LLM-powered Data Augmentation for Enhanced Cross-lingual Performance

Chenxi Whitehouse, Monojit Choudhury, Alham Fikri Aji

City, University of London, Microsoft, MBZUAI

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Introduction

Background and Motivation

- The success of NLP models greatly depends on the availability and quality of training data.
- It can be challenging to have sufficient labelled data, especially for multilingual scenarios.
- Recent powerful LLMs excel at handling general instructions and have shown promise in data generation tasks.
- We explore the potential of leveraging LLMs for data augmentation in multilingual commonsense reasoning datasets where the available training data is extremely limited.

Data Augmentation

Data Augmentation Process

- Start with instructions from the original dataset paper and iteratively improve
- Set the desired total number of examples to generate (about 3K in our experiments)
    - *Randomly* sample n examples from the training datasets (*ensure diversity*)
    - Append these examples to the instructions and prompt the model to generate additional m new examples.
    - Post-process and add valid and unique examples to the generation set
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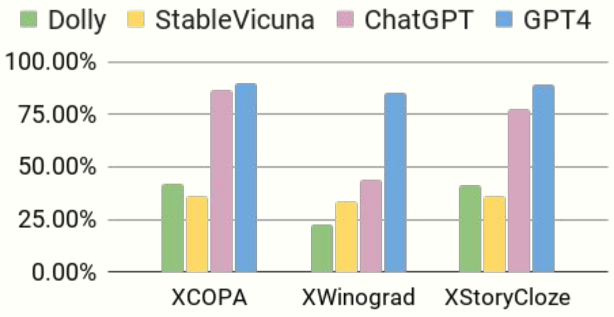
Data Augmentation

Datasets and LLMs

- 4 LLMs: Dolly-v2, StableVicuna-13B, ChatGPT, GPT-4
- 3 Datasets: XCOPA, XWinograd, XStoryCloze
- They show different data-generation success rates
  $actual\_valid\_examples \;/\; total\_requested\_examples$

Dataset	EN	Non-EN
XCOPA	400	0
XWinograd	1858	0
XStoryCloze	300	300

Training Examples of the original datasets.



Data-generation Success Rate

Instruction & Generation Examples

ChatGPT-generated Examples in XCOPA

We are collecting more examples for the COPA dataset which will be used to test a system's ability of Commonsense Causal Judgments. The format of the data:
A premise: a statement of something that happened, and two choices that could plausibly *occur as the result/be the cause* of the premise. The correct choice is the alternative that is more plausible than the wrong choice.
Here are 10 examples in English/Chinese ...:
Example 1: **Premise**: The man wanted to save money. What happened as a result? **Correct choice**: He cut back on making frivolous purchases. **Wrong choice**: He withdrew money from his savings account. ... Example 10: ...
Based on the examples above, generate m new examples in English/Chinese...

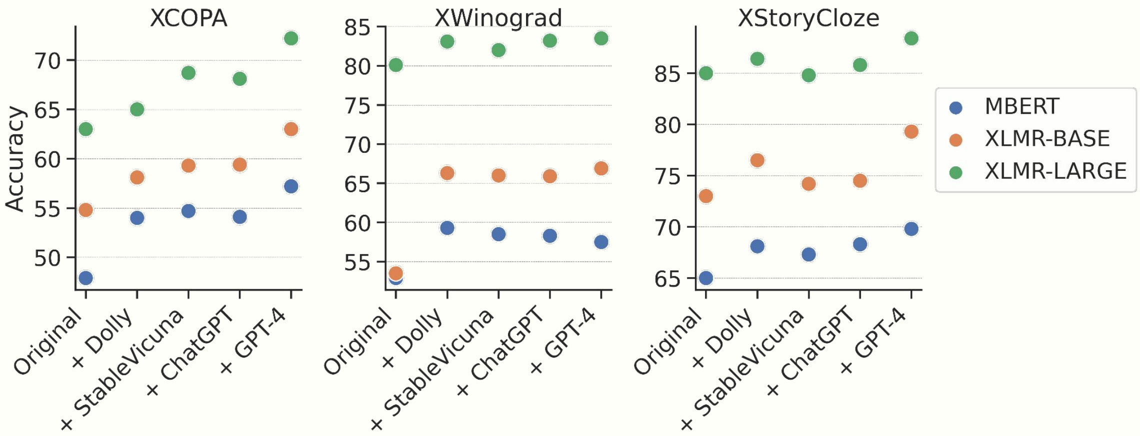
Premise: The politician made a controversial statement. What happened as a result?
Correct choice: The politician faced criticism from the media.
Wrong choice: The politician's approval ratings increased.

Premise: 我裤子口袋里的钥匙不见了。What was the cause?
Correct choice: 这个口袋上有一个洞。
Wrong choice: 裤子是新的。

Fine-tune Smaller Multilingual Models

Fine-tune mBERT, XLMR-Base, XLMR-Large

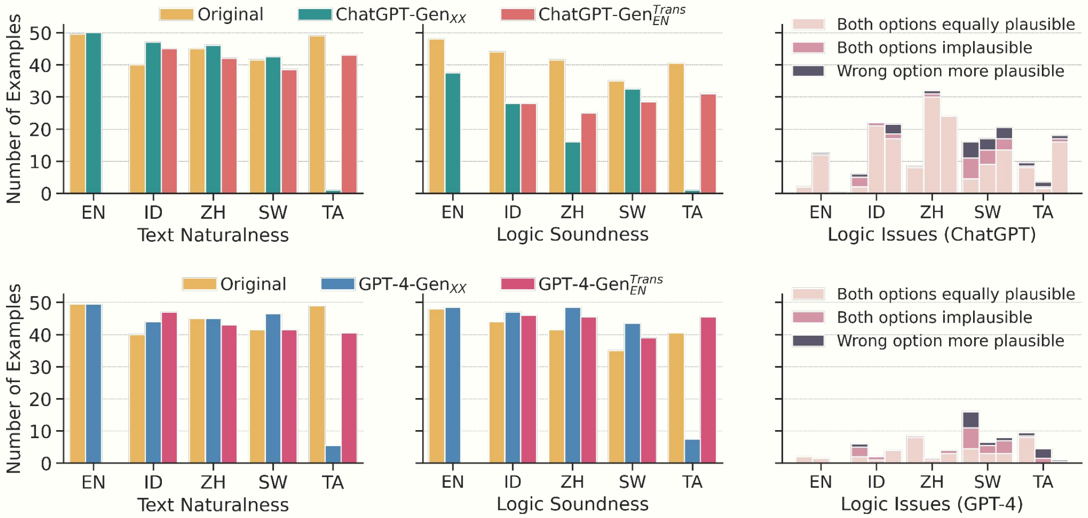
- Compare original & original + different LLM-generated EN data
- Training the models with *relatively large* synthetically generated data yields better performance than training with *limited* manually-created data
- Translating English-generated data with Google API is generally better than generating examples directly in target languages.



Evaluation by Native Speakers

Text Naturalness & Logic Soundness

- Compare original, ChatGPT and GPT-4 generated data in target language, and translations of generated English data (50 examples)
- Both models can mostly generate fluent text, GPT-4 stands out in logic soundness.
- Some languages are surprisingly bad, such as Tamil!



Conclusion

LLM-powered Data Augmentation is promising!

- LLMs demonstrate promises in Data Augmentation even for challenging multilingual commonsense reasoning tasks
  - Choice of LLM influences the performance of the fine-tuned models
  - LLMs such as ChatGPT and GPT-4 can generate high-quality data in many languages, but surprisingly struggle with certain languages such as Tamil.
- Future work could explore the effectiveness of more recent instruction-tuned or aligned open-source LLMs, e.g. LLaMA 2