ApproachCraft-AI: Fine-Tuning Phi-2 for Research Problem Solving

1 Project Title

ApproachCraft-AI: Fine-Tuning Phi-2 for Generating Research Approaches

2 Objective

The goal of this project was to fine-tune Microsoft's Phi-2 language model to generate high-quality *suggested approaches* for given *research problems*. By specializing the model on a domain-specific dataset, we aimed to enhance its ability to draft coherent, logical, and well-structured solutions to academic prompts.

3 Dataset Generation

The dataset for fine-tuning was self-constructed by programmatically retrieving research paper metadata from the arXiv repository. The steps involved were:

- **Search Query**: Retrieved papers related to topics such as "AI in education," "Intelligent tutoring," "Automated feedback," "LLM education," and "Student modeling."
- **Data Retrieval**: Used the `arxiv` Python package to retrieve 2,000 papers sorted by submission date.
- **Data Filtering**: Only papers with abstracts longer than 50 words were kept to filter out noise and short entries.
- **Data Structuring**: Each example was formatted as:
  - `prompt`: Paper title (representing the research problem)
  - `response`: Paper abstract (representing the suggested approach)
- **Saving**: Final dataset was saved in JSONL format (`ai_edu_dataset.jsonl`) with one JSON object per line.

4 Fine-Tuning Strategy

- **Base Model**: microsoft/phi-2 (Transformer-based Causal Language Model)
- **Tokenizer**: Phi-2 tokenizer with EOS padding
- **Adapter Method**: LoRA (Low-Rank Adaptation) applied to `q_proj` and `v_proj` layers
  - Rank (`r`) = 8
  - Alpha = 16
  - Dropout = 0.1
- **Training Setup**:
  - Batch size: 4
  - Gradient accumulation: 4 steps
  - Learning rate: 2e-4
  - Epochs: 3
  - Mixed Precision (fp16): Enabled
- **Loss**: Cross-entropy loss on Language Modeling objective
- **Hardware**: Mixed-precision training and LoRA adapters were used to save memory.

5 Inference and Evaluation

After training, predictions were generated for the test set and evaluated using:

- **ROUGE-1, ROUGE-2, ROUGE-L**: Measures n-gram overlap and sequence similarity between generated and gold responses.
- **Semantic Cosine Similarity**: Measures semantic closeness using sentence embeddings.

6 Results Summary

Metric	Score
ROUGE-1 F1	0.2779
ROUGE-2 F1	0.0607
ROUGE-L F1	0.2569
Average Semantic Cosine Similarity	0.7199

7 Analysis of Results

Strengths:

- The model captured general content and structure well (ROUGE-1 and ROUGE-L above 25%).
- High semantic similarity (approximately 72%) indicates that generated approaches conveyed the correct meaning even if phrasing varied.

Weaknesses:

- ROUGE-2 score was relatively low (around 6%), suggesting that exact phrasing differed from ground truth.

Interpretation:

- The model understands the research problem and drafts reasonable approaches.
- Flexibility in wording leads to lower n-gram matching scores but maintains strong semantic alignment.

8 Challenges Faced

- **Memory Constraints**: Addressed using Low-Rank Adaptation (LoRA) for efficient fine-tuning.
- **Consistency in Input Formatting**: Proper truncation, padding, and prompt engineering were critical.
- **Evaluation Complexity**: Semantic similarity was used to supplement ROUGE-based evaluation.

9 Conclusion

ApproachCraft-AI successfully demonstrates the capability of fine-tuning general-purpose language models like Phi-2 for domain-specific educational tasks. The fine-tuned model is capable of:

- Understanding complex research prompts,
- Generating logically coherent and relevant research approaches,
- Maintaining high semantic similarity with expert-written responses.

Overall, this project validates the effectiveness of lightweight fine-tuning (LoRA) and showcases a promising direction for domain-specialized academic AI models.

10 Future Work

- Expand the dataset to 5,000–10,000 examples for broader generalization.
- Explore reinforcement learning fine-tuning (e.g., DPO, RLAIF).
- Conduct human evaluation with academic experts for qualitative assessment.
- Experiment with more advanced LoRA settings or QLoRA to further optimize training.
- Investigate reward models to enhance output quality.