



Exploring performance of LLMs fine-tuned on synthetic code-switched text

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Introduction

Language models (LMs) often underperform in low-resource languages due to imbalanced training data¹. Our research aims to mitigate this bias by fine-tuning LMs on synthetic code-switched data, where multiple languages are mixed within sentences.

Motivation:

- **Language Imbalance:** High-resource languages dominate training data, disadvantaging low-resource languages.
- **Performance Gap:** LMs perform poorly in low-resource languages, creating inequities.

Research Questions:

1. Can synthetic code-switched data improve LLM performance in low-resource languages?
2. Does this fine-tuning affect high-resource language performance?

Methods

Data Generation:

Synthetic Code-Switched Text:

- **GPT-3.5:** Generated Hindi-English code-switched text using specific prompts.
- **mt5-Small²:** Controlled code-mixed text generation with language ratios in three buckets: [0, 0.167] (cmi 1), [0.167, 0.3] (cmi 2), and [0.3, 0.5] (cmi 3).

Dataset Preparation:

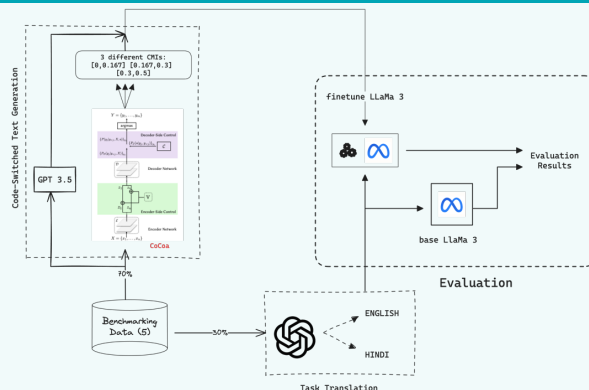
• **Common Sense Reasoning (CSR) Dataset:** Converted multiple-choice questions in English into code-switched text using the above methods, creating four datasets: GPT generated, CMI1, CMI2, and CMI3.

• **Fine-Tuning:** LLaMa3 model fine-tuned for 2 epochs on the code-switched CSR dataset.

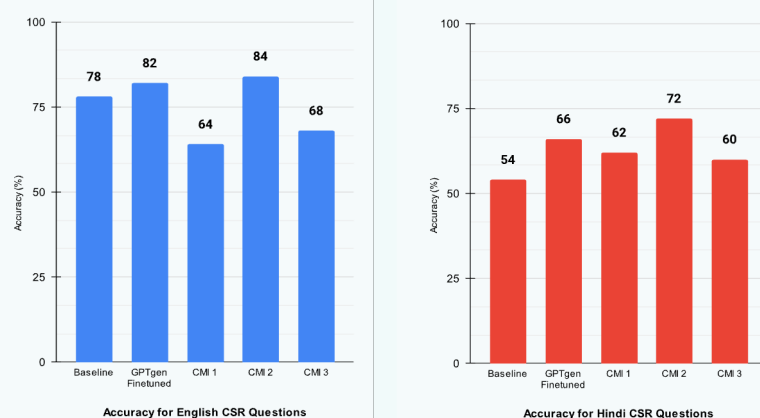
Evaluation:

- **Performance Metric:** Accuracy of correct answers over 5 iterations.
- **Baseline Comparison:** Calculated baseline scores for LLaMa3 without fine-tuning for comparison.

Methods Pipeline



Results



Key Findings:

- **Improvement in Hindi:** All fine-tuned models demonstrated significant improvements in Hindi accuracy, showcasing the effectiveness of synthetic code-switched text in enhancing performance in low-resource languages.
- **Preservation of English Performance:** Two models, GPTgen and CMI2, not only improved performance in Hindi but also preserved or enhanced performance in English, indicating a balanced approach to multilingual enhancement.

Conclusion

Our research demonstrates partial success in improving low-resource language performance using synthetic code-switched text. Models finetuned on GPTgen and CMI2 showed significant improvements in Hindi while preserving or enhancing English performance.

Future Work:

Further experimentation with more specific Code-Mixed Indexes (CMIs) is needed to identify the optimal language ratios.

Impact:

- **Language Equity:** Ensures fair treatment of all languages.
- **Real-World Benefits:** Enhances multilingual support in diverse linguistic settings.

References

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3. Zihao Li, Yucheng Shi, Zirui Liu, Fan Yang, Ali Payani, Ninghao Liu, and Mengnan Du. 2024. Quantifying Multilingual Performance of Large Language Models Across Languages. Retrieved July 22, 2024 from <http://arxiv.org/abs/2404.11553>

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