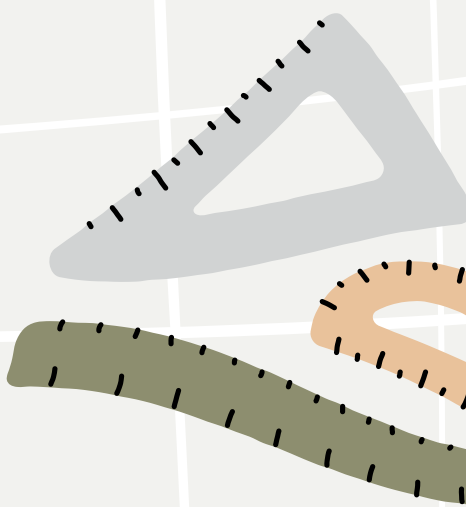
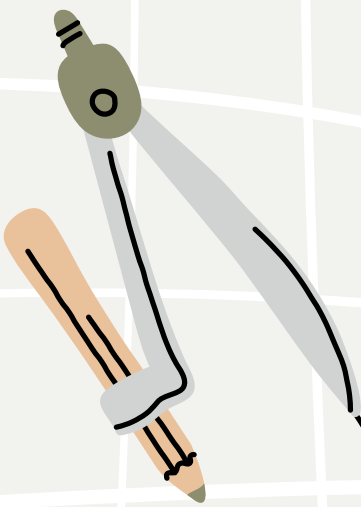


# Eedi – Mining Misconceptions in Mathematics

Group 4

NCKU 許宸華

NCKU 蕭力文



# Overview

You'll develop an NLP model driven by ML to accurately **predict the affinity between misconceptions and incorrect answers** (distractors) in multiple-choice questions.

If a student selects the distractor "13,"

## **Misconceptions :**

"Carries out operations from left to right regardless of priority order."

$$5 \times 4 + 6 \div 2 =$$



23



13

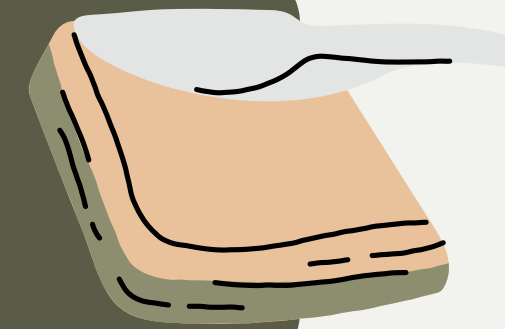


25

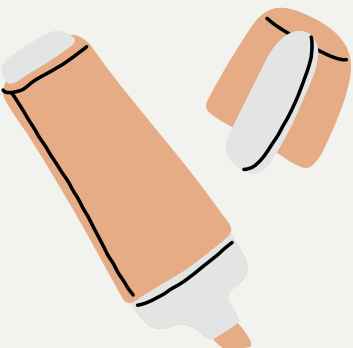


35

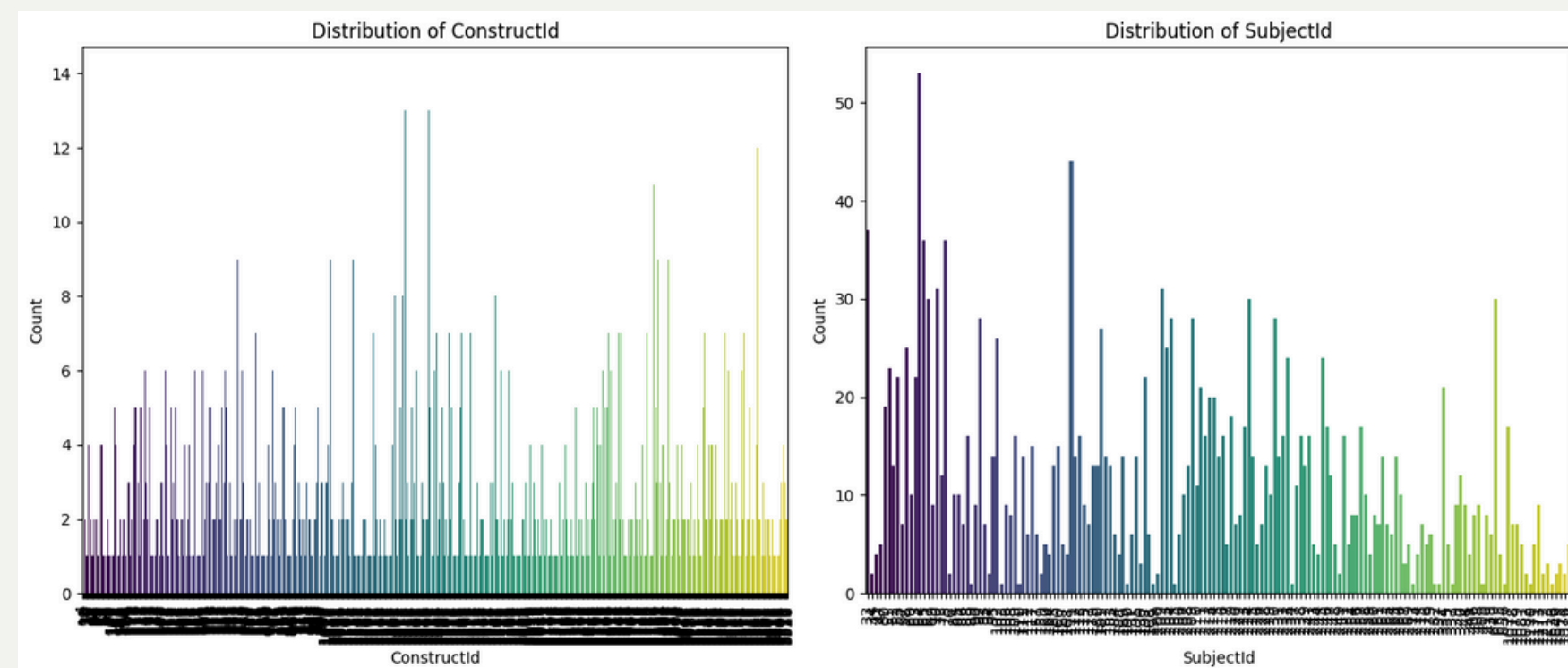
# About Dataset



## [train/test].csv:



- QuestionId - Unique question identifier (int).
- ConstructId - Unique construct identifier (int) .
- ConstructName - Most granular level of knowledge related to question (str).
- CorrectAnswer - A, B, C or D (char).
- SubjectId - Unique subject identifier (int).
- SubjectName - More general context than the construct (str).
- QuestionText - Question text extracted from the question image using human-in-the-loop OCR (str) .
- Answer[A/B/C/D]Text - Answer option A text extracted from the question image using human-in-the-loop OCR (str).
- **Misconception[A/B/C/D]Id** - Unique misconception identifier (int). Ground truth labels in train.csv; your task is to predict these labels for test.csv.



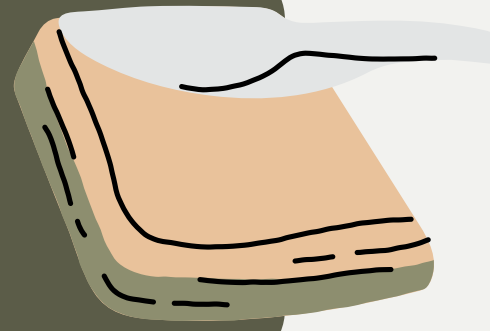
ConstructName: Calculate the square of a number,

Count: 14

SubjectName: Linear Equations,

Count: 53

# About Dataset



misconception\_mapping:

123



Does not know that angles in a triangle sum to 180 degrees

37



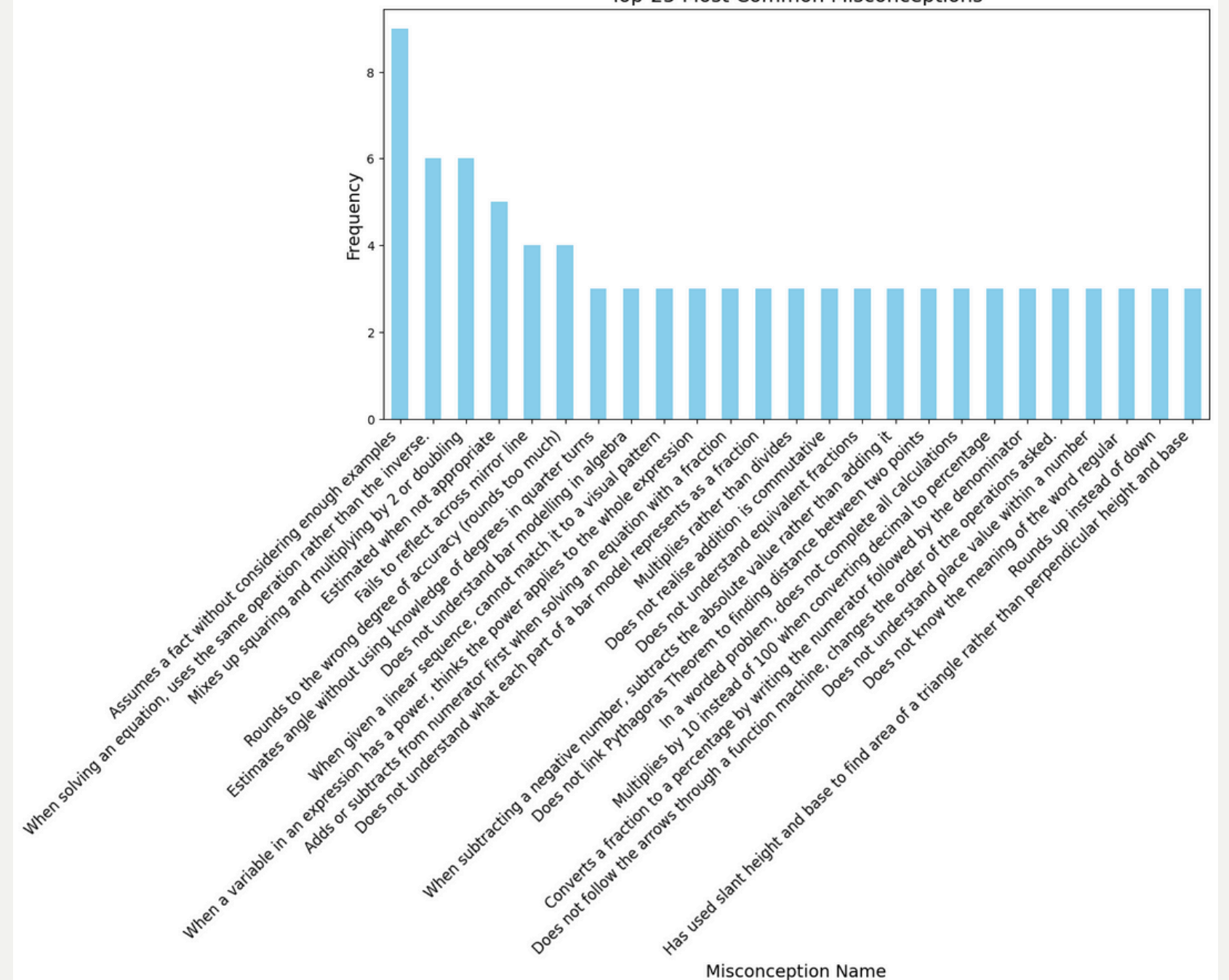
Uses dividing fractions method for multiplying fractions

246



Believes there are 100 degrees in a full turn

Top-25 Most Common Misconceptions



# Evaluation

## Equipment

U：觀測點的總數（即測試集的樣本數）。

n：每個樣本提交的預測數量（最多考慮前 25 個）。

P(k)：在第 k 名的精度(排名越前數值越大)

rel(k)：相關性指示函數，當第 k 名的標籤是正確答案時，rel(k)=1，否則為 0。

## Calculation formula:

$$\text{MAP@25} = \frac{1}{U} \sum_{u=1}^U \sum_{k=1}^{\min(n, 25)} P(k) \times \text{rel}(k)$$

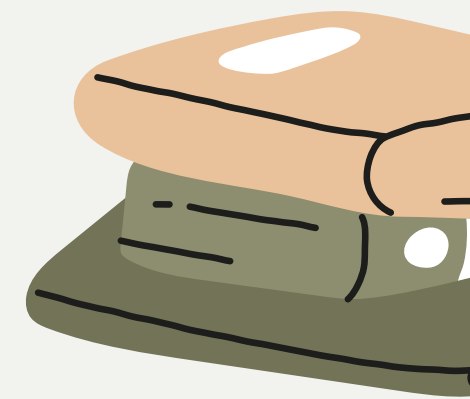
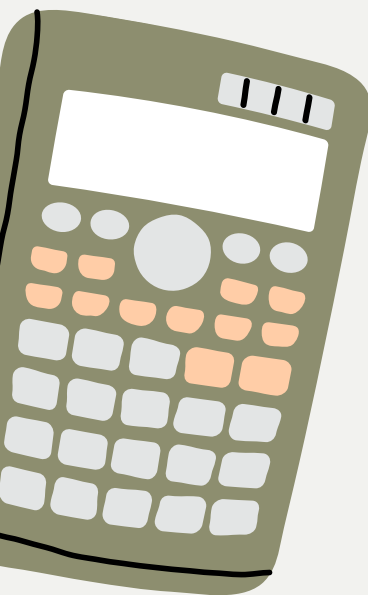
[A, B, C, D, E]

[A, A, A, A, A]

[A, B, A, C, A]

若A為正解，1、2、3皆為1

若B為正解，1、3皆為1/2



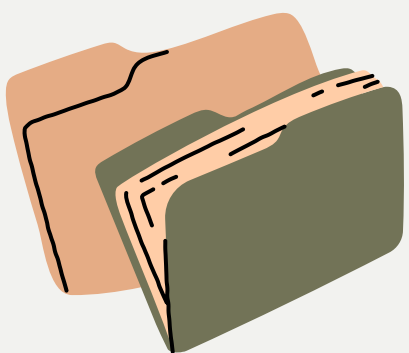
# Eedi Qwen32B vllm with logits-processor-zoo

## Qwen2.5-32B-Instruct-AWQ

- 採用 **Transformer 架構**，結合的技術如 RoPE（相對位置編碼）、SwiGLU（激活函數）、RMSNorm（正規化）以及 Attention QKV bias。
- 適合用於文本摘要、自然語言理解、程式碼生成與輔助
- 64 layers, with 40 attention heads for queries

## Lora Finetune

- 對模型進行finetune，在資源較少的Kaggle十分有效
- 生成一個高效、記憶體友好的量化微調模型，準備進行推理或其他應用。





# Code Review

Simply introduce code: Qwen14B\_Retrieval\_Qwen32B\_logits-processor-zoo

## Data Processing

- 生成每個選項（排除正確答案）作為錯誤選項的數據。
- 數據按照句子長度排序，確保短句和長句的填充處理一致。
- 利用 tokenizer 將文字轉為模型可處理的輸入格式。

## First Retrieval

- Embedding：使用"qwen2.5-14"模型透過 inference 函數將 query\_text 進行 embedding
- 使用 NearestNeighbors 找到最相似的25個嵌入向量對應的 misconception

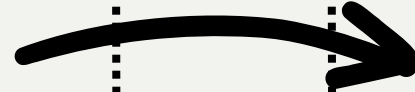
## Multiple Choice

- 使用 vLLM 調用 Qwen-32b-Instruct-AWQ 模型
- 逐輪篩選機制：3輪後選 misconception，從候選中選擇最優項加入到下一階段，最終排序25個 misconception
- 使用 LLM 根據生成的提示詞（text），通過多項選擇（Multiple Choice）生成每條數據的最佳選擇。

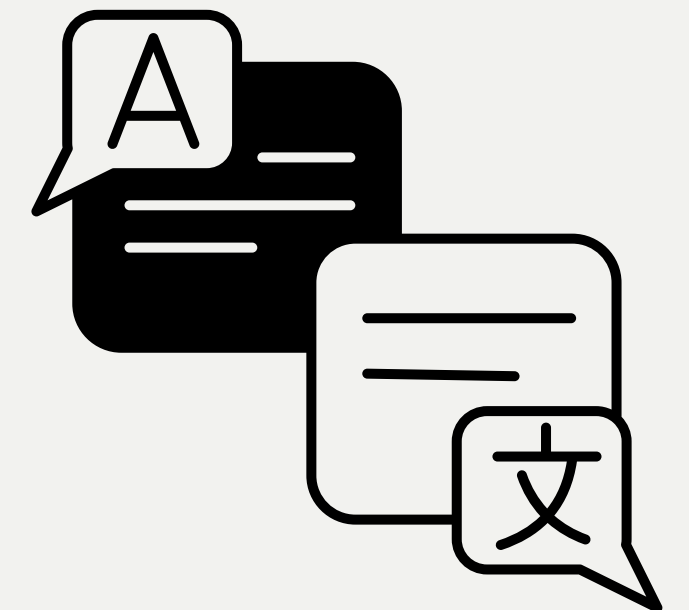
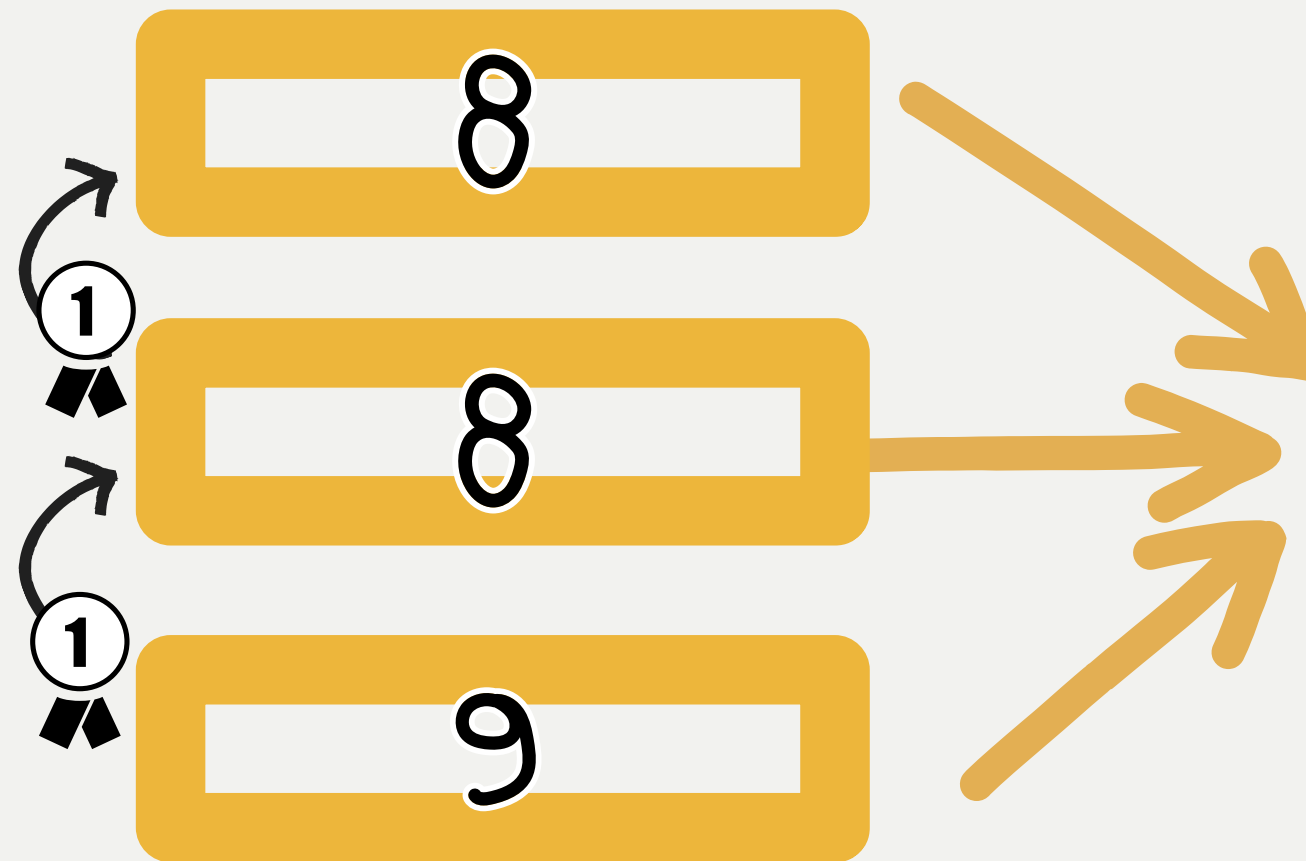
# Code Review

Simply introduce code: Qwen14B\_Retrieval\_Qwen32B\_logits-processor-zoo

First retrieval



get survivors





# Enhence

What we want to enhance code: Qwen14B\_Retrieval\_Qwen32B\_logits-processor-zoo

## Data Processing

- 將misconception的偏差值刪除
- 讓misconception有一致的格式

## First Retrieval

- 增加 n\_neighbors 的值
- 刪除數據中可能存在的異常值，它們會干擾最近鄰查詢的準確性。
- 使用不同於NearestNeighbors的初步篩選方法

## Mutiple Choice

- 增加每輪篩選的survivors，或者增加輪數
- 給予排序高者更大的權重，使其較不易動搖
- 更改prompt來增強LLM的判斷

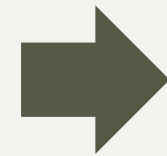
# Code Review

Simply introduce code: Eedi Qwen-2.5 32B AWQ two-time retrieval

## First-Time Retrieval

model: fine-tune model for Eedi dataset

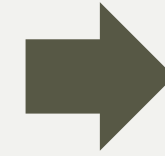
1. Pre-processing: features = ["ConstructName"] + ["SubjectName"]
2. Embedding: features & misconceptions
3. 以semantic\_search取出 top-100 misconceptions



## LLM Reasoning

model: Qwen 2.5 32B-instruct-AWQ

1. input: prompt
2. output: ["IImMisconception"]
3. Post-processing: output



## Second-Time Retrieval

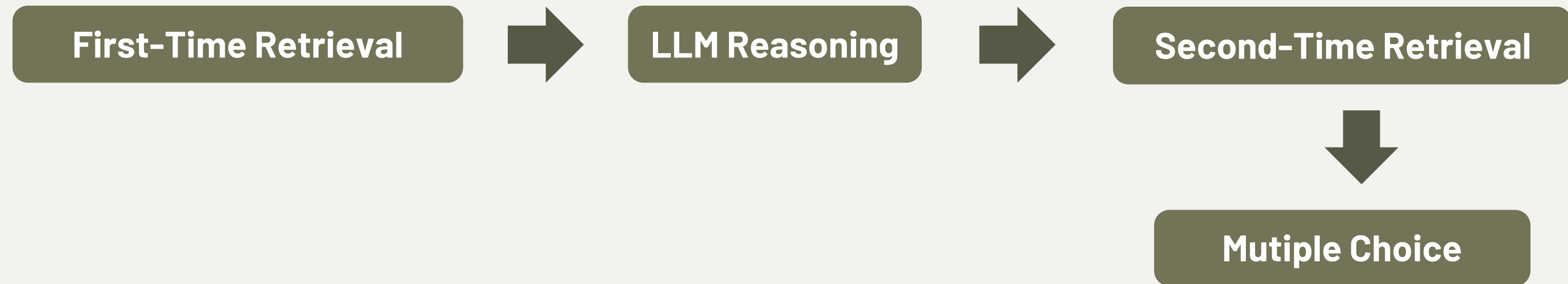
model: fine-tune model for Eedi dataset

1. Pre-processing: features = prompt + ["IImMisconception\_clean"]
2. Embedding: features
3. 以semantic\_search取出 top-25 misconceptions



# Our Experiments

Combine two methods



**Eedi Qwen-2.5 32B AWQ two-time retrieval - Version 3**

Notebook Threw Exception (after deadline) · 11h ago

# Our Proposals



1 Using Augmented Data

2 Change Embedding Model

3 Two-time Reranking

4 Enhanced Retrieval

**Thank you for listening.**

