Modelling Student Participation Using Discussion Forum Data

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Abstract. How can we identify and model the depth and quality of student participation using the messages that students post to course discussion forums? My work builds on two widely-used theoretical frameworks to characterise cognitive engagement through content analysis of discussion forum messages. I will use advanced techniques from natural language processing and machine learning to develop predictive classifiers that can assign labels to new data automatically. In the process I hope to discover new insights about what characterises a good discussion forum contribution in context.

Keywords: Learning analytics · Student engagement · Community of Inquiry · ICAP · Natural language processing · Machine learning

1 Introduction

Course discussion forums provide a rich source of material for researchers interested in studying how effective learning takes place through discussion [6]. In addition to their use in online and distance learning courses, text-based forums are increasingly used with large face-to-face classes. There is growing interest in using this data to create rich models of student engagement using natural language processing (NLP) and machine learning. The goal of these models is to measure engagement automatically from the data while the course is still in progress, enabling instructors to direct their attention where it is most needed.

My work specifically looks at depth and quality of participation in discussion forums using two popular frameworks for analysing learning: the Community of Inquiry (CoI) framework [6], which defines *cognitive presence* as the most basic of three 'presences' that contribute to successful learning; and the ICAP framework [2], which measures *cognitive engagement* with reference to students' overt, observable behaviours alone. CoI is one of the best-studied theoretical frameworks in online education [7], and ICAP has been used as a foundation for many studies on computer-supported collaborative learning [17]. My research

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will employ methods from NLP and machine learning to model participation in the context of these frameworks, using discussion forum data, in order to address my overall research question.

Research Question: How can we identify and model the depth and quality of student participation using the messages that students post to course discussion forums?

To address this question, I will use the labels assigned by CoI and ICAP to the same set of messages. Comparing the labels assigned by each framework will allow me to understand better where they agree and where they bring complementary perspectives. I will investigate the performance of machine learning models that use advanced NLP techniques, including word embeddings [11, 13], attention layers [19], and multi-task and transfer learning [3]. I will assess how well these models can assign labels to new data automatically and look at what they reveal about the factors that distinguish different levels of participation.

2 Background and Prior Work

The **Community of Inquiry (CoI) framework** has been widely used to analyse student learning in online courses, and several automated classifiers for the phases of cognitive presence have been developed [4, 5, 10, 12, 18]. Some of these studies [10, 12] also explored which linguistically-motivated features – things like text coherence, complexity, and readability scores – were most predictive of the different phases.

The **ICAP framework** has been used in many classroom and lab studies as well as for online learning [2, 15]. Prior work has demonstrated the feasibility of applying a modified version of the ICAP schema to MOOC discussion forum messages [16, 17] and to comments on an annotated electronic course text [20].

State-of-the-art neural network methods from NLP have produced accurate classifications in many domains using only the input text, without the need for extensive feature engineering [8]. Pre-trained language models known as **word embeddings** [11, 13] allow researchers to work directly from text while retaining generality. They automatically treat synonyms in similar ways, and can handle some common spelling errors. A recent study used word embeddings together with ICAP to classify contributions to an online teacher professional development community as either active or constructive [1].

The use of an **attention layer** when processing text in neural networks is often described as allowing researchers to 'see inside' what is otherwise a black-box technique [9, 19]. The learned weights in the attention layer can be seen as indicating the strength of influence of each of the input words on the final output. Meanwhile, work on **multi-task and transfer learning** [3] has shown that training a single neural network to learn from multiple target outputs at the same time can help to avoid over-fitting to the training data and produce better models overall. To the best of my knowledge, attention layers and multi-task and transfer learning have not yet been applied to the challenge of modelling discussion forum data.

3 Preliminary Ideas and Proposed Approach

My proposed approach begins by looking at the relationship between the CoI and ICAP frameworks, grounded in a specific context. Using a data set where every discussion forum message has been assigned a label by both frameworks, I plan to investigate similarities and differences between the frameworks using confusion matrices and Epistemic Network Analysis (ENA) [14]. My expectation is that the labels will not be closely correlated, indicating that the two frameworks provide complementary insights into the learning process.

Automating the labelling of discussion forum messages in a reliable way will allow the theoretical frameworks to be used with larger data sets, where manual annotation is impractical, and in an online setting while the course is still in progress. By using neural networks with pre-trained word embeddings, the influence of particular word choices is diminished. I expect that this approach could prove to be just as powerful as using the linguistically-motivated features from prior work, while adding flexibility.

An attention layer in the network could indicate which words and phrases are most indicative of the different modes of engagement in ICAP, and the different phases of cognitive presence in CoI. These results can be validated by comparison with prior work. I hope new patterns will also be revealed that have not been found before. I also plan to configure neural network models to learn the labels from both CoI and ICAP simultaneously. Assuming that the two frameworks are relatively independent, I expect this approach to improve the model's performance for both frameworks, in line with prior work.

4 Research Methodology and Contribution

My research is primarily quantitative and methodological, and my focus is on developing computational methods and models. In my next study, I will compare the CoI and ICAP frameworks using a quantitative approach by looking at co-occurrences of ICAP modes with phases of cognitive presence in a manually-labelled data set. The messages have already been labelled with phases of cognitive presence and the manual annotation of the ICAP modes of engagement is in progress, using a modified version of the extended coding scheme used in prior work [20]. This study will offer a useful contribution to the theoretical understanding of online learning and learning through discussion.

Later studies will develop neural network models that incorporate word embeddings and an attention layer. I will compare the performance of these models with simpler predictive models such as random forests – both in terms of model accuracy and also potential explanatory power. Training models on both frameworks at once using multi-task and transfer learning may also improve performance compared with models trained on each set of labels individually.

These studies will generate new insights into the textual factors that characterise the depth and quality of participation across both frameworks. One potential application of this research could be the automatic generation of hints for students about how to improve their own discussion contributions.

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