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Natural Language Processing
(10672352)

Automatic Essay Grading using Instruction-Tuned Transformers

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Abstract :

Manual essay grading is a labor-intensive process prone to inconsistency and bias. This project presents an automated essay grading system utilizing a 4-bit quantized instruction-tuned transformer model, specifically the *Mistral-7B-Instruct-v0.2*. The system is designed to assess student essays by referencing the original question, a model answer, and a predefined mark scheme. Using LoRA (Low-Rank Adaptation) and efficient fine-tuning techniques on limited computational resources, the model was trained to generate accurate scores (0–4) and provide rationale aligned with expert grading standards. Evaluation metrics indicate strong performance, with a Pearson correlation of 0.91 and a within-1 score accuracy of over 99%. Furthermore, the model demonstrates high semantic similarity between human and machine-generated rationales. This work highlights the potential of instruction-tuned LLMs for scalable, consistent, and interpretable assessment in educational settings.

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1. Introduction

Manual essay grading is time-consuming and often inconsistent. This project developed an automated grading system using a 4-bit quantized instruction-tuned language model, *Mistral-7BInstruct-v0.2*, to predict essay scores (0–4) and provide rationale for those scores. The system uses the essay question, a reference answer, the student's answer, and a mark scheme to simulate expert grading—offering consistency, scalability, and explainability.

2. Dataset Preparation

2.1 Source and Structure

The dataset included:

- Essay question
- Expert reference answer
- Student answer
- Mark scheme (0–4 points) sometimes more
- score (0–4)
- rationale

Data was stored in a structured JSONL format, and it was AI generated.

2.2 Instruction Formatting

Each entry was converted into a prompt designed to guide the model to act like an expert examiner, instructing it to assign a score based on the mark scheme and provide a rationale and these are some examples of the instructions put:

```
Instructions:
- Grade the student answer on a scale from 0 to 4 based strictly on the mark scheme. - For each
  criterion, assess whether it was satisfied.
- Provide a detailed and objective rationale explaining the score and make it related to the question and the
  answer contextually.
- Always provide a score of 4 even if you face more than 5 points in mark scheme try to combine everything
  and give a score of 4 the same goes when less than 4.
- Be concise, specific, and professional in your explanation."
```

2.3 Splitting and Tokenization

- Dataset split: 80% training (2,838), 10% validation (355), 10% test (355)
- Tokenization handled up to 2048 tokens

- Prompt-output pairs followed the format used by Unsloth and Mistral models

3. Model Fine-tuning

3.1 Model and Hardware

- Base model: "unsloth/mistral-7b-instruct-v0.2-bnb-4bit"
- Quantization: 4-bit (nf4), float16 compute.
- Training on Google Colab with Tesla T4 GPU

3.2 LoRA (Low-Rank Adaptation)

Used to fine-tune efficiently with limited resources. Final configuration:

```
model = FastLanguageModel.get_peft_model( model, r=32, lora_alpha=32, lora_dropout=0.0,
#cant do more because of unsloth target_modules=["q_proj", "k_proj", "v_proj", "o_proj",
"gate_proj", "up_proj", "down_proj"], bias="none", use_gradient_checkpointing=True,
random_state=42,
)
```

3.3 Training Setup

- Epochs: 1
- Effective batch size: 16
- Optimizer: AdamW (8-bit)
- Learning rate: 2e-4
- Losses: Training loss ≈ 0.28, Validation loss ≈ 0.34

3.4 LoRA Parameter Experiments

Tested various combinations:

- Ranks: 16, 32, 64
- Alpha: 32, 64, 128

Best setup: r=32, lora_alpha=32

- Balanced performance and efficiency
- Avoided overfitting
- Generalized well on unseen examples **Challenges with higher ranks (r=64):**

- Overfitting signs (verbose rationales, poor generalization)
- More memory usage and slower training Diminishing returns on small datasets

4. Model Evaluation

4.1 Setup and Inference

- Inference temperature: 0.1 (slightly varied outputs)
- Extracted score using regex
- Defaulted to 0 if no score found

4.2 Performance Metrics

Language Modeling

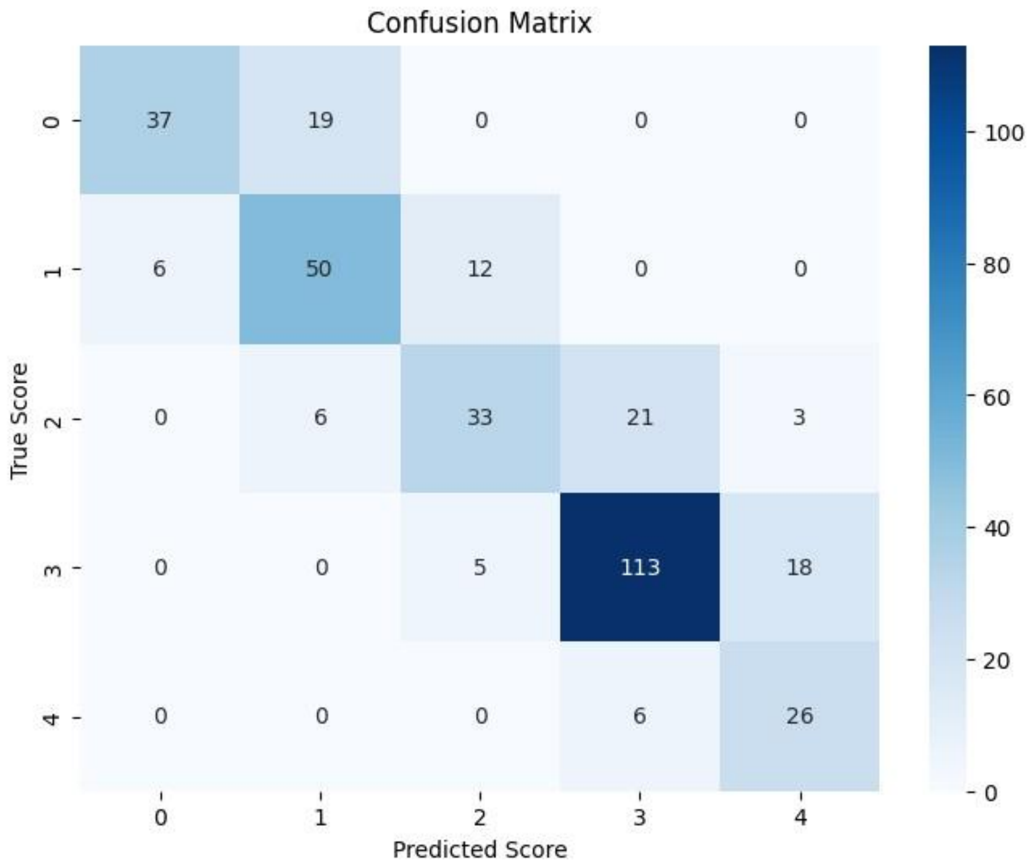
- **Perplexity**: 1.52 (indicates confident predictions)

Score Prediction Accuracy

- **Mean Absolute Error (MAE)**: 0.2789
- **Root Mean Square Error (RMSE)**: 0.5439
- **Pearson Correlation**: 0.9129 (strong linear correlation)
- **Exact Match Accuracy**: 72.96%
- **Within-1 Accuracy**: 99.15%

F1 Scores by Class

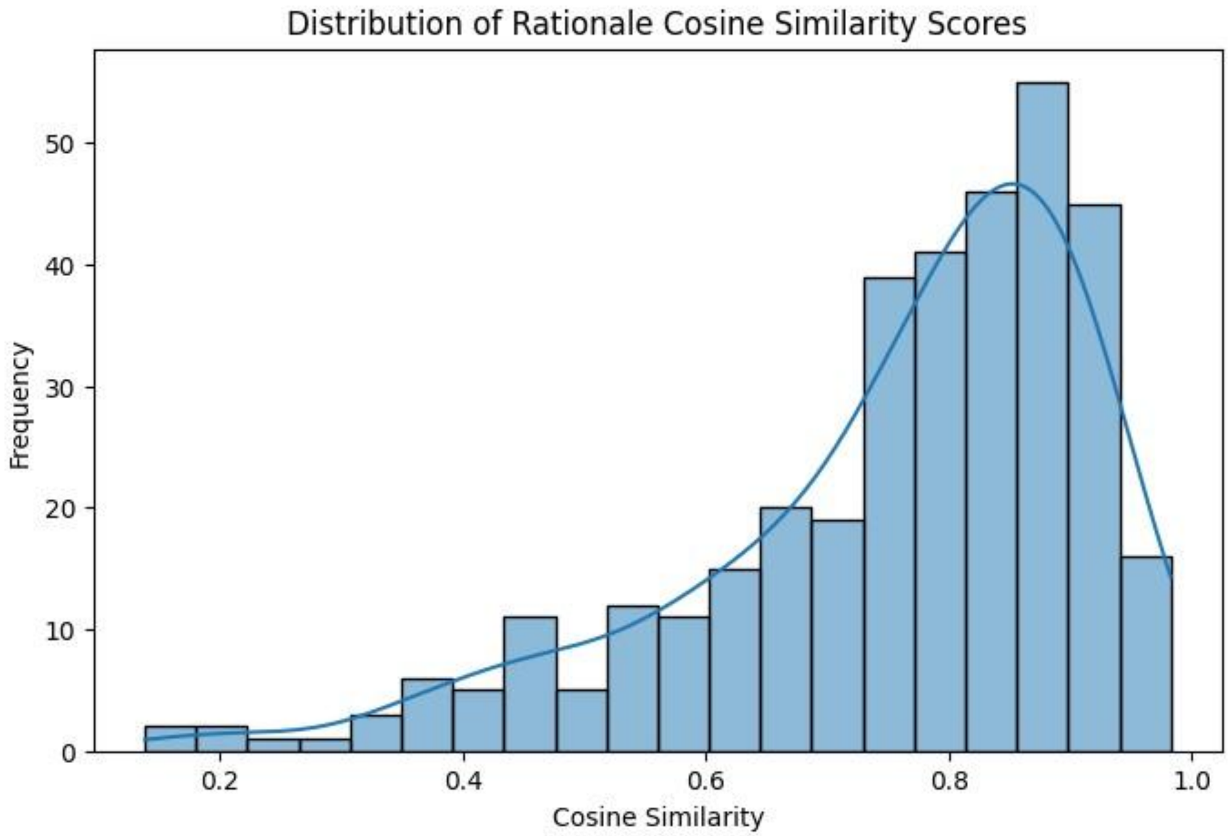
- Score 0: 0.75
- Score 1: 0.70
- Score 2: 0.58
- Score 3: 0.82
- Score 4: 0.66



Score 2 had the lowest F1, likely due to overlap with adjacent scores or fewer examples.

Rationale Similarity

- **Average Cosine Similarity** (model vs human rationale): 0.7561
- Indicates model-generated rationales are semantically close to human-written ones.



5. Results and Discussion

- The model effectively learned to replicate expert scoring behavior.
- **High exact match (73%)** and **near-perfect within-1 accuracy (99%)** show strong reliability.
- **Pearson correlation (0.91)** and **low MAE (0.28)** confirm predictive accuracy.
- **Rationale similarity (0.76)** supports interpretability.
- Best performance achieved with r=32, lora_alpha=32 — higher values led to overfitting or inefficiencies due to dataset size and limited compute resources.

6. Conclusion

This project successfully demonstrated that an instruction-tuned 4-bit *Mistral-7B* model can be fine-tuned to perform accurate and explainable essay grading, while still there is a margin of development using better datasets and better computational power. Key achievements include:

- Decent scoring accuracy

- Semantically meaningful rationale generation
- Efficient training using LoRA and 4-bit quantization
- Scalable grading system suitable for educational use