# Utilizing Natural Language Processing for Automated Assessment of Classroom Discussion\*

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Abstract. Rigorous and interactive class discussions that support students to engage in high-level thinking and reasoning are essential to learning and are a central component of most teaching interventions. However, formally assessing discussion quality 'at scale' is expensive and infeasible for most researchers. In this work, we experimented with various modern natural language processing (NLP) techniques to automatically generate rubric scores for individual dimensions of classroom text discussion quality. Specifically, we worked on a dataset of 90 classroom discussion transcripts consisting of over 18000 turns annotated with fine-grained Analyzing Teaching Moves (ATM) codes and focused on four Instructional Quality Assessment (IQA) rubrics. Despite the limited amount of data, our work shows encouraging results in some of the rubrics while suggesting that there is room for improvement in the others. We also found that certain NLP approaches work better for certain rubrics.

Keywords: Classroom discussion · Quality assessment · NLP

# 1 Introduction and Background

Instructional quality has been of great interest to educational researchers for several decades. Due to their cost, measures of instructional quality that can be obtained at-scale remain elusive. Previous work [5] has shown that providing automated feedback on teachers' talk moves can lead to positive instructional changes. We report here on initial attempts to apply Natural Language Processing (NLP) methods such as pre-trained language models or sequence labeling with BiLSTM [4] to automatically produce rubric scores for individual dimensions of classroom discussion quality from transcripts, building upon two established measures that have shown high levels of reliability and validity in prior learning research – the *Instructional Quality Assessment (IQA)* and the *Analyzing Teaching Moves (ATM)* rubrics [2,6].

Our corpus consists of 170 videos from 31 English Language Arts classrooms in a Texas district. 18 teachers taught fourth grade, 13 taught fifth grade, and on average had 13 years of teaching experience. The student population was considered low income (61%), with students identifying as: Latinx (73%), Caucasian

<sup>\*</sup> Supported by a grant from the Learning Engineering Tools Competition.

#### 2 Tran et al.

Rubric			Relevant $ATM$ code		
Short Description	Distribution	Avg	Code Label	Count	
S1: $T$ connects $S$ s	[51, 19, 9, 11]	1.8	Recap or Synthesize S Ideas	75	
S2: $T$ presses $S$	[7, 7, 9, 67]	3.6	Press	927	
S3: $S$ builds on other's idea	[65, 6, 8, 11]	1.6	Strong Link	101	
S4: $S$ support their claims	[28, 12, 8, 42]	2.7	Strong Text-based Evidence	403	
			Strong Explanation	286	
			Others	52687	

**Table 1.** Data distribution and mean (Avg) of 4 focused *IQA* rubrics for Teacher (T) and Student (S) with their relevant *ATM* codes. An *IQA* rubric's distribution is represented as the counts of each score (1 to 4 from left to right) (n=90 discussions).

(15%), African American (7%), multiracial (4%), and Asian or Pacific Islander (1%). The videos were manually scored holistically, on a scale from 1 to 4, using the IQA on 11 dimensions for both teacher and student contributions. They were also scored using more fine-grained talk moves at the sentence level using the ATM discourse measure. The current work focuses on only the **90** discussion transcripts that have already been converted to text-based codes.

As summarized in column 1 of Table 1, our classifiers are trained to predict 4 of the 11 IQA rubrics containing aspirational teacher (T) and student (S) 'talk moves' – T Links Student Contributions (score S1), T Presses for Information (S2), S Link Contributions (S3), S Support Claims with Evidence (S4). Besides the 5 ATM codes (column 4 in Table 1) related to these 4 IQA rubrics the rest are labeled as Others. The distributions of IQA scores for each rubric and of relevant ATM codes are summarized in columns 2 and 5 of Table 1, respectively. We notice that the frequencies of ATM codes related to S1 and S3 are very low (less than or approximately 1 per transcript). Below is an example excerpt with annotated ATM codes from our data:

**Teacher:** [The girls get the water and the boys do the herds, right?]<sub>Others</sub> [Where did you get that from the text?]<sub>Press</sub>

**Student**: [Other people, mostly women and girls who had to come fill their own containers, many kinds of birds, all flap, twittering and cawing. Herds of cattle had been brought to good grazing by the young boys who looked after them.]<sub>Strong Text-Based Evidence</sub>

In this paper we present several IQA classifiers, and show that using predicted ATM codes as features outperforms an end-to-end model. The long-term goal of our work is to use such classifiers in a tool for automated IQA assessment so that teachers and coaches can evaluate classroom discussion quality in real-time.

# 2 Methods

We train different models for *IQA* assessment to explore tradeoffs between scoring performance, explainability, and training set. Our baseline is a neural **end-to-end model**, as neural models often have high performance and do not require

feature engineering. However, since the IQA score of a specific rubric can be inferred from the number of times the relevant ATM codes are used (Section 1), we also develop IQA prediction models using ATM codes as predictive features. This in turn requires ATM models to predict the relevant 6 ATM codes. Specifically, for each sentence, these models will predict 1 of 6 ATM code labels in column 4 of Table 1. This is a 6-way classification task.

Hierarchical ATM Classification. We hypothesize that it would be easier to separate Others from the 5 focal ATM codes as they have specific usages. We perform a 2-step hierarchical classification at sentence level as follows. Step 1, binary classification, is to classify Other versus 5 focal ATM Codes. If the code is not Others, step 2 is to perform another 5-way classification to identify the final label. We train separate BERT-based classifiers for each step. The input for the classifiers is the current sentence concatenated with previous sentences in the same turn and sentences from one previous turn. Because each ATM code except Others can be only from one speaker, either Teacher or Student, we train two classifiers for the 5-way classification of Step 2, one classifier used to predict teacher codes (Recap or Synthesize S Ideas and Press) and one classifier specialized in student codes (Strong Link, Strong Text-Based Evidence and Strong Explanation). Depending on the speaker, only one of them is called for Step 2.

**ATM** Sequence Labeling. A classroom discussion can be considered as a sequence of sentences. This approach assigns a label (1 out of the 6 *ATM* codes) to each sentence in a conversation. Unlike the Hierarchical Classification approach that predicts the label of each sentence independently, in this approach, the label of a given sentence is more dependent on the labels of nearby sentences. We use BERT-BiLSTM-CRF as our sequence labeling model. BiLSTM-CRF has been widely used for sequence labeling tasks [4] and BERT [3] provides a powerful tool for sentence representation that can work well with that architecture.

Additional Techniques. During ATM classification, since Others constitutes more than 90% of the total labels, we downsample the training data to reduce the imbalance. For IQA classification, annotators tend to group consecutive sentences sharing the same functionality in one turn as one ATM code (e.g., one Strong Texted-Based Evidence code is used for two sentences in the excerpt in Section 1), but our prediction is done on sentence level. Merging adjacent ATM predictions that are the same into one code in the inference phase helps preserve this nature. Also, since the range of the IQA scores is very small (1 to 4), translating the absolute counting of ATM codes to IQA scores (see Section 1) can drastically shift the IQA scores due to misclassification of the ATM codes. To alleviate this sensitivity, we build separate linear regression models to estimate each IQA score from the counting of relevant ATMcodes, then use the nearest integers as the IQA scores.

### 3 Results

**ATM** Code Prediction results (macro average  $F_1$  scores) are shown in Table 2. The Non-hierarchical baseline is a BERT-based 6-way classifier given the

#### 4 Tran et al.

${f Method}$		6-way
Non-hierarchical Classification (All Data)	-	0.29(0.04)
/w 60% downsampling	-	0.49(0.03)
Hierarchical Classification (All Data)	0.56	0.41(0.04)
/w 60% downsampling	0.72	0.65(0.02)
Sequence Labeling (All Data)	-	0.45(0.03)
/w 60% downsampling	-	0.62(0.01)
Hierarchical with Oracle for Step 1 (All Data)	1	0.57(0.02)
/w 60% downsampling	1	0.68(0.04)

**Table 2.** ATM Codes 6-way Classification Results (F<sub>1</sub> scores over 5-fold cross-validation with standard deviations in parentheses).

same input as our hierarchical approach. Both Hierarchical Classification and Sequence Labeling outperform the Non-hierarchical baseline, whether using all data or downsampled data for training. The numbers also show that downsampling the proportion of the most popular class (*Others*) to 60% increases the performance of all models<sup>1</sup>. For the 2-step Hierarchical Classification approach, it improves the performances of both step 1 and the final 6-way classification. Additionally, the Sequence Labeling and Hierarchical approaches perform similarly. Although Sequence Labeling has a slightly higher score when all training data is used (0.45 vs. 0.41,  $\rho = 0.039$ ), it is inferior to Hierarchical Classification with 60% downsampling (0.62 vs. 0.65,  $\rho = 0.046$ ). Using a perfect Oracle model with 100% accuracy for Step 1 (*Others* versus 5 *ATM codes*) does not lead to a large gain in the 6-way classification results compared to our fully automated Hierarchical approach in the downsampled version (0.68 vs 0.65). We thus use the non-oracle models built with 60% downsampling rate for the inference of the classroom discussion quality (*IQA* scores) below.

IQA Score Prediction is performed based on the models for ATM codes prediction. The Quadratic Kappa (QK) scores for the estimations of the four rubrics of classroom discussion quality are reported in Table 3. The baseline for each rubric is an end-to-end Longformer model [1] which directly predicts the IQA scores given the raw text transcripts using a linear layer on top of the hidden representation of [CLS], ignoring the ATM codes. The results show that all variations of Hierarchical Classification and Sequence Labeling outperform the baselines, which emphasizes the importance of utilizing ATM codes to infer IQA scores. Besides increasing performance, the ATM-based models also increase model interpretability, useful for generating formative feedback in the future.

One notable observation is that using regression to estimate the IQA scores is always better than using absolute counting. This supports our assumption that regression will alleviate the sensitivity of miscounting and provides a smoother transition from the number of times ATM codes appear to the actual IQA scores. Using regression, the highest gain in QK scores for Hierarchical Classification (0.09) and Sequence Labeling (0.07) are from S3 and S2, respectively.

 $<sup>^1</sup>$  We tried different ratios and 60% provides the best results.

Bubria	Baseline	Hierarchical		Sequence	
Rubric		A.Count	Regression	A.Count	Regression
S1: Teacher connects Students	0.34	0.43	0.54	0.50	0.55
/w merged codes		0.48	0.55	0.52	0.57
S2: Teacher presses Student	0.35	0.60	0.65	0.55	0.62
/w merged codes		0.64	0.68	0.57	0.63
S3: Student builds on each other	0.20	0.42	0.51	0.47	0.51
/w merged codes	0.30	0.49	0.54	0.50	0.53
S4: Student support their claims	0.36	0.60	0.65	0.57	0.61
/w merged codes		0.65	0.70	0.61	0.63

**Table 3.** IQA Scores Estimation Results in Quadratic Kappa (QK) averaged over 5fold cross-validation, inferred from Absolute Counting (A.Count) and Linear Regression (Regression) after ATM prediction. **Bold** numbers are the best results for each rubric.



Fig. 1. IQA Score Estimation Results (QK) in relation to the amount of training data.

Merging consecutive same ATM codes into one also improves the performance of IQA score estimation as expected. For the same approach, the increases from this technique are mostly larger when absolute counting is used. The ATMclassification was on sentence level and absolute counting is more sensitive to over-counting, so the merging technique is more effective for this method.

While Sequence Labeling yields the best S1 results, the best results for the other rubrics come from Hierarchical Classification. Our reasoning is that for S1, the relation to adjacent sentences plays a more important role to identify the relevant ATM code as there should be multiple students speaking out their ideas before the teacher can connect/synthesize them. Thus, Sequence Labeling, which focuses more on dependencies between sentences, performs better. This suggests that certain approaches are more suitable for certain rubrics.

Finally, Figure 1 demonstrates the performance of our best models (with *re-gression* and *merged codes*) over training size. While the baselines do not improve much after a certain size of training data, the lines of Hierarchical Classification

6 Tran et al.

and Sequence Labeling maintain upward trends, suggesting that these models will continue to benefit from more data as we complete our video transcription. Even using only 90 discussions, the QK results show that ATM-based model reliability is already substantial for S2 and S4, and moderate for S1 and S3, even though there were infrequent instances of relevant codes in the corpus.

# 4 Conclusion and Future Directions

We experimented with NLP approaches to automatically assess discussion quality using the IQA, and to deal with imbalanced ATM data and imperfect ATMcode prediction. Our results show that IQA models using either Hierarchical Classification or Sequence Labeling to first predict ATM codes outperform baseline end-to-end IQA models, while each of the ATM-based IQA models performs better than the other in certain IQA rubrics. Once the full corpus is available, we will generate a validity argument for whether automated scoring replicates known associations in the corpus, and incorporate the demographic information into our analyses. We will also utilize ATM codes beyond the 5 relevant to the focused rubrics to add more context for ATM prediction. To mitigate the limited size of even the full corpus, we will explore whether techniques such as transfer learning that can take advantage of classroom discussion data from math [8] or high school [7] that are now being made available to the community.

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