Exploring the Potential of Social Annotations for Predictive and Descriptive Analytics

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ABSTRACT
In this paper, we illustrate the successful implementation of a social annotation tool within a content authoring platform that allows students to discuss learning material with their fellow classmates. The tool also allows students to self-report on their cognitive, metacognitive and affective states by self-coding their annotations as they journey through the learning material. We explore the predictive potential of such self-reports against the students completion rate and assessment scores and examine how the visualisation of these annotation classifications can help instructors easily identify issues and better support their students and improve learning material.

CCS CONCEPTS
- Applied computing → Interactive learning environments; Distance learning; E-learning; Collaborative learning.

KEYWORDS
annotations, self-report, e-learning, prediction, learning analytics

1 INTRODUCTION
Many large courses today use online discussion forums to allow educators and students help one another understand the teaching material [6]. However, in a large course, it can be difficult for instructors to find the student and the comments that need the most assistance, especially if they do not have the capacity to read or respond to every comment. The use of automatic identification or machine learning approaches also struggle when the comments in the forum are not rich, has misspellings or use poor vocabulary—making it difficult for the classifier to distinguish between more nuanced affective states, such as confusion, curiosity and so on [4]. Determining these nuanced affective states and experiences have ramifications for instructors aiming to provide interventions for their students, as an instructor would likely have different response for different types of reported encounters. Another related problem is the overload of disparate discussions that are all lumped into the same place with little context of what the conversation is about [6].

To mitigate these challenges, our work presents a practical strategy for collecting nuanced affective states and experiences in learning material. We developed an annotation interface that supports self-coding of student posts using predefined annotation categories. We choose this method as student authors may be one of the best sources regarding their own affective state and the approach provides us an easy and accurate way to acquire labeled and contextual dataset. The subsequent sections discuss the features of the annotation tool and some preliminary results on the predictive potential of the self-coded annotations as well as the value of annotation data in helping educators improve the teaching material and instructions.

2 THE ANNOTATION TOOL
Numerous studies [3] [5] cite annotation as useful for learners but there is lack of investigation on how it could be used to inform teaching changes. The annotation tool we adopted for this study has been extended from Hypothes.is [1]. It allows students to asynchronously annotate learning material in a chat-like fashion.

Figure 1 shows what the student sees after accessing the reading material and highlighting a specific passage on a page. The six pre-defined annotation options available to the students are Comment, Question, Errata, Important, Confusing, and Interesting. Upon selecting one of the options, a conversation window opens in the right hand pane where the student can pose a question or post a comment. The annotation categories and custom tags are searchable and can be used to connect with others working on the same topic or to follow a group’s annotation activity across the material. Annotations are public by default but can be made private.
3 PRELIMINARY RESULTS
We trialed the annotation tool in a Python programming workshop, which was conducted over two weeks. A total of 37 students enrolled in the workshop. Students were given a 20 page preparatory reading to complete in their own time (online) before attending a 3 hour face-to-face (F2F) workshop in the second week. The annotation platform was integrated with the content authoring platform. The choice to annotate was completely voluntary and no marks were awarded for making annotations, however, students were informed that the annotations made would be used to adapt the teaching focus in the F2F workshop session. Fine-grained data regarding annotations, author and posting timestamp was captured.

3.1 Students use of the annotation tool
A total of 307 annotations were made by 36 out of the 37 students in the 20 page document. The average annotations made per page was 15.3 (SD = 2.2) and the average annotation posts per student at 8.57 (SD = 3.1). The average interactions with an annotation by a student (up-vote/view/read) stood at 24.6 (SD = 4.3).

3.2 Predictive Ability of Annotation Data
The next step was to investigate whether annotations had an effect on completion rate and student performance in the course. This was carried out by considering the degree of linear relationship (strength and direction) between the annotation variables using the Pearson’s correlation coefficient, r. Looking at the correlation matrix, there was a strong positive correlation between the total annotations made and the completion rate, \( r = 0.536, n = 36, p < 0.001 \). Total number annotations made also had a strong positive correlation with quiz performance, \( r = 0.503, n = 36, p < 0.001 \).

By categorising annotations by their classifications, we saw that Help and Confusing annotations had strong negative correlation (\( r = -0.6, n = 36, p < 0.001 \)) and (\( r = -0.584, n = 36, p < 0.001 \)) with the completion rate. Similarly, Help and Confusing annotations also had negative correlation with quiz performance with \( r = -0.463 (p < 0.005) \) and \( r = -0.435 (p < 0.005) \) respectively. Having seen the correlations between the predictors and the outcome variables, we built linear regression models to study the relationship between the annotating behaviour with completion rate and quiz performance. We found that students who had a significant percentage of their annotations created using the help or confusing label were the ones who have incomplete readings and lower quiz performance. Our model for course completion rate showed that we could predict 26.7% of the variability in students completion rate by taking into account the number of annotations they make during pre-reading. When we add the percentage breakdown of these annotations (categories), we found that we could predict almost 46% more of the variability in student completion (adjusted \( R^2 = 72.7\% \)). In term of quiz performance, we found that including the proportion of each annotation category and total annotations made predicted 56.1% of the variability in student performance.

3.3 Descriptive Insights from Annotation Data
One of the benefits we foresee from using annotation data is that it provides contextual and qualitative feedback to instructors for actioning interventions—something that is much needed in programming courses to understand students’ difficulties with content and concepts. Using the annotation data, we built a simple dashboard (Fig. 2) to provide instructors with a birds-eye view of annotation hotspots in the course material (Fig. 2). The colour of the bubble corresponds to the category of annotation and the size corresponds to the frequency of annotations made on that module. Clicking on the bubble leads the instructor to an itemized list of all annotations that were made on that page corresponding to their classification.

Figure 2: The annotation breakdown report
The philosophy behind the Annotation Breakdown Report is based on Just-in-Time-Teaching [2], which uses feedback from students to immediately inform teachers on where students are routinely grappling with difficult concepts. In this instance, by inspecting the dashboard, the instructor of the workshop was able to easily spot high occurrence of confusion in Module 4.6 and intervened by creating a guided tutorial on the confusing concept. Additionally, the instructor was able to tailor his teaching strategy and time allocation for topics in the face-to-face session based on the distribution of help and confusing annotations posted in various modules.

4 CONCLUSION
Whilst the main limitation of this study is that—it is based on small number of students, the fact that there is strong correlation between the nature of annotations with performance and completion rate is encouraging. The novel use of tagged pre-reading data can be very promising—as by referring to annotations as feedback of students’ learning, instructors can make decisions and intervene instantly. We showed that the categorisation of annotations is a good predictor of the completion rate and performance. Percentage (%) of confusing and help annotations seem to be the dominant predictor in both the models. We also showed the potential use of descriptive analytics from annotation data to improve teaching material and approaches. Our next step is to further explore the data and to also take this experiment to the next level, that is from the small scale pilot workshops to larger university offerings to validate the findings.

REFERENCES