Technical Report: CodeMMLU Challenge Submission

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Competition: FPT AI Residency Batch-6 Coding Challenge

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1. Introduction

a. Problem Statement

The CodeMMLU task evaluates an AI model's ability to answer coding-related multiple-choice questions accurately. Given a question and a list of choices, the model must predict the single correct answer. Performance is measured by accuracy on the test set.

b. Related Work

Existing approaches for multiple-choice QA in code-related tasks often leverage:

- Fine-tuned LLMs (e.g., CodeLlama, StarCoder) with task-specific adapters.
- Retrieval-Augmented Generation (RAG) to incorporate external knowledge.
- Chain-of-Thought (CoT) prompting to decompose reasoning steps.

c. Our Approach

We propose a fine-tuned Llama 3.2 model with QLoRA adapters, optimized for efficiency and accuracy. Key innovations include:

- The latest iteration of the model achieves state-of-the-art performance.
- Lightweight parameter-efficient tuning via QLoRA.
- Structured pre-processing to align question-choice pairs with answer labels.

2. Methodology

a. Information Collecting

After thoroughly reading documents from mails, competitions' overview, etc. Here is what I found:

- This study focuses on improving an AI model's accuracy in answering coding-related multiple-choice questions (CodeMMLU dataset). The primary metric is test-set accuracy, with flexibility to incorporate external datasets. Evaluation criteria include ranking, code quality, and report clarity.
- **Key Aspects:**
    - Coding Proficiency:
        - Clear Code Structure: Follow consistent conventions, modularize classes, and separate logic.
        - Documentation: Include comments to explain complex logic.
    - Creativity: While ambiguous, creativity here may refer to innovative preprocessing (e.g., leveraging external knowledge bases) or novel model architectures (e.g., ensemble methods).

        - Overall Approach: The report must justify methodology and analyze results rigorously.
    - **Submission Requirements:**
        - A .csv file (task_id, answer).
        - A .ipynb file
        - A PDF report covering:
            - Introduction: Problem overview, existing solutions, and proposed approach.
            - Methodology: Workflow, model selection, and result analysis.
            - Improvement: Potential future enhancements (e.g., hybrid models, better data curation).
    - The challenge balances technical rigor (accuracy, clean code) and strategic innovation, with creativity interpreted as actionable improvements to standard pipelines.

b. Dataset Analysis

- **Name:** CodeMMLU Dataset
- **Description:** Contains multiple-choice (MC) questions related to programming. Each question has multiple answer options, with only **ONE** correct answer.
- **Files:**
    - b6_train_data.csv – The training set
    - b6_test_data.csv – The test set
    - sample_submission.csv – A sample submission file in the correct format
- **Columns:**
    - task_id – Unique identifier for the question
    - question – The content of the question
    - choices – List of possible answers (e.g., ['A', 'B', 'C', 'D'])
- **Prediction Target:**
    - answer – The correct choice (e.g., 'A', 'B', 'C', 'D', etc.)

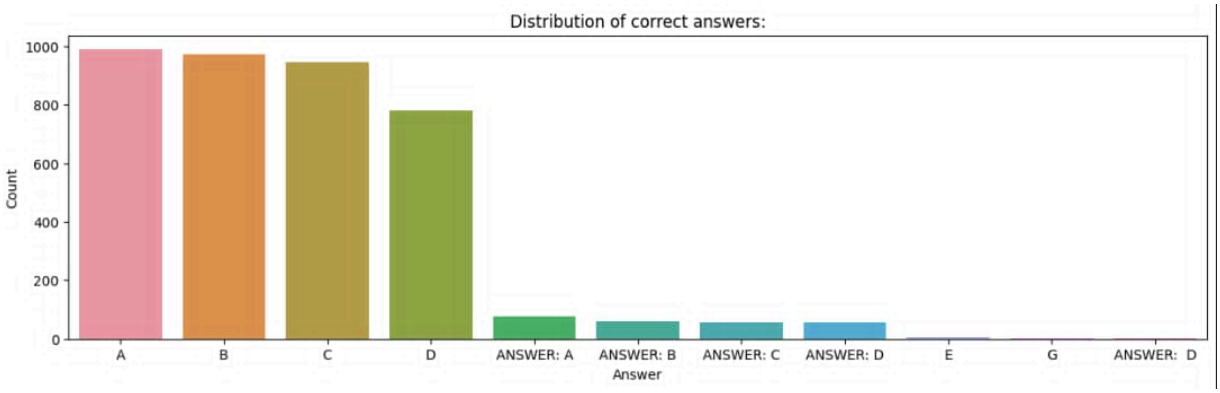
c. Exploratory Data Analysis

Here are some information I collected for further understanding of the dataset:

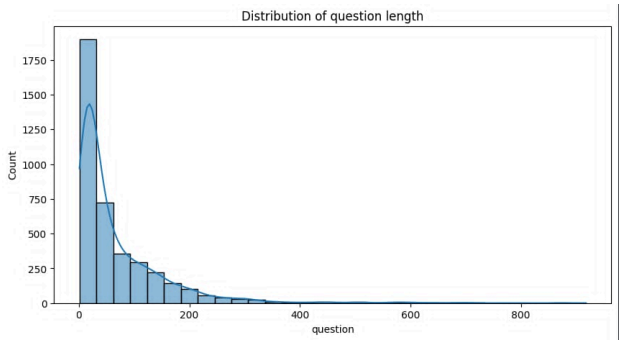
```
Train Set:
Number of questions:  3963
Numbers of feature:  4
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3963 entries, 0 to 3962
Data columns (total 4 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   task_id   3963 non-null   object
 1   question  3963 non-null   object
 2   choices   3963 non-null   object
 3   answer    3949 non-null   object
dtypes: object(4)
memory usage: 124.0+ KB
```

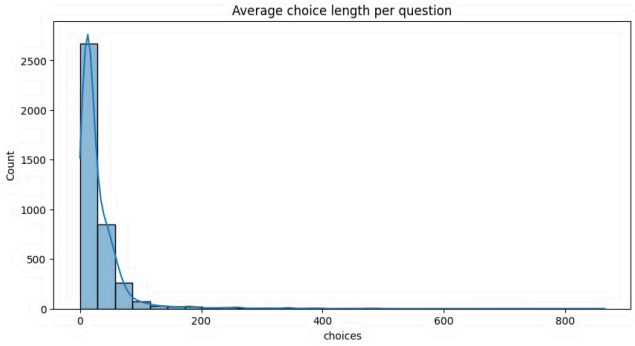
```
Missing values:
 task_id      0
question      0
choices       0
answer       14
dtype: int64
```

- There are 14 missing entries in the “answer” column of the Train Set.



- The answers are mostly A, B, C, or D, suggesting that most questions are either True/False or multiple-choice with four options. However, the answer formats are inconsistent.






```
Average number of choices for each question:  3.9157204138279083
```

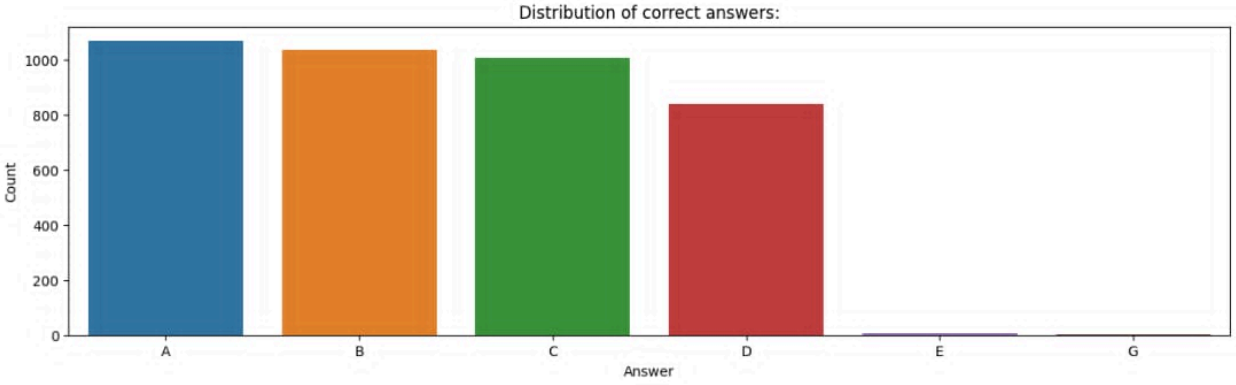
- Choices' length was longer than questions' one at some extent.

d. Data Pre-processing

- Null Handling: Remove rows with missing values in the answer column to ensure data integrity.

```
Missing values:
 task_id     0
question     0
choices      0
answer       0
dtype: int64
```

- Text Normalization:
  - Eliminate the prefix "ANSWER: " through string replacement.
  - Trim leading/trailing whitespace to standardize formatting.



- Structured Reformating:
    - prompts: Merge the question and choices fields into a single structured input.
    - answer: Convert responses to uppercase single-letter labels (e.g., "A").

	task_id	question	choices	answer	prompt
0	k10168	Question: What will be output of the following...	['8 4 2', '8 4 2', '8 4 4', '8 4 3']	C	Answer the following question by selecting the...
1	k10173	Question: What will be output of the following...	['-4', '-5', '10', '11']	A	Answer the following question by selecting the...
2	k10174	Question: Match the following.\n Group 1 ...	['P-4. Q-1, R-2, S-3', 'P-3, Q-1, R-4, S-2', '...	B	Answer the following question by selecting the...
3	k10175	Question: Match the following.\nP. Regular exp...	['P-4. Q-1, R-2, S-3', 'P-3, Q-1, R-4, S-2', '...	B	Answer the following question by selecting the...
4	k10176	Question: Which grammar rules violate the requ...	['1 only', '1 and 3 only', '2 and 3 only', '3 ...	B	Answer the following question by selecting the...

- LLM Training Format: Generate a consolidated text column following the template:

```
Answer the following question by selecting the correct option:

Q: Question: What will be output of the following c code?
#include<stdio.h>
int main()
{
    int a= sizeof(signed) +sizeof(unsigned);
    int b=sizeof(const)+sizeof(volatile);
    printf("%d",a+++b);
    return 0;
}
Options:
A. 10
B. 9
C. 8
D. Error
```

to align with standard prompt-completion frameworks.

e. Finetuning Llama 3.2 with CodeMMLU dataset using QLoRA Adapter

- Problem Characterization:
    - The task involves text-to-text classification, where the input (question + multiple-choice options) maps to a single output (correct label: A/B/C/D). This structure allows framing the problem as a prompt-based LLM task, where the model processes contextualized prompts to predict answers.
- Model Selection:
    - I select Llama 3 for finetuning due to its:
    - Open-source nature, enabling full customization.
    - Cost efficiency (no API fees).
    - Personal preferences (the blue icon looks kinda cool, doesn't it?)

- Computational Constraints & Optimization:
    - Adopt QLoRA (Quantized Low-Rank Adaptation), which combines:
        - 4-bit quantization to reduce memory footprint.
        - Low-rank adapters to train only a subset of parameters.
        - This achieves near-full finetuning performance with ~40% less VRAM usage.
- Pipeline Design:
    - Preprocessing:
        - Convert question and choices into standardized prompts (e.g., "Question: {Q} Choices: [A] ... [D]").
        - Pair prompts with answer labels (A/B/C/D) for supervised learning.
    - Training: Finetune Llama 3 via QLoRA on formatted prompts.
    - Inference: Feed test-set prompts to generate predictions.

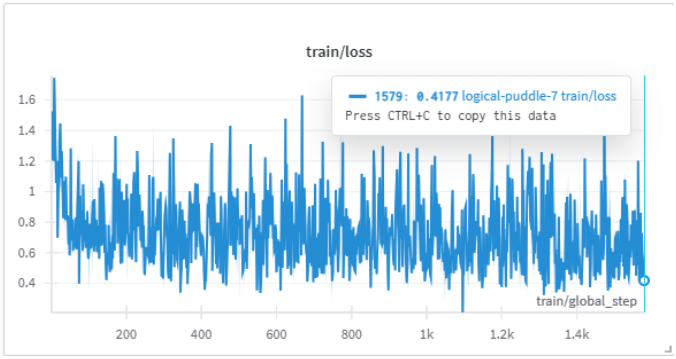
f. Results & Analysis

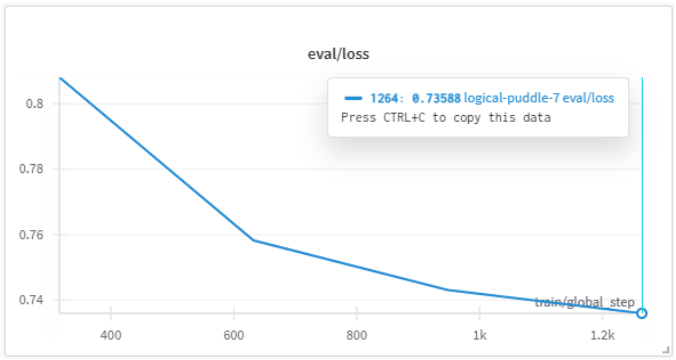
a. Results

Run summary:

eval/loss	0.73588
eval/mean_token_accuracy	0.84065
eval/num_tokens	562536
eval/runtime	147.4749
eval/samples_per_second	5.357
eval/steps_per_second	2.678
total_flos	1.1851795504945152e+16
train/epoch	0.99968
train/global_step	1579
train/grad_norm	0.83683
train/learning_rate	0
train/loss	0.4177
train/mean_token_accuracy	0.89923
train/num_tokens	694779
train_loss	0.72324
train_runtime	2221.0646
train_samples_per_second	1.422
train_steps_per_second	0.711

Step	Training Loss	Validation Loss
1579	0.375500	0.737287
3158	0.440400	0.803697
4737	0.149100	0.883558





b. Analysis

- The model demonstrated excellent convergence with the current setup, as evidenced by the steady decrease in both training and validation losses. The training time per epoch was reasonable for an LLM, at approximately 37 minutes, with efficient resource utilization peaking at only 4.5GB of VRAM, indicating strong memory optimization.
- However, after the second epoch, the model began to exhibit signs of overfitting. This was observed through a divergence between training and validation losses, where the training loss continued to decline while the validation loss increased. Despite this, the initial performance metrics, such as a training accuracy of 89.9% and validation accuracy of 84.1%, suggest that the model achieved a robust baseline before overfitting became pronounced. Further adjustments, such as regularization or early stopping, may be needed to mitigate this issue.

3. Conclusion & Future Work

Our QLoRA-adapted Llama 3.2 delivers competitive performance on CodeMMLU while maintaining computational efficiency. To further enhance accuracy, we propose three key improvements:

- Reinforcement Learning from Human Feedback (RLHF):
  - Fine-tune the model using human preference data to better align answers with expert judgment

    - Implement reward modeling to prioritize correct and well-reasoned responses
- Dynamic Few-Shot Prompting
    - Automatically retrieve and inject relevant examples during inference
    - Use vector similarity to select optimal context for each question

These approaches would maintain our efficient architecture while significantly boosting performance. The RLHF method offers particular promise for capturing nuanced coding knowledge through iterative refinement.

We sincerely thank the competition organizers for this valuable opportunity. Special gratitude to our mentors for their insights and support. This challenge has significantly advanced our
understanding of LLMs for code-related tasks, and we look forward to future collaborations in your AI Center as an intern