literature review and will primarily focus on describing the current research done in the field of student feedback analysis. Section II will provide the background of the student evaluation tool namely, FACETS used in our university and then explain the role of feedback on teaching and learning process. Section IV describes the conceptual framework for analysing students' feedback. Section V describes a case study of the application of this framework. In this section, we focus on design, development, experiments, and results, and we conclude in section VI.

II. Literature review

In this section, we briefly review related research in three different areas namely, student feedback and its role in supporting the learning process, learning analytics, and techniques used for mining qualitative data.

A. Use of student feedback to improve learning outcomes

The use of feedback to improve quality is not novel. However, the use of feedback in itself does not equate to the usefulness of feedback. The latter depends on how the feedback data is being analyzed and utilized. According to Brennan and Williams [3] all institutions collect various forms of feedback to improve the quality of the education - this includes aspects such as instruction/teaching, course material and assessment. According to Biggs and Tang [4], there should be an alignment between teaching and learning methods, intended learning outcomes, and assessments.

The underpinning assumptions here are that effective use of student feedback can lead to improved teaching and curriculum, which in turn would lead to enhanced student learning experience and outcomes. This generates two questions: (1) whether student feedback leads to improved teaching and curriculum, (2) whether improved teaching and curriculum lead to enhanced student learning experience and outcomes. An underpinning assumption in answering the first question is that the feedback questionnaire is valid and reliable. Cohen (1980) attempted to answer the first question through a meta-analysis comparing feedback at tertiary level and came to the conclusion that student feedback had a modest but significant contribution to the improvement of teaching. This finding has been well-supported by other studies over the years [6, 8]The possible explanation for this causality could be that (1) instructors have reflected on the feedback received, (2) perhaps have undergone some interventions, and (3) taken necessary steps to improve their quality of teaching and curriculum. The answer to the second question is more obvious – it underpins the purpose of universities and the necessity for teachers.

In our university, we ask students to provide qualitative responses on their perceptions about the course and instructor. However, the long list of qualitative feedback is given to the instructor as a "pdf" document which makes it very tedious for analysis and gaining focused insights that would help to enhance the student learning experience.

B. Learning analytics

Learning Analytics is a research field that is dedicated to the study of educational data mining to discover insights and aid in decision making process. Learning analytics and in particular text mining is one technique that will allow for qualitative analysis of student feedback at school and university-level. Such techniques have been more popularly used in the commercial fields such as marketing and social media [9, 10]. This trend is also moving to the educational setting. For instance, Gamon et al.[11] built a system that clustered topics and classified sentiments with intuitive visualizations to provide a more in-depth analysis. Rashid et al. used generalized sequential pattern mining and association rule mining with 87% accuracy to analyze opinion words from student feedback [12]. Law et al. proposed key phrase and Natural Language Processing (NLP) techniques to study assessment and curriculum framework in higher education [13].

In order to implement learning analytics, one could us1e commercial Computer Aided Qualitative Data Analysis Software programs (CAQDAS) such as NVivo and SPSS Qualitative analysis tools. The advantages of the commercial tools are that they are readily available. However, they do not cater to deeper analysis, especially in terms of relational analysis between multiple variables and in conducting longitudinal studies. Further, these tools do not provide features for analysing the correlation between the qualitative and quantitative feedback. Hence there is a need to develop a custom tool for supporting student feedback analysis. In this paper, we provide a conceptual framework for analysing the student feedback on various dimensions such as topics, sentiments and suggestions, and the prototype tool Student Feedback Mining System (SFMS) that implements this framework.

C. Techniques for mining qualitative data

The traditional approach of processing text information involves human actions in information gathering, analysis, and dissemination. However, with text mining and analytics many domains are benefiting from using textual data for improving business value (Hearst, 1999). We first begin with applications of qualitative data mining in general domains and then discuss some of the recent works in educational domain.

Hoteliers find text mining useful in environmental scanning of customer intelligence by analysing customer newsgroups, online bulletin boards, and online customer surveys [14]. Travel industries extract customer intelligence from online discussion groups for improved customer service decisions [15, 28]. Student comment analysis using text mining techniques and the benefits and limitations are described by Ila et al [29].

In educational domain, sentiment analysis is implemented in order to explore the hidden knowledge and the comments from open-ended questions in the evaluation process. Most researchers focus on quantitative data analysis. However, some works have been done on qualitative data using sentiment analysis. For example, El-Halees studied feature-based sentiment analysis to course quality evaluation [16]. Balaji introduced the idea of automated sentiment analysis from teacher feedback assessment using sentiment classification [17]. In a study of student evaluations, the authors examined a scenario of one lecturer who applied their system to learn the sentiment from students' comments before moving to the next part of his lecture [19]. 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' 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. In this way, the faculty can re-adjust the pedagogy and improve the student leaning outcomes.

However, topic-based sentiment analysis and suggestion analysis is not widely studied yet.

Opinion mining, Topic extraction and Natural Language Processing (NLP) techniques [25, 26, 27] from the text analytics and linguistics research are widely popular for mining users' comments in social media. Sentiment mining techniques are widely used for product review mining in consumer business world [9]. We leverage these techniques for developing the conceptual framework for analysing the student feedback comments.

III. Background

In this section, we first describe the background of the student evaluation tool, FACETS, used in our university. Understanding the tool gives the background on the data gathered from the students and limitations of the tool. We will then present the importance of this data in the teaching and learning cycle.

A. *FACETS - Student Feedback Tool*

Our university's end-of-term student feedback questionnaire "FACETS" is designed to gather students' perceptions of the instructor and their learning experience in the course. "FACETS" stands for "For Assessment of Continuing Excellence in Teaching". The questionnaire was developed in 2012 and it has been used since then. The questions were adapted and developed from the literature on measuring tertiary teaching and learning. The questionnaire is administered online by the Centre for Teaching Excellence (CTE) at the end of every term.

The questionnaire comprises (1) 17 Likert-scale items, and 2 qualitative questions on students' perceptions about the instructor and course, (2) 1 Likert-scale question on course load, and (3) 1 Likert-scale question on course challenge. In addition to this, schools and faculty members have the option to ask 2 Likert-scale questions and/or open-ended custom questions each. Students will complete the questionnaire in this order. At present, the FACETS system generates an individual FACETS report for each of the faculty members. The report consists of comparative summarized data for the Likert-scale items on core and non-core courses at the school and university-wide levels. However, students' qualitative comments are presented in raw form.

Sample feedback report is in shown in Figure 1. Faculty members use the feedback in their FACETS reports to identify their strengths and areas for improvement. They reflect on their teaching and curriculum and take steps to improve their instructional strategies and course materials to create a more positive learning experience for future students.

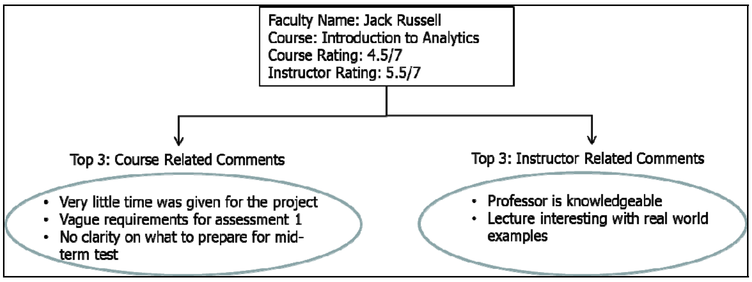

Fig. 1. Example students' feedback for faculty and the course. Both qualitaive and quantitative feedback is collected by student evaluation system.

On a similar note, the school deanery takes into consideration the information in FACETS reports to improve future course offerings and faculty's teaching effectiveness. Areas of strengths and concerns are communicated during faculty appraisal meetings so that faculty members are aware of the deanery's expectations. Student feedback is also a source of information for faculty recruitment and personnel decisions, as well as teaching awards nominations. In one school, administrative staff members assist the deanery to summarize qualitative comments from the FACETS reports during their annual faculty appraisal. Although this will greatly help the deanery in making a more informed decision, it is not a common practice across all the schools as the task requires a lot of resources in manual processing.

There are a number of challenges in using the qualitative data in our context. First, there is minimal coordinated analysis done at the school and university-level. The qualitative data analysis is left to the individual faculty members to be interpreted. Such independent analysis could be problematic as there is no comparison to overall feedback [18]. Second, data collected on "module-specific" and more generic "programme-wide" questions to compare across programmes are not collectively analysed [3]. Again, they are left to individual coordinators (to use their own means) to analyse. This can also lead to variations in analysis and impact reliability. Since validity and reliability of interpretation of student feedback will affect the choice of remedial interventions, it is crucial that we employ a university-level qualitative analysis system.

B. Role of student feedback in teaching and learning cycle

Using student feedback to improve teaching and curriculum is illustrated in the teaching and learning continuous improvement cycle as shown in Fig 2. It is a four step process. In step 1, the students' experience the course when the instructor delivers the course. In step 2, the students give feedback on their experience. This feedback can include both quantitative and qualitative data. In step 3, the instructor analyses the feedback. In step 4, based on the insights gained from the analysis the instructor re-designs the teaching approach and the curriculum content. This cycle can be repeated for the next run of the course or alternatively applied multiple times within one run of the course.

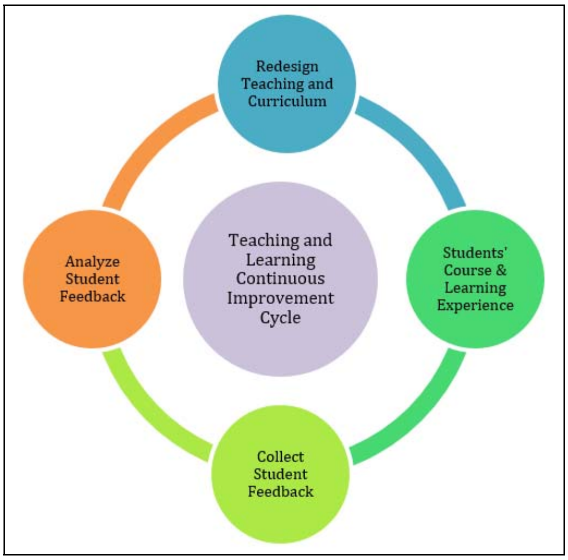

Fig. 2. Teaching and Learning Continuous Improvement Cycle

If student feedback is collected but not used completely, that is, only quantitative data is used, then the teaching and learning continuous improvement cycle may not be completed effectively.

Examining the feedback data shown in Figure 1, it is obvious that the quantitative data, for example "Course Rating = 4.7/7, on its own does not provide fine-grained insights that will help the faculty to implement actions to enhance the learning process. However, for example, the qualitative data "Vague requirement for assessment 1" provides more clarity on what needs to be changed. The challenge is that there are bound to be 100s or 1000s of comments in each course which makes it tedious for the instructor to read these comments and then decide on which comments to act upon in order to improve student learning experience.

Sentiment analysis techniques helps to computationally identify and categorize text comments and classify them as positive, negative, or neutral.

The student learning experience can be improved by studying the sentiments or opinions of the students during the course delivery period and intervening accordingly in the teaching process. The sentiment analysis can help the instructor to analyse students' comments. At the same time, the instructor can change their teaching style after finding out students opinions over time periods or repeat a part of the content that most students did not clear. Improving student learning by integrating the student feedback in the teaching and learning process is the motivation for our empirical research and drives a need for developing a conceptual framework that provides the structure to support the implementation of the Student Feedback Mining System (SFMS).

IV. CONCEPTUAL FRAMEWORK FOR STUDENT FEEDBACK ANALYSIS

We will first introduce a few basic concepts used in the framework.

1. **Comment:** Qualitative feedback given by a student for a course taken at a university. For example, "The course project is very difficult and challenging" is a comment from the Enterprise Integration course (IS301).

2. **Topic:** A topic (interchangeably called 'aspect') is the subject or target of a student's comment. For example, in the comment, "The course project is very difficult and very challenging", "project" is the topic of the comment. Though in many comments students talk about a single topic, there are few instances that they may span across many topics in a single comment. A comment with multiple topics is not a focus of our work and we leave it to future work.

3. **Sentiment**: Sentiment refers to the positivity or negativity of a given comment. For example, given the comment, "The course project is very difficult and very challenging", the sentiment is "negative". In some applications, a neutral sentiment is also widely used. In our preliminary studies, we observed that the students' comments are mostly negative or positive.

4. **Suggestion:** Suggestions refer to comments, which provide actionable feedback to the decision makers such as administrators and faculty members. For example, "The course needs to focus on the code as much as the business side" is a suggestion from the student feedback on the course content whereas, "sounding a little more upbeat may help with the class energy level" is a suggestion for instructor.

5. **Correlation:** Correlation refers to the dependency between sentimental comments (qualitative) and numerical (quantitative) scores of students' feedback.

Figure 3 shows the conceptual framework for analysing students' feedback. It comprises four components namely, Text Analytics Model, Data Processing, Extraction and Summarization. The framework uses student qualitative feedback as input and processes the data to generate visual outputs for the users of the evaluation system to improve the teaching and learning process.

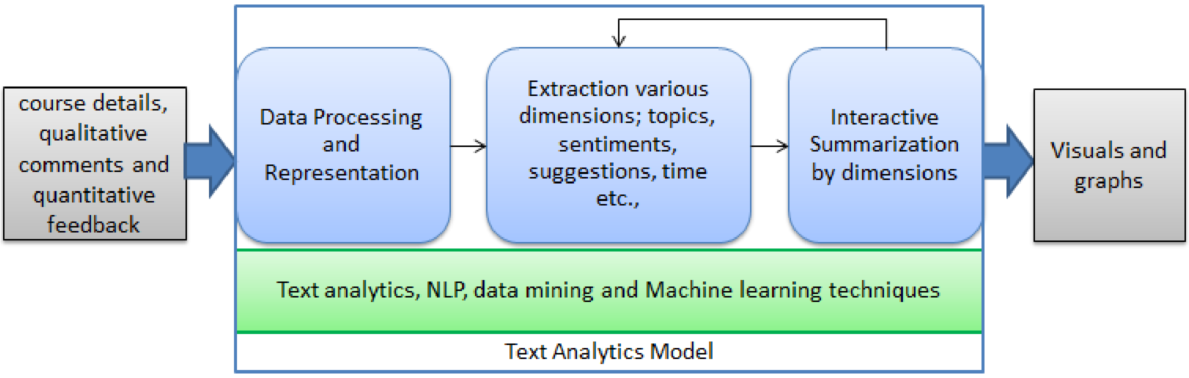

Fig 3. Conceptual framework for student feedback analysis

A. *Text Analytics Model*

The goal of text analytics also referred to as text data mining or text mining is to derive high-quality information from text. Typical text mining tasks include; text categorization, text clustering, concept or entity extraction, production of granular taxonomies, sentiment analysis, document summarization, correlations, and entity relation modelling. In education data mining research, text mining has been used to analyse the content of discussion boards, forums, chats, web pages, documents, and so forth. Natural Language Processing (NLP) and text analytics methods are applied in e-learning environments for processing textual content [21]. Various techniques such as stopword removal, stemming, entity extraction, named entity taggers (NER), keyphrase extraction, parts of speech (POS) tagging, topic modeling, text summarization etc., are popularly used for mining information from unstructured text. In our framework, text analytics model layer is the foundation layer that provides the techniques and tools.

B. *Data processing*

The objective of data processing is to collect and prepare the raw text data for the extraction phase. The data preparation stage relies on the student evaluation systems employed in the institutions. A well-developed student evaluation system such as FACETS, aids in collecting student feedback effectively. Processing the quantitative feedback is more straight-forward than the qualitative data. The qualitative data needs to be cleaned and represented in structured format for extracting useful information. Some of the challenges include; noise words such as “a”, “an”, “for” etc., which are of little value in helping us, same form of words such as “project”, “projects” that represent the same topic and the sentiment words embedded within the textual feedback such as “too fast”, “not easy” etc. Data processing stage handles such data challenges and prepares the data for the next stage.

C. *Extraction*

Extraction is the most crucial component of the framework. This stage extensively uses the text mining and machine learning techniques to discover useful information from the data. The below are various categories of useful information and examples that can be extracted from students’ feedback.

1) Topics, Sentiments and Suggestions

It is important to extract the relevant topics, sentiments and suggestions from the collection of student feedback comments. Figure 4 shows sample comments with the corresponding sentiments. Table I shows sample comments with sentiments mapped to “positive” and “negative”, and indication of whether a comment is a suggestion.

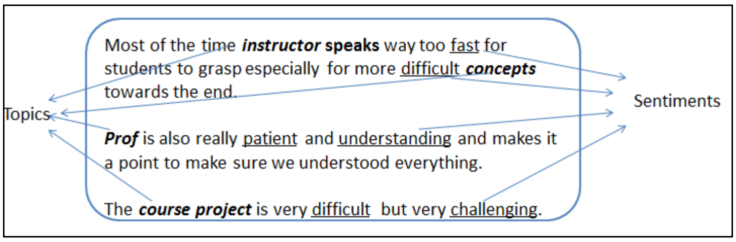

Fig. 4. Example comments with topics and sentiments highlighted.

TABLE I. SAMPLE COMMENTS FROM STUDENTS WITH SENTIMENTS AND SUGGESTIONS

Comment	Sentiment	Suggestion
very knowledgeable, patient and easygoing - sounding a little more upbeat may help with the class's energy level	+ve	Y
sometimes he went through the concepts a bit too fast for us to grasp.	-ve	N
Asks challenging questions to get us to think deeper.	+ve	N
The course needs to focus on the code as much as the business side.	-ve	Y

D. *Correlating Quantitative and Qualitative feedback*

To focus of this task is to study the correlation between quantitative scores and qualitative comments. The correlation studies are performed on all the courses on various questions and link them to the topics within the qualitative feedback for deeper analysis. This would allow us to gain deeper insights and justifications for the high or low quantitative scores for the student evaluation questions. Further, correlations can aid in

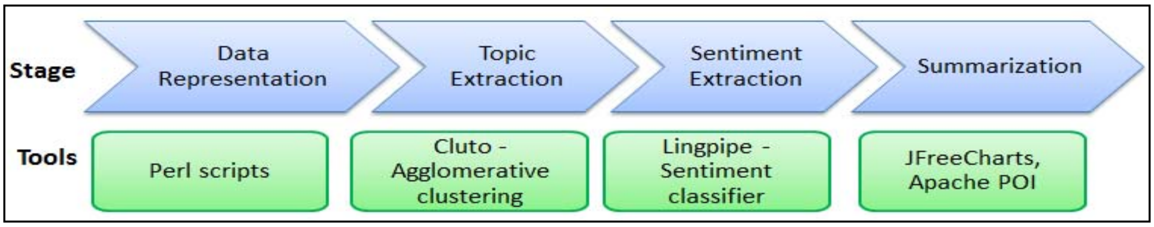

Fig. 5. Case study - Student Feedback Mining System

identifying representative texts/comments for the given numeric ratings by the students as shown in Figure 1.

E. *Summarization*

Summarizing the outputs of the extraction stage effectively yields greater efficiency in terms of comprehending the comments and being able to make informed decisions in teaching and learning process. It is to be noted that only with a flexible set of interaction reports and visuals the users will able to perform the student feedback analysis effectively. This highlights the importance of visual interactions in any textual summarization effort and this component of the framework is critical as the users of the analysis will be relying heavily on this for the continuous efforts of teaching and learning improvement process cycle.

V. CASE STUDY

To evaluate the effectiveness of the framework proposed in Section IV, we implemented the framework as prototype system, Student Feedback Mining Systems (SFMS) and tested it on selected courses from the School of Information Systems. Figure 5 shows the stages and the tools of SFMS.

The SFMS prototype can be viewed as two layers. The first layer in SFMS architecture comprises of four main stages of the system. The second layer depicts the tools or techniques used to accomplish the tasks in each of the four stages. In the first stage, a dense matrix of comments is generated after pre-processing the data. In the second stage, comments are clustered based on their primary common "topics" (e.g. "instructor" "assessment", etc.). In the third stage, sentiments of each comment are extracted, and finally in the fourth stage, topics and sentiments are aggregated for comprehensive reporting.

A. *SFMS Development*

The SFMS was developed using a Java platform and tested using student feedback from a selected few undergraduate courses. In total, 7 courses are evaluated each term yielding 5,341 comments for evaluation.

We created SFMS as a desktop application with simple UI for each stage. The first stage of SFMS system is to generate document matrix. To generate the document term matrix, we use doc2mat perl scripts provided in Cluto library [22]. Cluto API is an easy-to-use platform that combines a variety of different clustering algorithms. We use vcluster in toolkit to generate clusters. All our experiments are based on agglomerative clustering with cosine similarity. For sentiment classification, we use [20] which provide a sentence based logistic regression classifier for sentiment classification.

B. *SFMS Evalution*

We evaluated SFMS on both topic extraction and sentiment extraction tasks. The details of the experiments and results for each stage are described below.

1) *Topics Extraction Results*

We set the number of clusters to ten after some preliminary experiments. Sample ten clusters generated by Cluto API from our dataset are shown in a graphical representation in Figure 6. Mountain view shows the properties of the clusters of comments.

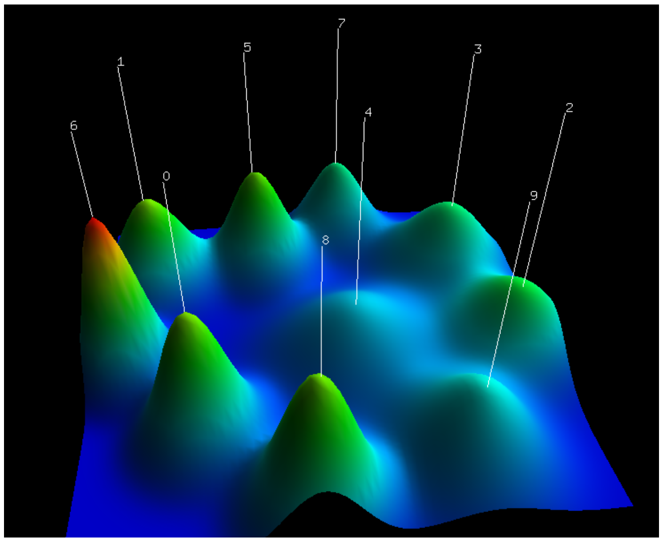

Fig. 6. Sample clusters from our dataset in mountain view using gcluto – a graphical version of Cluto. Each peak represents a cluster. Distance between peaks represent the dissimilarity of clusters. Height depicts internal similarity, volume represents the number of objects and color depicts the internal standard deviation of cluster's objects, red being low.

Table II shows sample results of Topic extraction from the SFMS prototype. The top words in each cluster and the manual labelling of clusters is depicted in the table. Note that the human labelling is subjective and usually uses the top 5 to 10 words for generating the labels.

TABLE II. SAMPLE RESULTS OF TOPICS FROM SFMS PROTOTYPE

Cluster #	Top frequency words	Topics (human labelling)
1	approachable, friendly, enthusiastic, consultation, help	Faculty interaction
2	helpful, feedback, concepts, understanding, encouraging, help	Faculty feedback
3	project, heavy, time, requirements, lot	Project
4	challenging, lab , test, project, exercises	Labs
5	understand, concepts, help, questions, explain	Concepts understanding
6	teaching, lesson, fast, nice, lessons	Classroom delivery

2) Sentiments Extraction Results

In the sentiment extraction stage, we use human labelling for training the data and testing the accuracy of SFMS. Since Lingpipe uses logistic regression, we evaluated the effect of domain on the training of the classifier and further compared it with a lexical approach which constructed a probability of polarity for each comment based on a dictionary of words that have a sentiment probability attached to each word. In our experiment, we found that training the classifier with a ten-cross validation on the "education domain" gave best results instead of the standard "Internet Movie Database" (IMDB) dataset provided by Pang et al, 2005. The lexical approach by Esuli et al. performed better than the movie domain and was comparable in performance to the education domain as shown in Table III [27].

TABLE III. EVALUATION OF SENTIMENT CLASSIFCATON TASK

Function	Precision	Recall	F-Score
Log Regression (Movie domain)	0.656	0.421	0.513
Log Regression (Education domain)	0.801	0.864	0.835
Lexicon (Senti Wordnet)	0.815	0.733	0.772

Overall, the sentiment extraction phase with training on education domain has a precision of 80.1%, recall of 86.4% and F-Score of 83.5% which is significantly higher than IMDB trained classifier.

3) Summarization

Results from the previous two stages (Topics and Sentiments) were charted using JFreeCharts[1]. Figure 7 and provides reports on various aspects of the course and instructor. We observe that the students provides comments on aspects such as project, labs, skills, etc. of IS200 (IS software foundations) course, which is programmatic in nature. However, the faculty feedback and interaction is not of their concern.

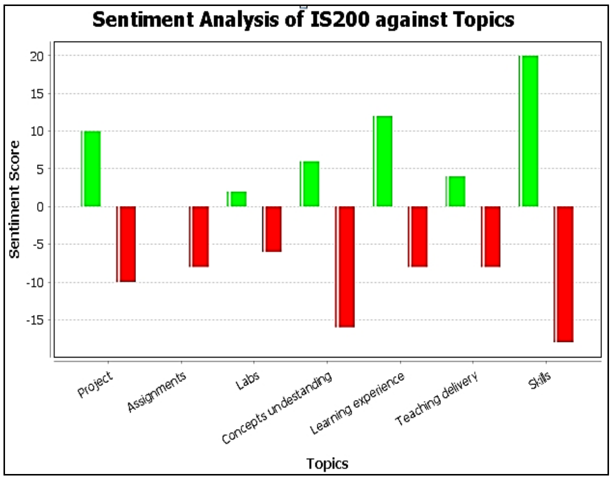

Fig. 7. Topics and sentiments chart for IS200 course.

This evaluation showed that SFMS provided meaningful clusters of comments and words for Topic extraction task with a cluster purity of 93.4% and precision of 80.1% for Sentiment extraction task. Thus implementation and evaluation of SFMS has demonstrated the feasibility of the framework for student feedback analysis shown in Figure 3.

This case study is only a partial implementation of the proposed conceptual framework, topics and sentiments. The case study also used a desktop application for the development approach and has limitations of maintenance. In our future work, we propose the web based application architecture. We further study the approaches for suggestion analysis and the correlations between qualitative and quantitative student feedback.

VI. CONCLUSION

Universities collect feedback from students upon course completion to improve instruction, curriculum and students' learning experience. However, it is often difficult to fully decipher the qualitative feedback effectively and efficiently and this data is left untapped. In this paper, we present a learning analytics solution which applies text analytics techniques to quantify and analyse the qualitative feedback from students.

The paper proposes a conceptual framework for student feedback analysis that provides a reference point for the community of stakeholders to consider how qualitative and quantitative feedback can help in making informed decisions with respect to teaching, learning, and curriculum improvements. Furthermore, in this paper, we present a case study where the framework is applied to a selection of courses within one school through the implementation of the prototype SFMS. The case study shows an application of this

[1] http://www.jfree.org/jfreechart/

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