NLP: Student Answer Scoring on Data Structure & Algorithms

Nathan Beer, Tomer Bengayev, Orel Cohen

Project Definition & Motivation

Motivation:

- Grading open-ended student answers is time-consuming and subjective.
- Automated scoring provides quick feedback, consistency, and scalability in large classes.

Models / Data / Metrics:

- **Dataset:** Mohler dataset with teacher answers and corresponding student answers + scores.
- **Model:** NLP embedding + regression (e.g., BERT embeddings + linear/regression layer).
- **Metrics:** Mean Squared Error (MSE), Pearson correlation, R^2 score.

Project Definition:

- Build an NLP model to score student answers to Data Structures & Algorithms questions.
- Compare student answers against teacher reference answers.
- Output a regression score indicating similarity/quality.

Achievements & Novelty

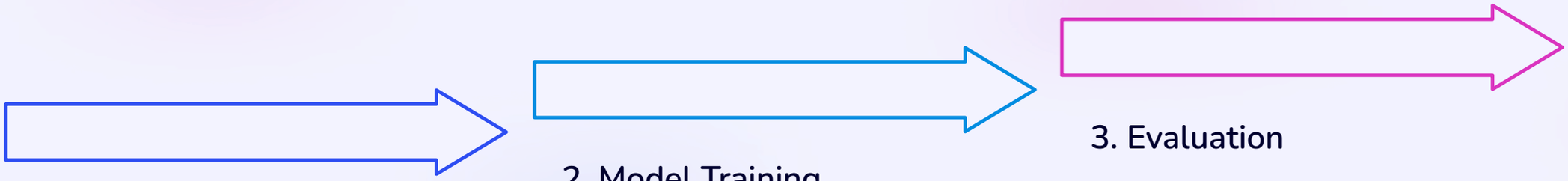
Project Achievements:

- Preprocessed Mohler dataset for model training and evaluation.
- Trained NLP regression model to predict student answer scores.
- Achieved high correlation with teacher scores (e.g., 85%).
- Developed a robust pipeline for easy evaluation of new answers.

Novelty:

- Focus on DSA open-ended answers, which are more complex than typical short-answer datasets.
- Combines semantic embeddings with regression scoring, moving beyond simple keyword matching.
- Potential for real-time automated feedback in programming education.

Methodology



1. Data Preparation

Cleaned dataset by removing duplicates and normalizing text. Generated comprehensive embeddings for both teacher and student answers using advanced NLP techniques.

2. Model Training

Fed embeddings into a sophisticated regression model. Split the dataset into training, validation, and test sets to ensure robust model development and unbiased evaluation.

3. Evaluation

Assessed model performance using MSE, Pearson correlation, and R^2 metrics. Conducted extensive hyperparameter tuning to maximise predictive accuracy and model generalisability.

Efforts for High Quality

Experimented with multiple embedding models (e.g., BERT, TF-IDF, Word2Vec) to capture diverse semantic nuances.

Applied rigorous preprocessing techniques, including lowercasing, punctuation removal, and tokenisation, to refine input data.

Implemented k-fold cross-validation to prevent overfitting and ensure the model's reliability across various data subsets.

Results: Predicting Student Scores

The scatter plot above illustrates the strong correlation between our model's predicted scores and the actual teacher scores. Each point represents a student answer, showing the model's ability to approximate human grading.

Example of Model Performance

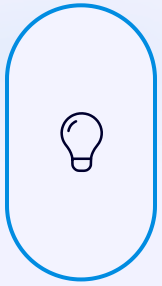
Question	Teacher's Answer	Student's Answer	Actual Score	Pred. Score	Error
What is a linked list?	A linear collection of data elements, called nodes, where each node points to the next.	It's like a chain of blocks holding data.	2	1.8	-0.2
Explain Big O notation.	Describes algorithm efficiency in terms of input size growth.	It shows how fast code runs when you have more data.	1	1.1	0.1
Advantages of Hash Map?	Fast average O(1) lookups, insertions, and deletions.	Very quick to find things if you know the key.	2	1.9	-0.1

Visualization Notes: The table demonstrates how our model assigns scores close to human grading. High vs. low discrepancies can be further analysed to refine the model's accuracy.

Conclusion & Future Work

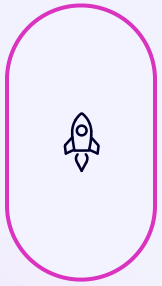
Conclusion

Achieved high correlation between predicted and teacher scores, validating the model's effectiveness. Demonstrated an automated scoring pipeline for DSA student answers.



Lessons Learned

Preprocessing significantly affects model performance. More data is needed for rare answer formulations. Some answers require semantic understanding beyond embeddings.



Future Work

Incorporate explanation generation alongside scoring. Expand to other CS topics. Test student feedback integration for iterative learning processes.