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

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Full Paper

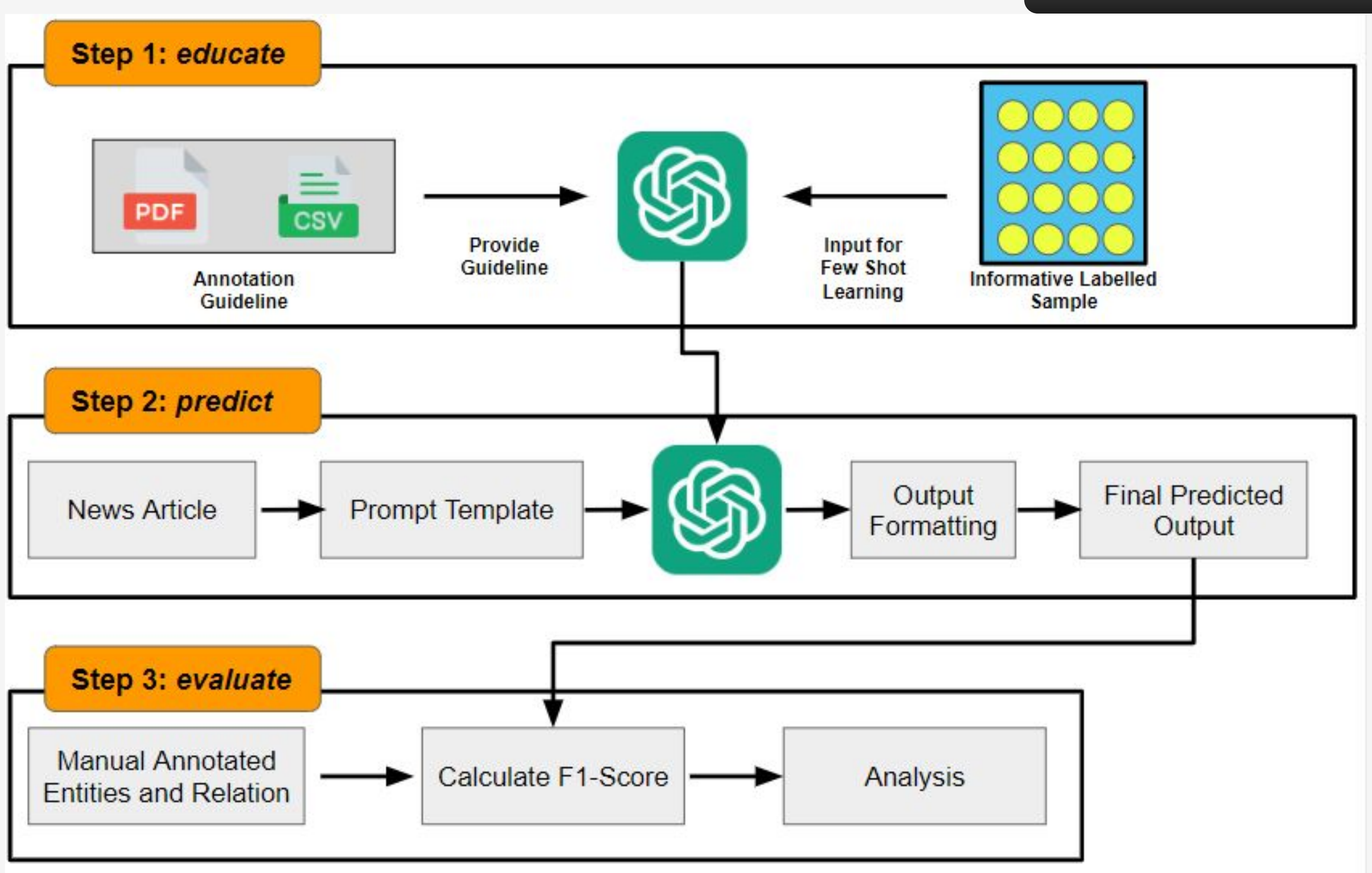
Motivation

1. ChatGPT has demonstrated strong performance across various NLP downstream tasks in Standard English. However, ***how effective is ChatGPT capable of extracting entities and relations from Malaysian English News?***
2. This question has been raised as **Malaysian English (ME)** is a widely used language in Malaysia that exhibits morphosyntactic adaptations like usage of **loan words, compound blend and derived words**.

Contribution

1. Proposed a novel **evaluation approach** to identify and extract entities and relations from any document or text by providing sufficient contexts to ChatGPT. This is approach is called ***educate-predict-evaluate***.
2. Evaluated performance of ChatGPT on **M**alaysian **E**nglish **N**ews (**MEN**) Dataset based on proposed methodology. A total of **18 different prompt settings** have been carefully engineered to evaluate ChatGPT's capability in NER and RE.

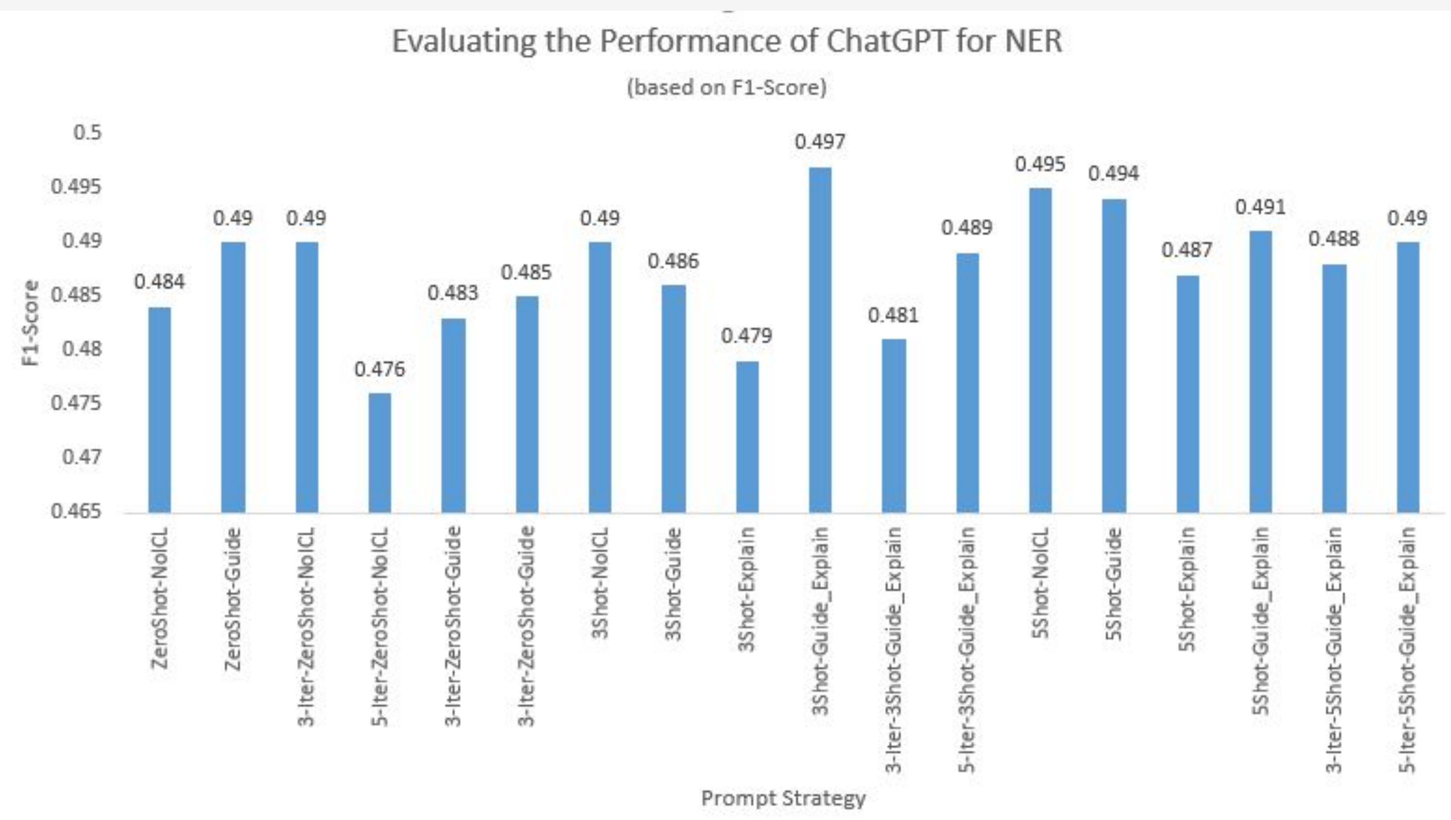
Methodology



1. ***educate***: Enhancing ChatGPT by enabling **In-Context Learning** (ICL) with annotation guideline, and annotation explanations.
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.

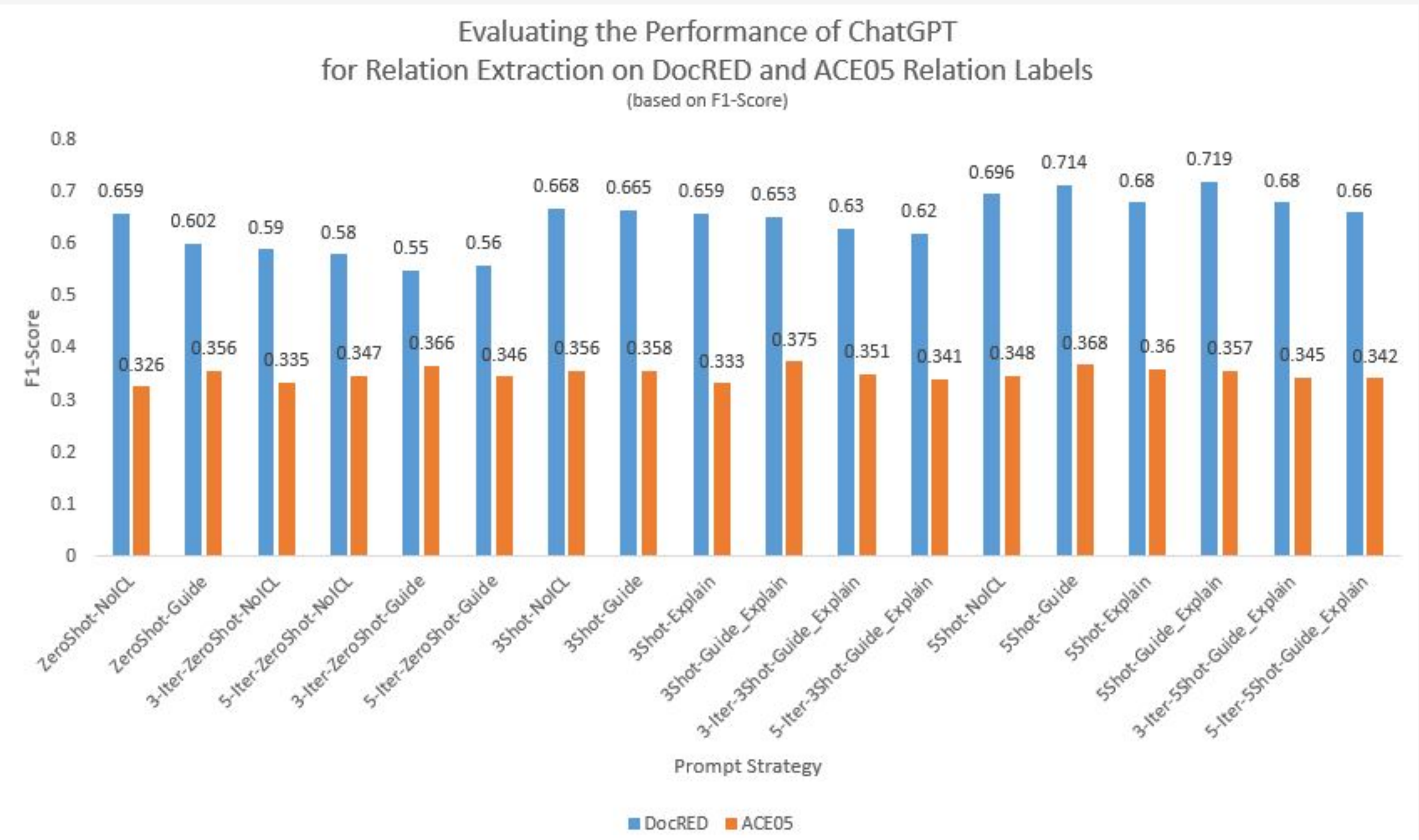
Evaluating ChatGPT for Named Entity Recognition (NER)



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 ± 0.01**. The highest F1-Score is 0.497.
   b. During MEN-Dataset annotation, the **Inter-Annotator Agreement** evaluated using **F1-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**.

****View Section 5: Result and Analysis in Full Paper for more examples**

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 morphosyntactic 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

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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.

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