

Qualitatively Exploring Electronic Portfolios: A Text Mining Approach to Measuring Student Emotion as an Early Warning Indicator*

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ABSTRACT

The collection and analysis of student-level data is quickly becoming the norm across school campuses. More and more institutions are starting to use this resource as a window into better understanding the needs of their student population. In previous work, we described the use of electronic portfolio data as a proxy to measuring student engagement, and showed how it can be predictive of student retention. This paper highlights our ongoing efforts to explore and measure the valence of positive and negative emotions in student reflections and how they can serve as an early warning indicator of student disengagement.

Categories and Subject Descriptors

J.1 [Administrative Data Processing]: Education; K.3.0 [Computer Uses in Education]: General

General Terms

Measurement, Performance

Keywords

Analytic Approaches & Methods, Natural Language Processing, Predictive Analytics, Text Mining, Emotions, Affect, Reflecting Learning, Quantified Self

1. INTRODUCTION & BACKGROUND

In previous work [1, 2], we showed that the efficiency of retention prediction systems based on academic performance

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alone can improve significantly when features that serve as a proxy to student engagement are incorporated. We used data describing student interactions with their electronic portfolios (ePortfolios) to quantify the amount of time and energy engineering students were allocating to a set of introspective assignments that invited them to reflect on their future careers as engineers. In [2], we paired that information with outcome data to show that the distributions of those ePortfolio feature values were statistically significantly different across students who were retained after a year, and those who did not persist. Further, in [1], we showed that these features were also quite predictive.

In this paper, we show how responses provided by students to reflective assignments given half way through, and towards the end of their first semester in college, can externalize both positive and negative sentiments, and how these sentiments could be used to predict end-of-semester outcomes.

By text mining student reflections about their interest in majoring in engineering from their ePortfolios, we seek to show that both the arousal and valence of student emotion can be an early warning indicator that a student is disengaging over time. In addition, we seek to continue to show the predictive potential of electronic portfolios as a rich data source for next generation learning analytics. Electronic Portfolios are a web space, story, and system that function as a workspace and showcase in which to collect, select, reflect, publish, link, archive, and demonstrate knowledge, skills, reflections, and more as multimedia evidence.

2. CONTEXT

Our work in this paper is focused on the reflections of 419 first year engineering student to the following two questions asked in the middle and at the end of the semester, respectively: (1) “*Engineering is a very broad field of study. What is it about engineering that interests you?*” (2) “*What does it mean to be an engineer? How does engineering fit into your interests?*”

Based on known outcomes of whether a student continued in or left the engineering program after the first semester, we classified 48 of the students as “Leavers” and 371 of them as “Stayers”. Of the students in the “Leavers” class, we selected 15% of them using a stratified sampling method (without

replacement) for our experiments. Because of the significant imbalance in the dataset, we also sampled an equal number of students from the “Stayer” class. These two subsets were combined and make up our sample set.

3. TEXT MINING

According to [4], the words people use reveal a great deal about them. They provide insight into the emotional, social and even physical state of a person. A person’s deeper motives and fears can sometimes be inferred by the words they use even if it is unknown or unacknowledged by the author. It is, therefore, within reason to suggest that when applied in a limited context, a study of the words used by an author (such as a student) while introspectively reflecting on a topic can be informative with regards to the degree to which the author is interested or disinterested (affective state) about the particular topic they are writing about. Building on the work previously done by [2, 1], we attempt to discover the degree to which first year engineering students (2012 cohort) are engaged or disengaged by analyzing the words they use.

3.1 Word Frequency Analysis

After removing stop words (e.g., *a, it, the, an, etc*) and excluding the words “Engineer”, “Engineering” and “Engineers” (which were disproportionately more frequent than any other words across the vast majority of the students’ writing), we generated a simple word frequency count of the mid-semester and end of semester reflections for each class of student (“Stayers” and “Leavers”). While the set of words used by each class varied, they were not informative in discriminating between members of each class.

3.2 Measuring Emotion

Basic approaches to sentiment analysis use machine learning algorithms to simply identify the polarity of sentiment in text: positive, negative or neutral. They do not deal with the strength of the sentiment, account for the existence of both positive and negative emotions in the same text, or identify the discrete emotions that exist within text (fear, love, sadness) [6]. While this may be sufficient in some applications, in others, it is necessary to not only identify the presence of both positive and negative sentiment, but it is also important to measure the strength of the sentiment expressed. For example, programs that are designed to identify at-risk users in online communications would need to be sensitive not only to the balance of sentiments expressed by a particular user, but also to the strength of the sentiments expressed [3].

Alternative approaches to sentiment analysis attempt to go beyond the single polarity classification method discussed earlier, to the identification of the existence of emotion (positive and negative) in unstructured text. One such approach is to perform a word frequency analysis on text for the occurrence of words from a dictionary of positive or negative words (such as love, hate or like). The Linguistic Inquiry and Word Count (LIWC) tool [5], makes use of this approach. It uses simple word counting and an extensive and pre-defined list of emotion-bearing words to detect positive or negative emotion in text. The list of emotion bearing words used by LIWC have been compiled and validated by panels of human judges and have undergone statistical testing. Rather than determining the overall emotion or emotional strength of a body of text, LIWC calculates the prevalence of emotion in

the text.

Applying the LIWC tool to both the mid-semester and end of semester student reflections shows a skew in positive emotions among “Stayers” and a skew in negative emotions among “Leavers”. While these results are only those of a sample set, we believe that our process when applied to the entire data set would produce very similar results. Going forward, we intend to do just that, as well as explore other methods of sentiment analysis against our data set in order to better predict student outcomes.

4. CONCLUSION & FUTURE WORK

Our preliminary results show that simply using word frequency counts as a predictor of outcome is ineffective or insufficient at best. While there seemed to be a slight variance in the distribution of words used by “Leavers” and “Stayers”, the inferred information value of word frequency alone appears to be low. However, the measurement of the arousal and valence of student emotions as a predictor of outcome, as determined by the LIWC tool, shows promise.

Current and future research includes: (1) Applying the methods utilized in this research to a larger data set. (2) Deploying an early intervention plan based on student disengagement alerts and predictive metrics provided by the quantitative and qualitative data gathered from student ePortfolios. (3) Evaluating the predictive value of other text mining methodologies (i.e. parts of speech analysis, concordances, named entity extraction, summarization, classification and clustering).

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