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Analysis of Active Learning Mechanism Applied to Language Models for Computer Assisted Short Answer Grading

September 27, 2022

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Agenda

1. Motivation
2. Problem Statement
3. State of the Art
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6. Evaluation
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Motivation

In universities with an increase in number of student every semester, the number of tests conducted also increases. This means that:

- The professor spends more time in correcting student exams than preparing for lectures.
- If students are not assigned full scores for on a test, they expect a meaningful feedback from the professor.

Motivation

Consider the following dummy scenario:

- 80 students enrolled in a class.
- Tests are conducted bi-weekly.
- Professor requires 15 minutes to evaluate one student test.
- Total time spent by the professor to evaluate all tests per week is 10 hours.

Problem Statement

- Automate the evaluation of student tests while still keeping the oracle/professor in the loop.
- Allow the assignment of meaningful feedback to student answers indicating their mistakes.

Related Work

- Wu et al. (2021) designed an system to assign feedback called ProtoTransformer for evaluating programming based questions but not for short text answers. It used limited number of examples.
- Ghavidel et al. (2020) passed raw text through a transformer as input and used the output of classification model (CLS) token as feature.
- Mieskes and Pado, (2018) compared score assignment between automated and human assignment for RF, SVM, and DT classifiers across multiple datasets.

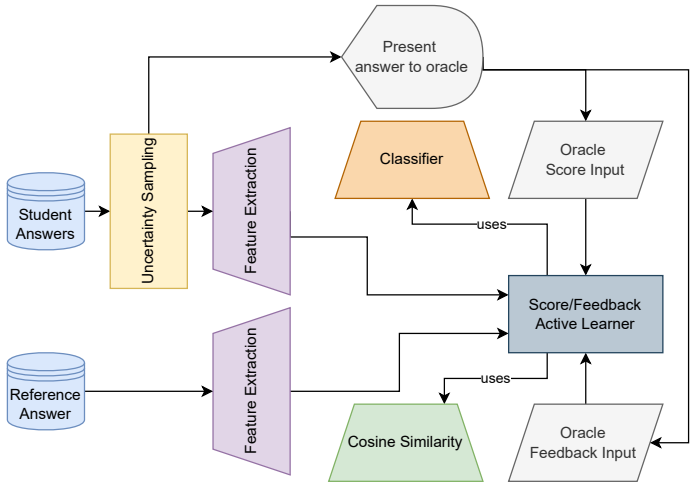
Approach

Contributions

- Implement four methods to alter text for feature extraction.
- Implement feedback assignment for short text answers.
- Test performance with five pre-trained language models and two classifiers.

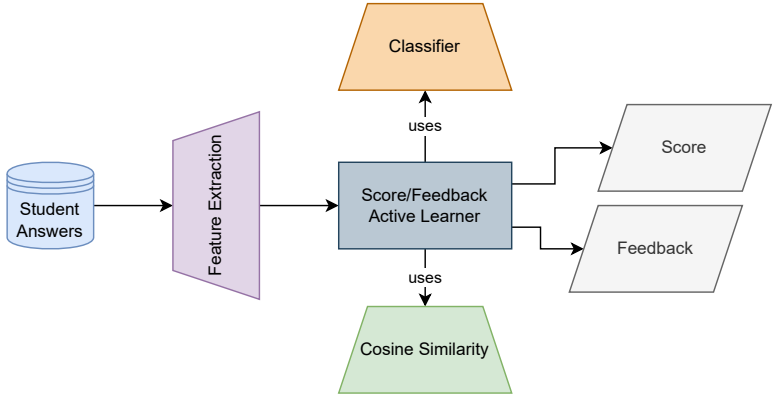
Approach

Training Cycle



Approach

Prediction Cycle



Dataset

Dataset	Domain	No. of Questions Pairs	No. of Responses
Mohler[1]	Computer Science	81	2237
NN Exam	Neural Network & AI	40	1137
AMR Exam	Robotics	5	190

Table 1

[1] **mohler-etal-2011-learning**.

Approach

Uncertainty Sampling

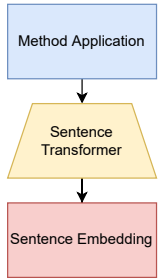
Uncertainty sampling is a query strategy that queries the instances about which it is least certain how to label. We use uncertainty sampling variant might query the instance whose prediction is the least confident:

$$x_{LC} = argmin_x P(\hat{y}|x;\theta) \tag{1}$$

Where x is the feature, y is the class label prediction, and $\hat{y} = argmax_y P(y|x;\theta)$ is the class label that has the largest posterior probability using model θ.

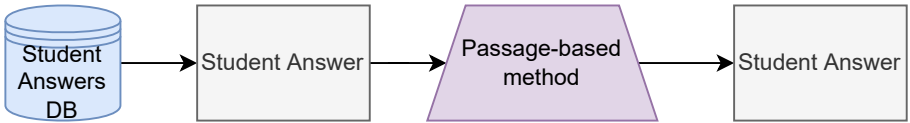
Approach

Feature Extraction: Overview



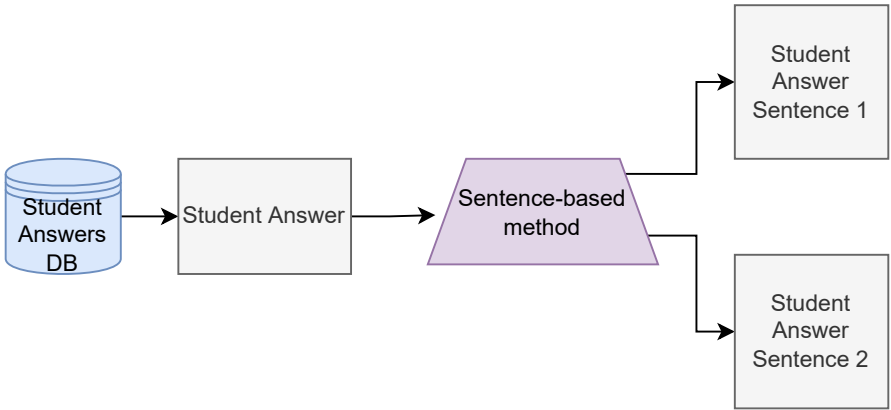
Approach

Feature Extraction: Passage-Based Method



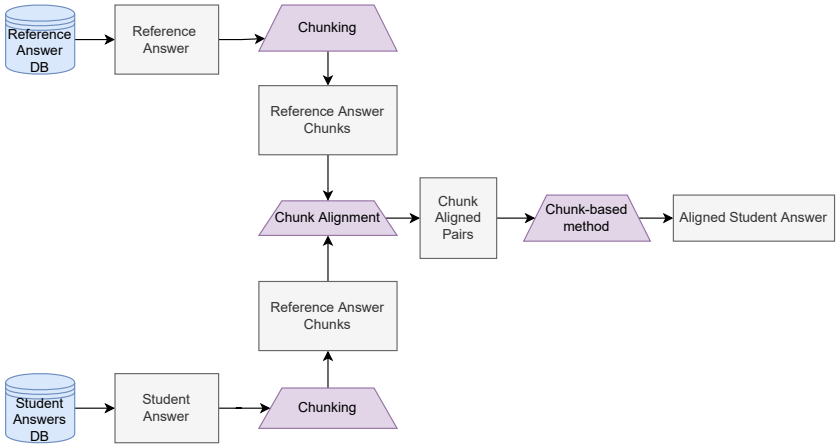
Approach

Feature Extraction: Sentence-Based Method



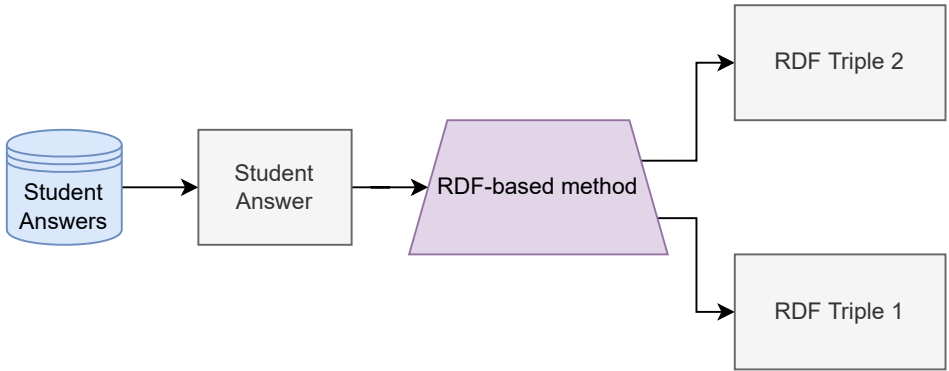
Approach

Feature Extraction: Chunk-Based Method



Approach

Feature Extraction: Resource Description Framework (RDF) Based Method



Approach

Language Models

Language Model:	Base model	Number Training tuples
all-mpnet-base-v2**SBERT**	microsoft/mpnet-base.	1.17B
all-distilroberta-v1**SBERT**	distilroberta-base	1.12B
all-MiniLM-L12-v2**SBERT**	microsoft/MiniLM-L12-H384-uncased	1.17B
multi-qa-distilbert-cos-v1**SBERT**	distilbert-base	214M
all-MiniLM-L6-v2**SBERT**	nreimers/MiniLM-L6-H384-uncased	1.17B

Table 2: Displays pre-trained language models with their base model used in training and number of training tuples used**SBERT**.

Evaluation

Score

- Pearsons Correlation

$$\rho(y, \hat{y}) = \frac{cov(\vec{y}, \hat{\vec{y}})}{\sigma_y \sigma_{\hat{y}}} \tag{2}$$

- RMSE Score

$$RMSE = \sqrt{\frac{1}{n} \Sigma_{i=1}^{n} (\hat{\vec{y}_i} - \vec{y}_i)^2} \tag{3}$$

Where $\vec{y}$ represents actual grade and $\hat{\vec{y}}$ represents predicted grade with σ_y and $\sigma_{\hat{y}}$ computed as the standard deviation of $\vec{y}$ and $\hat{\vec{y}}$

Evaluation

Feedback

Question	What is a variable?
Reference Answer	A location in memory that can store a value.
Student Answer	A value/word that can assume any of a set of values
Feedback A	Correct
Feedback B	Missing keywords: Location in memory
Feedback C	A variable is a location in memory that stores a value

Table 3: Presented survey to participants.

$$Agreement\ Score = \frac{Model\ generated\ most\ rated\ feedback}{Total\ Number\ of\ Participants}$$

Results

Notations

Method	Notation
Passage-based Methods	M1
Sentence-based Method	M2
Chunk-based Method	M3
RDF-based Method	M4

Language Model	Notation
all-mpnet-base-v2	LM1
all-distilroberta-v1	LM2
all-MiniLM-L12-v2	LM3
multi-qa-distilbert-cos-v1	LM4
all-MiniLM-L6-v2	LM5

Results

Score: Pearson Correlation (Methods)

Dataset	M1	M2	M3	M4
Mohler	**0.826**	**0.791**	**0.816**	0.782
NN Exam	**0.941**	**0.828**	0.561	**0.846**
AMR Exam	**0.658**	0.458	**0.640**	**0.428**

(a)

Dataset	M1	M2	M3	M4
Mohler	0.689	0.627	0.687	**0.792**
NN Exam	0.889	0.791	**0.638**	0.664
AMR Exam	0.622	**0.474**	0.593	**0.428**

(b)

Table 4: Comparison of Pearson Correlation between Random Forest (a) and AdaBoost (b) classifiers. Where M1: Passage-based, M2: Sentence-based, M3:Chunk-based, and M4: RDF-based method.

Results

Score: Pearson Correlation (Language Models)

Dataset	LM1	LM2	LM3	LM4	LM5
Mohler	**0.802**	**0.797**	**0.796**	**0.796**	**0.789**
NN Exam	**0.732**	**0.670**	**0.705**	**0.755**	**0.760**
AMR Exam	0.453	**0.518**	**0.525**	**0.523**	**0.503**

(a)

Dataset	LM1	LM2	LM3	LM4	LM5
Mohler	0.659	0.673	0.211	0.544	0.499
NN Exam	0.614	0.653	0.704	0.698	0.605
AMR Exam	**0.502**	0.440	0.430	0.508	0.467

(b)

Table 5: Comparison of Pearson Correlation between Random Forest (a) and AdaBoost (b) classifiers with language models (LM).

Results

Score: Root Mean Square Error (Methods)

Dataset	M1	M2	M3	M4
Mohler	**0.893**	**0.949**	**0.920**	0.942
NN Exam	**0.296**	**0.520**	**0.433**	**0.522**
AMR Exam	**0.596**	0.716	**0.596**	**0.736**

(a)

Dataset	M1	M2	M3	M4
Mohler	1.218	1.226	1.169	**0.920**
NN Exam	0.405	0.571	0.495	0.741
AMR Exam	0.616	**0.707**	0.630	0.741

(b)

Table 6: Comparison of RMSE score between Random Forest (a) and AdaBoost (b) classifiers with methods (M).

Results

Score: Root Mean Square Error (Language Models)

Dataset	LM1	LM2	LM3	LM4	LM5
Mohler	**0.931**	**0.941**	**0.941**	**0.941**	**0.956**
NN Exam	**0.484**	0.591	**0.558**	**0.490**	**0.492**
AMR Exam	0.735	**0.680**	**0.676**	0.684	**0.698**

(a)

Dataset	LM1	LM2	LM3	LM4	LM5
Mohler	1.182	1.163	1.667	1.278	1.363
NN Exam	0.632	**0.582**	0.587	0.587	0.650
AMR Exam	**0.692**	0.748	0.718	**0.682**	0.736

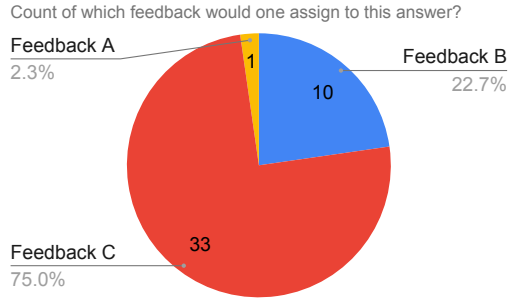
(b)

Table 7: Comparison of RMSE score between Random Forest (a) and AdaBoost (b) classifiers with language models (LM).

Results

Feedback: Survey Results

Question	What is a variable?
Reference Answer	A location in memory that can store a value.
Student Answer	a value/word that can assume any of a set of values
Feedback A	correct
Feedback B	missing keywords: location in memory
Feedback C	A variable is a location in memory that stores a value



Results

Feedback: Agreement Scores (Methods)

Classifier	Methods			
	M1	M2	M3	M4
Random Forest	**60.00**	22.73	31.82	35.91
AdaBoost	**60.00**	22.73	31.82	35.91

Table 8: Mean agreement scores for Random Forest (a) and AdaBoost Classifier (b) with methods.

Results

Feedback: Agreement Scores (Models)

Classifier	LM1	LM2	LM3	LM4	LM5
Random Forest	25.11	26.82	24.66	**37.05**	21.25
AdaBoost	25.11	26.82	24.66	**37.05**	21.25

Table 9: Mean agreement scores for Random Forest and AdaBoost Classifier with Language Models.

Results

Summary: Scores

Dataset	Method	Model	CL
Mohler	M1	LM1	RF
NN Exam	M1	LM5	RF
AMR Exam	M1	LM3	RF

Table 10: Pearson Correlation Performance Summary

Dataset	Method	Model	CL
Mohler	M3	LM1& LM4	RF
NN Exam	M1	LM2	RF
AMR Exam	M1& M3	LM3	RF

Table 11: RMSE Score Performance Summary

Results

Feedback

Dataset	Method	Model	Method-Model	Classifier
Mohler	M1	LM4	M1-LM4	RF

Table 12: Results of feedback evaluation

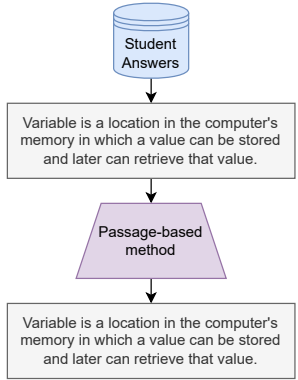
Summary

In this project the following was done:

- Four methods were implemented to alter student answer text.
- Pearson Correlation and RMSE score were used as metrics for score evaluation.
- A survey was created and used in the evaluation of the feedback assigned by the model.

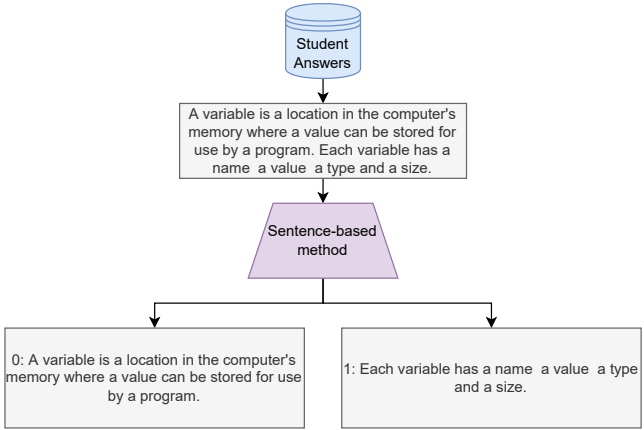
Approach:Extra Slides

Feature Extraction: Passage-based method



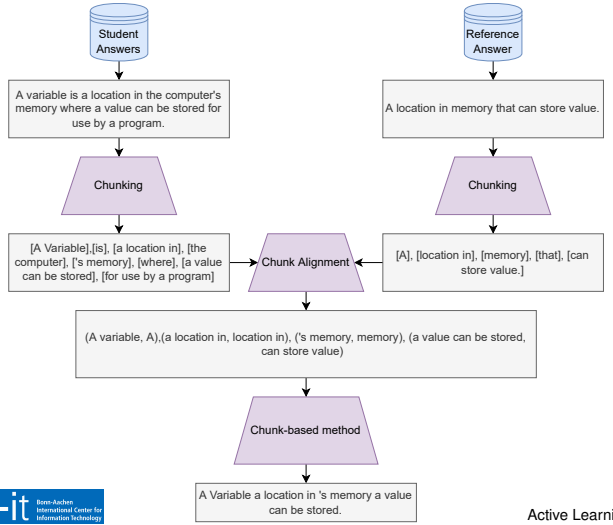
Approach

Feature Extraction: Sentence-based method



Approach

Feature Extraction: Chunk-based method



Approach

Feature Extraction: RDF-based method