

# **MathGenie: Generating Synthetic Data with Question Back-translation for Enhancing Mathematical Reasoning of LLMs**

Zimu Lu, et al

The Chinese University of Hong Kong

September 11, 2024

## Abstract

- There is a performance gap between open / closed source LLMs
  - New method for generating diverse and reliable math problems
- We suggest MathGenie
  - This augmentation increased open-source models' performance

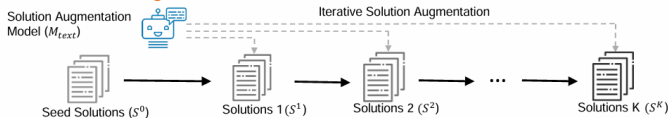
## Introduction

- Three main types of solution
  - CoT, PoT, Code-Integrated solution
  - Code-Integrated solution is superior
  - MathGenie generates Code-Integrated solution

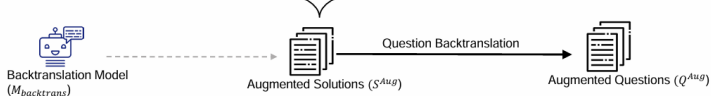
# MathGenie Framework

- **Iterative Solution Augmentation:** Gives variation to solutions
- **Question Back-Translation:** Invert solutions to questions
- **Verification-based Solution Filtering:** Verify question-solution pair

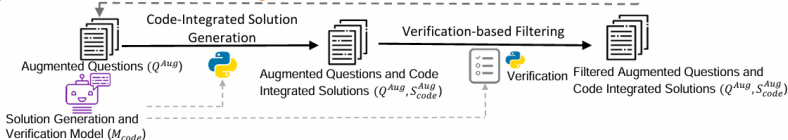
## Step 1 : Iterative Solution Augmentation



## Step 2: Question Backtranslation

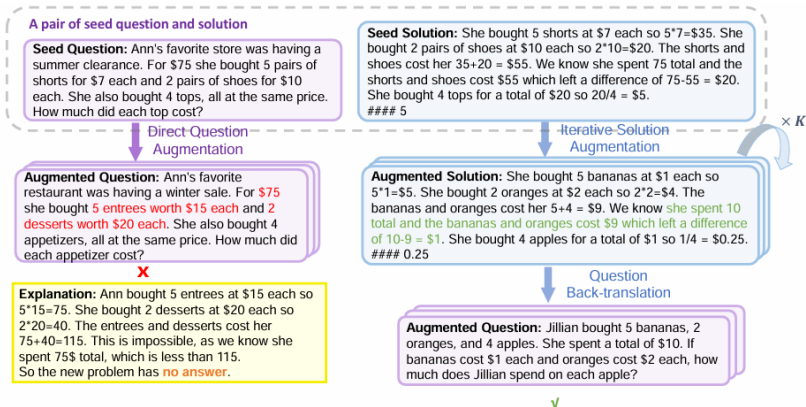


## Step 3: Verification-Based Solution Filtering



# Question Back-Translation

- Direct Question Augmentation (Left)
  - It may produce question with no answer
- Question Back-Translation (Right)
  - Correctly augments the question



## Experiment

- Fine-tunes pretrained models (Llama Family) with MathGenie
  - This results in [MathGenieLM](#)
- Prepare 5 datasets
  - [In-domain](#): GSM-8K, MATH
  - [Out-domain](#): SVAMP, Simuleq, Mathematics
- Compare MathGenieLM with various models
  - [Open source](#): Mammoth, MathCoder, ToRA
  - [Closed source](#): GPT-3.5, GPT-4, PaLM-2

## Result and Conclusion

- MathGenieLM achieved SOTA for open-source models
  - However, there was noticable gap compared to GPT-4
- Limitation
  - It requires significant GPU resource
  - It cannot process images as input