

# How well ChatGPT understand Malaysian English? An Evaluation on Named Entity Recognition and Relation Extraction

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## What is Malaysian English

Malaysian English (ME) has evolved into a unique form of English incorporating local words from languages like Bahasa Malaysia, Chinese and Tamil.

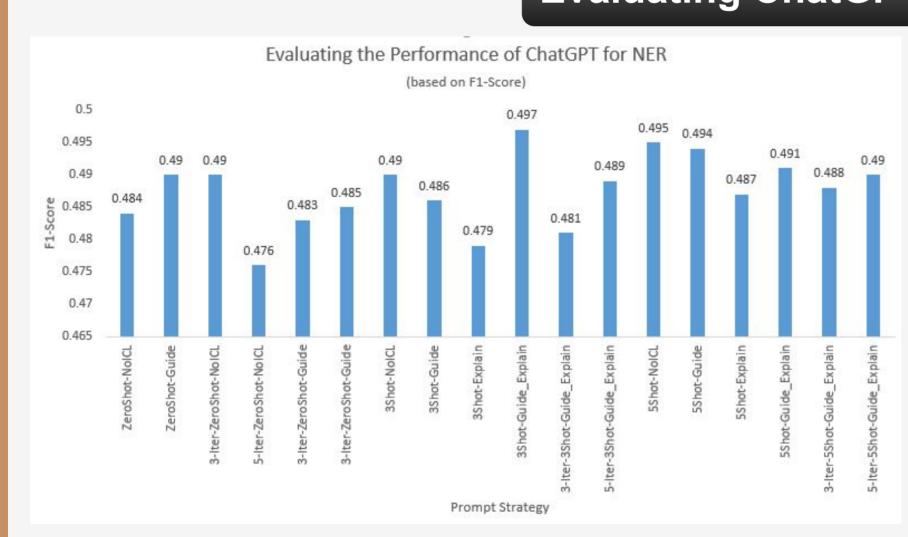
# educate-predict-evaluate Step 1: educate Input for Guideline Step 2: predict **Final Predicted** Output Prompt Template News Article Formatting Output Step 3: evaluate Manual Annotated Calculate F1-Score Analysis **Entities and Relation**

### Introduction

- ChatGPT has demonstrated strong performance across various NLP downstream tasks in Standard English.
- 2. However, this has raised a question How effective is ChatGPT capable of extracting entities and relations from Malaysian English News?
- This question has been raised as Malaysian English exhibits morphosyntactic adaptations like usage of loan words, compound blend and derived words.
- 1. *educate*: Enhancing ChatGPT by enabling In-Context Learning (ICL) with annotation guideline.
- 2. *predict*: Predicting entities and relations using ChatGPT with different prompting techniques like, **Zero Shot Prompting**, **Few-Shot Prompting and** Few-Shot with Explanation Prompting.
- 3. *evaluate*: ChatGPT's NER and RE **performance** were rigorously evaluated via **F1-Score** calculations, benchmarked **against human annotations**.

There are 18 different prompt settings has been used in this evaluation. Those 18 different prompt settings are based on different ICL, and prompting techniques.

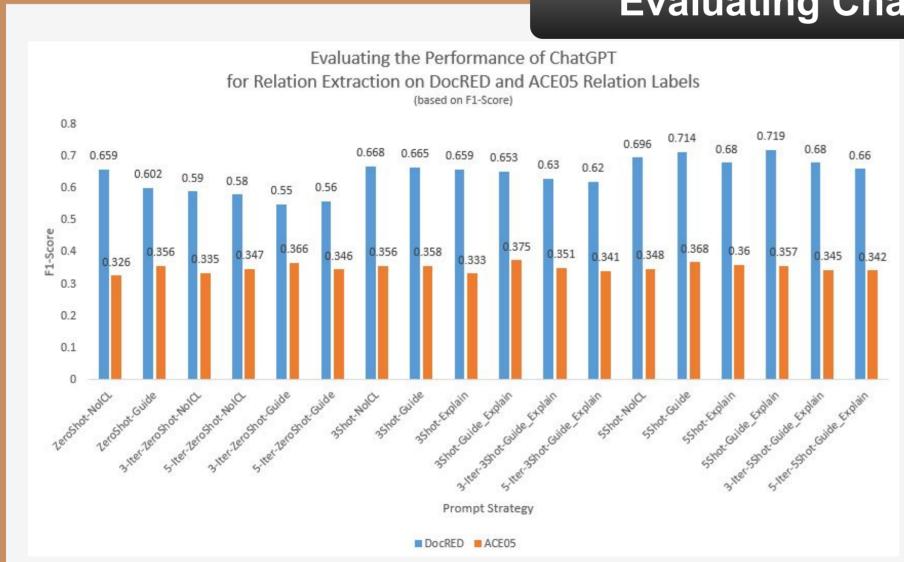
# **Evaluating ChatGPT for Named Entity Recognition (NER)**



- 1. How well did ChatGPT perform in extracting entities from Malaysian English? Does it perform better?
  - a. Although various prompting techniques has been evaluated, the overall difference of F1-Score recorded is  $0.488 \pm 0.01$ . The highest F1-Score is 0.497.
  - b. During MEN-Dataset annotation, the Inter-Annotator Agreement score is 0.81, while ChatGPT highest F1-Score of 0.497, revealing performance limitations.
- 2. What are the limitations of ChatGPT in extracting entities? Were there specific types of entity labels that ChatGPT consistently struggled to extract or misidentify?
  - a. For entity label PERSON, we noticed most errors due to exists of Compound Blend.
  - b. ChatGPT not extracting abbreviations of ORGANIZATION.
  - c. For NORP, we noticed most of the errors as they are Derived Words.

#### \*\*Scan Result and Analysis QR for more details

## **Evaluating ChatGPT for Relation Extraction (RE)**



- 1. How accurate was ChatGPT in extracting relations between entities, and were there any notable errors or challenges?
  - a. Average F1-Score for relation adapted from DocRED and ACE05 are 0.64 and 0.35 respectively. This gap is due to complexity in understanding relation labels.
  - b. In-Context Learning improved the performance of ChatGPT in identifying the relations.
  - c. 5 Shot Learning slightly improved the performance of ChatGPT, compared to 3 Shot Learning of various prompting techniques.
  - d. Although no morphosyntactical adaptation is required for predicting relations, the performance of ChatGPT in relation prediction is influenced by its understanding of the context within the news article

\*\*Scan Result and Analysis QR for more details

# Conclusion

- 1. Experiment results show morphosyntactic adaptation significantly influenced ChatGPT's entity extraction in Malaysian English news articles.
- 2. As future work, we will expand the experiment to various LLM and various downstream tasks.





