UNCOVERING THE NATURE AND POTENTIAL OF AFFECTIVE FEEDBACK IN INTERACTIVE TEACHING AND LEARNING

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Abstract

In this paper, we demonstrate our experience and assessment of the impact of integrating affective (emotional) feedback into assessment and interactive activities during class meetings. In typical class meetings without tools and activities to gather and integrate affective feedback, the evaluation of students' state and learning is primarily based on summative and infrequent cognitive assessment methods, such as attendance, in-class participation, assignment grades, etc. By affective feedback, we refer to actively measuring and collecting specific emotions and sentiments of students during class meetings, especially in the service of on-going teaching and learning processes. Moreover, we can also look for these affective measures from direct feedback polls and students' text-based responses from in-class activities such as reflective posts and forum discussions. In the work reported in this paper, these activities were facilitated by the Discovery Teaching platform; a web application with several tools designed to support interactive and evidence-based teaching and learning in classrooms. A regular activity conducted during classes was the submission of reading reflections, as forum posts, ahead of an upcoming class corresponding to pre-class readings or materials. We also looked at direct student feedback comments after individual classes, and also course feedback at the end of the semester. The experience and impact assessment of affective feedback reported in this paper is based on data collected from three Computer Science courses during the spring 2019 and spring 2020 semesters when affective feedback activities were utilized as parts of a larger interactive computer-supported pedagogy.

In our data analysis, we took into account the correlations between students' sentiments and emotions and their performance on formative and summative activities. This would inform us whether affective feedback serves as a good indicator of students' learning, the teaching (pedagogy), and feedback to class materials and activities. We also looked at the sentiments of students in their reading reflections before every class and how they felt after the class to see if this, often hidden, unused, and subtle affective feedback is informative and useful in understanding and improving the teaching and learning processes. To uncover these measures in our textual data, we used the IBM Watson Natural Language Understanding library. Our overall experience and results demonstrate that affective feedback can facilitate instructors' understanding of the class and individual student's learning, progress, challenges, nature of engagement with class materials and activities, and serves as a valuable resource in assessing and improving the quality of the teaching and learning processes (pedagogy) in pursuit of better learning and teaching outcomes, equitable and inclusive pedagogy, as well as an informed and evidence-based agile pedagogy. In this study, we also assess the emotional evidence and impact of the COVID-19 pandemic as seen in the analysis of the data from mid-spring 2020.

Keywords: emotion analysis, education technology, emotion feedback, affective feedback, formative assessment, interactive teaching.

1 INTRODUCTION

Feedback in classrooms has always been important and suggests ways for instructors and teachers to improve their classes. Although summative and formative assessments provide a snapshot of student learning and are constantly done in classrooms, affective (emotional) feedback is largely under-utilized or ignored, even though studies suggest that student emotions play an important role in learning outcomes [4]. Most of the work done on affective feedback in classrooms using sentiment and emotion analysis has been to define a system for collecting and processing feedback and not on doing something with/on the results that these systems have generated in the scholarship of agile pedagogy.

In recent years, the use of sentiment analysis has taken off and has revealed insightful behavioral and affective trends. From being used to predict the stock market [11] to collecting political sentiments and predicting election results, sentiment analysis has proved to be an effective tool [2].

Course feedback and text-based responses serve as a great outlet for students to express their emotions and thus also a place where sentiment analysis could provide us with insightful trends. Through the analysis of this data, we demonstrate our experience and assessment of the impact of integrating affective feedback into the classroom feedback channels and overall - agile pedagogy.

The majority of the data collected in this paper has been through the use of Discovery Teaching, a web-based application designed to support interactive and responsive teaching and learning in the classroom.

The data collected for this research was from three different courses. One of the courses was a Web Technologies & Development class whereas the other two were Data Structures classes. All three classes employed rich flipped classroom approaches, involving short lectures, feedback polls, forum discussions in and outside of class times, formative assessment activities, and group-work assessment, all of which were facilitated by Discovery Teaching.

In the following sections, we explore similar works and their results. We then explain our research methodology in collecting and analyzing the sentiments and emotions from the data. Lastly, we present our findings and discuss their implications and also talk about future work regarding the research.

2 BACKGROUND

Online teaching and learning has been gaining increasing popularity, especially in time of the COVID-19 pandemic, and has served as both alternatives and supplements to the traditional in-person classrooms [8]. Online learning resources, widely ranging from Massive Open Online Courses (MOOCs), virtual classrooms to learning from pre-recorded lecture videos are favored for their flexibility, offering anytime and anywhere learning [15]. It can be learned from former studies that student success positively correlates with the level of significant interactions and active participation [12], [6] which reflect clearly in the student satisfaction, engagement, and concentration throughout the class. These factors, in a face-to-face classroom setting, could be effortlessly created and recognized by the instructors; therefore, they could be actively upheld and promoted. On the other hand, a wide range of online learning platforms lack opportunities and measuring capabilities to record students' sentiments and attitudes toward the course materials and their learning, as the main supported types of interactions are limited to forum discussions, text messages, and media sharing.

In this work, we attempt to create an online learning platform that supports real-time interaction, active participation, and most importantly, sentiment and emotion measurements in order to bridge the gap between a face-to-face classroom and the online/remote learning experiences. Our implementation offers a comprehensively interactive classroom with a diverse toolset for evaluating and measuring student sentiment, attitude, and level of understanding and participation in real-time with the use of Discovery Teaching in order to facilitate prominent social, teaching, and sentimental elements for online classroom settings [3][9]. As it is integrated with the ability to track students' sentiment and engagement at any point during the class, Discovery Teaching serves as a potential approach to improving teaching and learning experiences, class participation, as well as instructors' understanding of each and every student's progress. Therefore, Discovery Teaching is necessary for evaluating whether affective feedback is informative and useful in understanding and improving the teaching and learning processes.

Our experiment also took into account the model of a flipped classroom, in which students are responsible for covering the class materials on their own before class and reflecting on pre-class readings and resources while instructors serve as coaches during the class to guide and engage students in class discussions and hands-on activities. As demonstrated in our previous study [13], the flipped classroom has proven to be highly effective in facilitating a deeper understanding of the materials while reducing the number of materials needed to be covered during the class.

3 RELATED WORK

Menaha et al proposed a systematic approach to analyzing both qualitative and quantitative feedback from students [10]. The paper proposes a system whereby the data from the students are first filtered through natural language toolkit functionalities such as tokenization and stop word removal. The data is then clustered into respective categories, which are then mined using their own sentiment analysis algorithm and are displayed in graphs to give the instructor a proper idea of the feedback. Although Menaha et al propose a working system, the research doesn't implement its ideas with actual data nor does it provide insights into the usefulness of affective feedback.

Yang et al mined collective sentiment from forum posts from three different Massive Open Online Courses (MOOCs) [14]. The research focused on a programming course, a teaching course, and a literature course. Results from the research revealed correlation between higher sentiment scores and dropout rate was more than the correlation between negative sentiment scores and dropout rates. The paper also revealed that the correlation between sentiment and dropout rate varied based on a course and how intuitive assumptions of higher sentiment leading to better performance were actually false upon analysis. Yang et al examined the data in a time series model, where they not only examined the first and last feedback but also mine data throughout the courses. Although the research is extensive and perceptive, having only mined the sentiment from MOOCs and none of face to face classes, the results are limited. Although there are a lot more prior studies that mine sentiment from educational data, very little has been done in terms of analyzing real feedback and in-class text material from actual classes.

Alaymoun in his research explores the use of data mining in computer-supported collaborative learning (CSCL) [1]. Alaymoun uses functionalities such as chats to facilitate learning in the classroom and uses the data generated from those to provide insights into how students learn. A significant correlation between participation and course grade leads us to believe that timely intervention could help students learn better. Emotion regulations also influence the success of a student along with other myriad factors such as environment etc [5].

Thus we see the importance of assessing the affective state of a student while learning and the timely intervention needed to help them.

4 EXPERIMENTAL DESIGN

4.1 Class setting

Our first experiment was carried out during an intermediate level Web Development course with enrollment open to undergraduates. Web Technologies and Development is a 200-level Computer Science course focusing on providing students with basic and intermediate web development knowledge, including but not limited to HTML, CSS, JavaScript, TypeScript, and Angular. The class took place in the Spring 2019 semester, consisting of 20 students, and met twice a week for 1 hour and 15 minutes each class. The course consisted of 26 interactive class meetings.

Our second experiment took place in two intermediate level Data Structures courses during the Spring 2020 semester, specifically during the COVID-19 pandemic. The two courses ran in parallel and covered a variety of data structure concepts including linked list, stack, queue, hash table, heap, tree, and graph and consisted of 38 students in total, meeting twice a week for 1 hour and 15 minutes each class. Because of the special social situation in which the course took place, all of the activities during the second half of the course (the last 10 class days) were carried out online through WebEx with the support of Discovery Teaching.

As these courses utilized the Discovery Teaching platform as the main learning and teaching tool, interactions between students and with the instructors were stimulated and facilitated by a wide variety of methods provided by the tool, ranging from forum discussions, in-class assessments, pre-class reading reflections, to real-time student sentiment tracking. Since the class implemented a flipped-classroom pedagogy, before every class, students were required to read the class materials and write a reading reflection on what they learned, how they felt about the lesson, and what questions they had. All of the reading reflections were shared with the class on Discovery Teaching as forum discussion posts and students could comment on others' posts. As students had already covered the materials on their own, the majority of class time was spent on engaging students on hands-on activities and tasks that reinforced and consolidated their understanding and mastery of the concepts.

By doing sentiment analysis on this collected data as well as students' reading reflection posts in the Forum, we could see if there is a correlation between a student's state of emotion and their performance on summative assessments, including homework assignments, tests, and projects.

4.2 Data collection

Our data was gathered from two main sources: Discovery Teaching and Moodle, an open source platform to manage students' assignments and tests and to track their scores. From Discovery Teaching, we collected students' reading reflections and feedback in the Forum throughout the course. This type of data, when combined, demonstrates how students feel about the course overall, as each of the data points shows how they felt for a particular class day. This serves as our source of sentiment and emotion data. On the other hand, the scores we collected from the Moodle site reflected students' performance on formative and summative assessments throughout the course. These scores are students' overall course grades which were balanced and calculated from a variety of evaluating methods, including quizzes, homework assignments, programming projects, a mid-term test, and a final project.

4.3 Methodology

In order to analyze the sentiment of students' reading reflections, we utilized the IBM Watson Natural Language Understanding library [7]. The tool works as an API: we send the reading reflections to an endpoint provided by IBM Watson and receive a breakdown of the writing's emotions, which include five ratings: "sadness", "joy", "fear", "disgust", and "anger", each represented by a number in the range from 0 to 1 with 0 represents none of the specific emotion while 1 represents a strong feeling of that emotion. For example, a student's reflection can be analyzed and broken down into these statistics using IBM Watson emotion analyzer:

- Joy: 0.7
- Sadness: 0.3
- Fear: 0.1
- Disgust: 0.4
- Anger: 0.05

To convert those 5 ratings into one single rating representing an article's overall sentiment, we used the following formula:

$$\text{Sentiment Score} = (\text{Joy} - (\text{Sadness} + \text{Fear} + \text{Disgust} + \text{Anger}) / 4) \times 100$$

Or in other words, we take the positive emotion score and subtract from it the average of the negative emotion scores. Therefore, the higher the sentiment score, the more positive the reading reflection, thus the more satisfied the student feels.

5 RESULTS AND DISCUSSIONS

5.1 Students' strongest emotion counts for each class.

This analysis is concerned with data collected from the class from our first experiment, Web Development. To find a student's dominant emotion for each class day, we took the emotion with the highest score from their reflection's analysis using IBM Watson library then kept track of how often they repeated for each class. Fig. 1 below demonstrates the count of the students' strongest emotions in each class. As seen from the graph, in most of the classes the highest count of dominant emotion is joy except for the 17^{th} class where the highest count of dominant emotion is sadness.

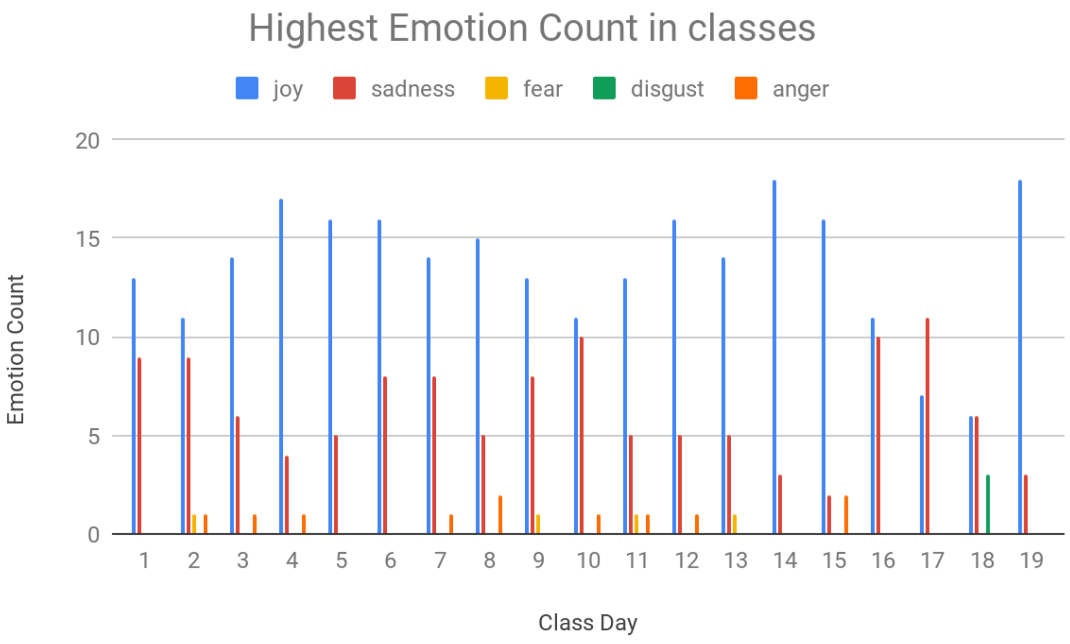

Figure 1. Emotion counts in students' reading reflections per class.

5.2 Sentiment and summative assessments

This analysis follows the results we obtained from the previous analysis of data from Web Development class. In this study, we took into account a student's sentiment score, which is calculated from their reading reflections throughout the course, and their summative score, which is simply their cumulative course grade at the end of the semester, to see whether there is a correlation or trend between them.

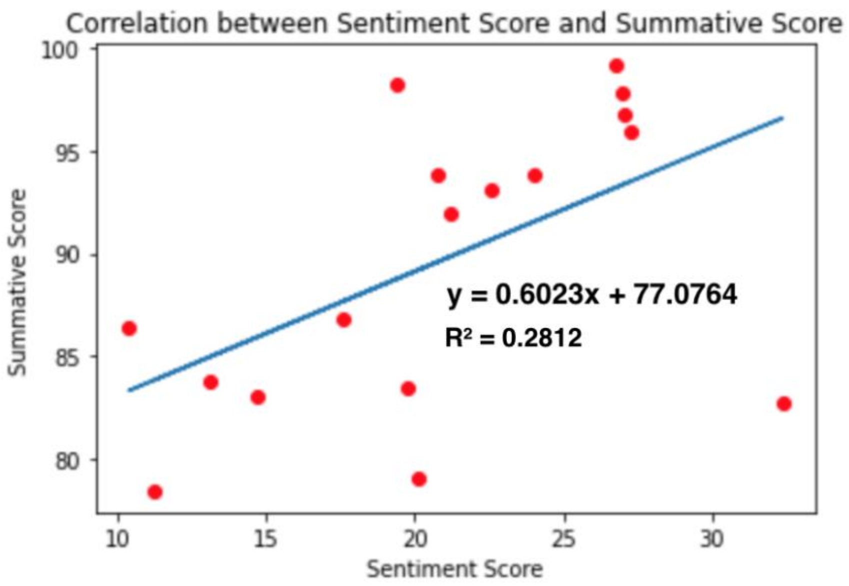

Figure 2. Sentiment Score vs. Summative Score

The data is plotted in Fig. 2 with a line of best fit. Each data point in the research graph above represents one student, with the x axis being their sentiment score and the y axis corresponding to their summative score (overall course grade). From the graph and the line of best fit, we can see that there is a positive correlation between a student's sentiment and their performance on summative assessment activities, as the line of best fit is a line with a positive slope. The coefficient of determination of our linear regression is 0.28, meaning that 28% of the variance in the summative score is predictable from the emotion score. Although

5.3 Effects of COVID-19 pandemic on emotions of students

In this section, we do sentiment and emotion analysis of data collected from two Data Structures classes during the second half of the spring 2020 semester, late March to mid May 2020. As the second part of these two courses took place during the COVID-19 outbreak, by looking at and analyzing their collected data, we could see if there is any trend in students' emotion during the pandemic. For these courses, we only focused on data from the last 10 class days, which were during the pandemic. Specifically we analyzed text from regular pre-class reading reflections or feedback poll summaries where students reported whether they were 'Engaged', 'Bored' or 'Confused' during various times throughout class time.

Fig. 3 below demonstrates the count of the students' strongest emotions in each class, similar to what we investigate for the first analysis above. As seen from the graph, in most of the classes the highest count of dominant emotion is joy throughout the course of study; however, the counts of 'joy' witnessed a decreasing tendency as the course went forward, from 16 in class day 1 to 10 in the last class day. On the other hand, the count of 'sadness' tended to increase as the course moved forward. From these trajectories, we can see that as the pandemic went on and students had to adjust to online learning, relocate, and deal with numerous other personal and general challenges, their emotions seemed to get less positive and more negative.

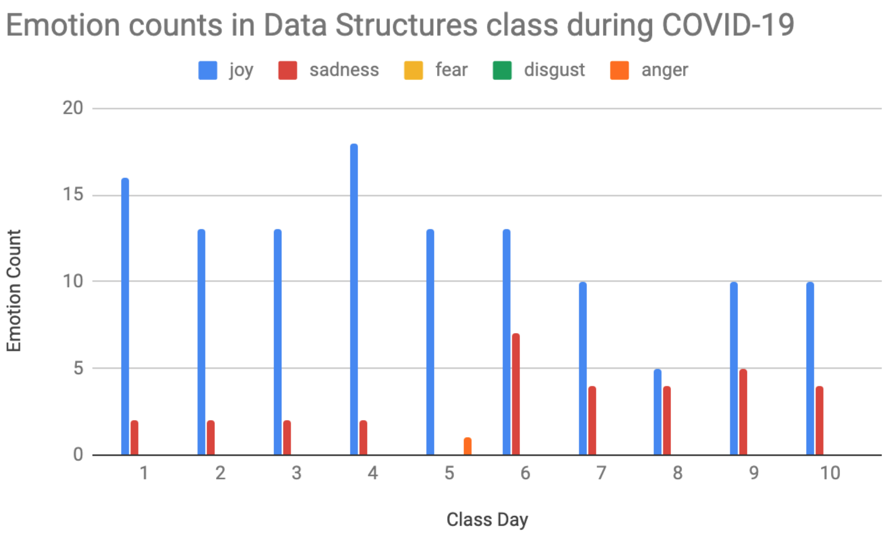

Figure 3. Emotion counts in two Data Structures classes in Spring 2020

To better understand the trend in students' emotion during the pandemic, we took into account the average Sentiment Score of all students in each class day as calculated using the aforementioned formula in the Methodology section. Fig. 4 below shows the line connecting points that represent the score for each class day. As we can see from the graph, there is indeed a decreasing trend in Sentiment Score as the courses went on, thus representing the fact that during the global pandemic, students' emotion got more negative.

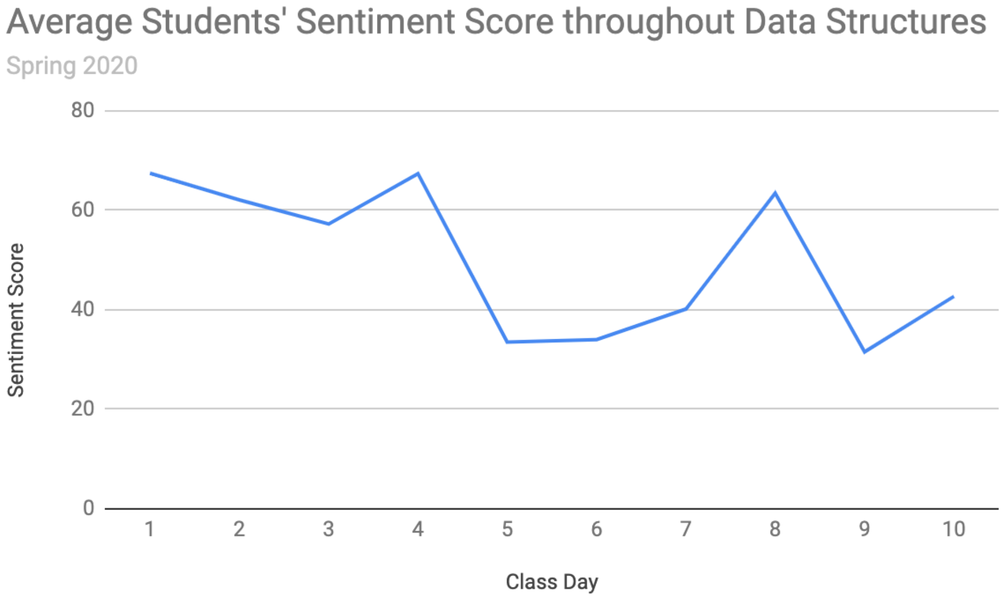

Figure 4. Average students’ emotion scores throughout two Data Structures courses in Spring 2020

6 CONCLUSIONS

Our findings illustrate the importance of integrating affective feedback into more aware, supportive and agile pedagogies and classrooms and how it could be used for timely intervention and support of students in struggle, emotional distress and jeopardized learning capabilities. As you will see, these findings further re-enforces our previous studies and suggestions [13].

The data analysis consisted of mining sentiment and emotion from a range of class material, from student reading reflections, their feedback on the course materials, their own learning and class sessions, to several forms of formative and summative measures; largely by using the IBM Watson Natural Language Understanding API. By doing this we were able to observe whether subtle affective feedback present in student classwork and classroom feedback, which is largely ignored in a typical classroom setting, is informative and useful in understanding and improving the teaching and learning processes. By juxtaposing the sentiment and emotion data alongside summative and formative assessments we were able to paint a picture into whether affective feedback serves as a good indicator of success or struggle in students, teachers and the overall pedagogy at large. By graphically visualizing the different emotions of the students we were also able to see changes in not only the emotions of the individual students but also general trends in the classrooms.

The results of our first analysis show a positive correlation between students’ sentiment and emotion scores and their summative scores. Our experience and results demonstrate that affective feedback can, in fact, be used to facilitate an instructor's understanding of the class and students' learning and progress, and hence serve as a reliable predictor of student emotional and cognitive progress, and as well as an indicator of when intervention and support are needed.

From our second analysis concerning teaching and learning during a time of pandemic, we were able to observe that there is an explicit decline in students’ positive emotion as classes went on due to the COVID-19 pandemic. The increasing count of sadness being the strongest emotion as the classes went on relays an important feedback to the instructor.

Utilizing these kinds of feedback in an actual classroom would enable instructors to identify students who are having difficult times and potentially help them. This further proves that integrating affective feedback into a classroom setting would provide integral and real-time feedback which could be used for timely intervention and rescue and improve student learning outcomes.

In the future, we plan on integrating these findings and suggestions into the next version of Discovery Teaching so that instructors are able to get timely and evidence-based affective insights and suggestions that would help with timely pedagogical intervention and student awareness. We also plan on creating our own sentiment analysis model to fit the contexts of face-to-face and contemporary online, remote, and hybrid class modalities and their course content.

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