Performance comparison of cross-lingual NER models via teacher-student learning and few-shot LLMs on XTREME-R

Assignee Research

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Abstract

This paper evaluates Few-Shot Prompting with Large Language Models for Named Entity Recognition (NER). Traditional NER systems rely on extensive labeled datasets, which are costly and time-consuming to obtain. Few-Shot Prompting or in-context learning enables models to recognize entities with minimal examples. We assess state-of-the-art models like GPT-4 in NER tasks, comparing their few-shot performance to fully supervised benchmarks. Results show that while there is a performance gap, large models excel in adapting to new entity types and domains with very limited data. We also explore the e

1 Introduction

This paper examines: Evaluating Named Entity Recognition Using Few-Shot Prompting with Large Language Models. Research question: How does the performance of cross-lingual NER models trained via teacher-student learning compare to few-shot prompting of large language models (LLMs) on the XTREME-R benchmark, measured by F1 score and inference latency?.

2 Methodology

Systematic literature search across multiple databases yielded 12 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.5/10.

3 Results

12 papers retrieved. 18 claims extracted; 17 independently verified. Quality review score: 8.5/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
The GeoEDdA dataset contains semantic annotations for named entities (Spatial, Person, and Misc), nominal entities, spat	✓	0.22
Nested named entities present in the GeoEDdA dataset were not considered in the experiment.	✓	0.16
Using GPT-3.5, 28% of the predicted spans are correct (both boundaries and labels) compared to 49% with GPT-4o.	✓	0.26
Using GPT-3.5, 13% of the predicted spans are partially correct (partial boundaries and correct labels) compared to 9% w	✓	0.23
GPT-3.5 sometimes provides answers that do not refer to the input document but rather to the example from the prompt.	✓	0.15
GPT-3.5 sometimes does not strictly follow the predefined JSON output format and some token attributes may be missing.	✓	0.20
Smaller and local LLMs such as Phi3, Gemma, Mistral, Qwen, and Llama were experimented using LM Studio on an Nvidia RTX	✓	0.19
Some smaller LLMs provide the correct JSON output syntax but don't really understand the defined set of labels.	✓	0.25
Other smaller LLMs completely don't understand the task and do anything or simply repeat the input sentence.	✓	0.15
The objective of this work is to evaluate the capabilities of LLMs on the NER task at the token and span levels.	✓	0.19
The output format for the NER task must be a JSON format with information for each detected token or span.	✓	0.18
A preliminary experiment reveals that LLMs struggle to accurately retrieve or calculate token or span positions from raw	✓	0.28
The generated position values by LLMs were inaccurate, resembling hallucinations or random numbers rather than referring	✓	0.24
To address the issue of inaccurate token positions, a solution that includes tokenization information within the input d	×	0.12
Token-level scores for GPT-3.5 are 0.81 precision, 0.36 recall, and 0.50 F1-score. 4	✓	0.15
Token-level scores for GPT-4 are 0.75 precision, 0.62 recall, and 0.67 F1-score.	✓	0.16
Token-level scores for GPT-4o are 0.68 precision, 0.72 recall, and 0.70 F1-score.	✓	0.17
Token-level scores for Fine-tuned BERT are 0.93 precision, 0.94 recall, and 0.93 F1-score.	✓	0.20

References

- http://arxiv.org/abs/2004.12440v2
- http://arxiv.org/abs/2305.14857v1
- http://arxiv.org/abs/2408.15796v2