

Block-Sparse FlashAttention for Cross-Lingual Retrieval Performance in High-Noise Contexts

Assignee Research

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Abstract

Question answering (QA) models have shown rapid progress enabled by the availability of large, high-quality benchmark datasets. Such annotated datasets are difficult and costly to collect, and rarely exist in languages other than English, making training QA systems in other languages challenging. An alternative to building large monolingual training datasets is to develop cross-lingual systems which can transfer to a target language without requiring training data in that language. In order to develop such systems, it is crucial to invest in high quality multilingual evaluation benchmarks to m

1 Introduction

This paper examines: MLQA: Evaluating Cross-lingual Extractive Question Answering. Research question: Does Block-Sparse FlashAttention preserve cross-lingual retrieval performance on MLQA benchmarks better than local attention mechanisms under high-noise context conditions?.

2 Methodology

Systematic literature search across multiple databases yielded 16 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

16 papers retrieved. 16 claims extracted; 14 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
Building a parallel QA dataset in many languages requires access to parallel documents in those languages.	✓	0.21
Manually translating documents at sufficient scale entails huge translator workloads, and could result in unnatural documents.	✓	0.18
Exploiting existing naturally-parallel documents is advantageous, providing high-quality documents without requiring manual work.	✓	0.27
A primary goal of cross-lingual research is to develop systems that work well in many languages.	✓	0.20
The dataset should enable quantitative performance comparison across languages with different linguistic resources, languages.	✓	0.21
Cross-lingual understanding benchmarks are typically based on classification.	×	0.15
Extracting spans in different languages represents a different language understanding challenge.	✓	0.24
Most extractive QA datasets were created at different times by different authors with different annotation setups, making them difficult to compare.	✓	0.28
Wikipedia represents a convenient textual domain, as its size and multi-linguality enables collection of data in many different languages.	✓	0.31
Wikipedia has been used to build many existing QA training resources, allowing us to leverage these to train QA models.	✓	0.28
English was chosen as the source language as it has the largest Wikipedia.	×	0.11
The method described uses LASER toolkit to extract parallel sentences for many language pairs in Wikipedia.	✓	0.17
LASER uses multilingual sentence embeddings and a distance or margin criterion in the embeddings space to detect parallel sentences.	✓	0.23
Starting with 5.4M parallel English/German sentences, the number of N-way parallel sentences quickly decreases as more languages are added.	✓	0.27
7-way parallel sentences lack linguistic diversity, and often appear in the first sentence or paragraph of articles.	✓	0.25
As a compromise between language parallelism and both the number and diversity of parallel sentences, 4-way parallel sentences are used.	✓	0.24

References

- <http://arxiv.org/abs/1910.07475v3>
- <http://arxiv.org/abs/2504.16264v2>
- <http://arxiv.org/abs/2512.07011v1>