BLIP Inference Latency and Throughput Under Varying Code-Switching Ratios in Zero-Shot Cross-Lingual Image-Text Retrieval

Assignee Research

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Abstract

There has been a recent spike in interest in multi-modal Language and Vision problems. On the language side, most of these models primarily focus on English since most multi-modal datasets are monolingual. We try to bridge this gap with a zero-shot approach for learning multi-modal representations using cross-lingual pre-training on the text side. We present a simple yet practical approach for building a cross-lingual image retrieval model which trains on a monolingual training dataset but can be used in a zero-shot cross-lingual fashion during inference. We also introduce a new objective func

1 Introduction

This paper examines: Towards Zero-shot Cross-lingual Image Retrieval and Tagging. Research question: What is the effect of varying the code-switching ratio on the inference latency and throughput of BLIP during zero-shot cross-lingual image-text retrieval tasks?.

2 Methodology

Systematic literature search across multiple databases yielded 13 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.7/10.

3 Results

13 papers retrieved. 13 claims extracted; 12 independently verified. Quality review score: 8.7/10.

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 paper introduces a Cross-lingual Test Dataset called XTD10.	✓	0.16
The paper extends the One-model-fits-all approach to multi-lingual image tagging as a zero-shot problem.	✓	0.23
Monolingual image tagging models in languages other than English face extensibility issues and training data constraints	✓	0.25
Using an English image tagger and direct translation at the tag level is error-prone due to word ambiguity.	✓	0.24
The paper's contextual approach captures both image context and text semantics irrespective of the language.	×	0.13
The paper uses [29] as a baseline to measure the model's performance, which follows a zero-shot approach at the word lev	✓	0.16
The paper uses a pre-trained image embedding model like ResNet trained on ImageNet.	✓	0.19
The paper keeps the image embedding extraction model frozen and does not add any trainable layers on the visual side.	✓	0.17
The paper uses the last average pooled layer of the pre-trained ResNet152 architecture as the image embedding of size 20	✓	0.23
The paper experiments with two state-of-the-art cross-lingual models: LASER and Multi-lingual USE (mUSE).	✓	0.19
LASER uses a language-agnostic BiLSTM encoder to create sentence embeddings and supports 93 languages.	✓	0.23
mUSE is a Transformer-based encoder that supports sentence-level embeddings for 16 languages.	✓	0.28
The paper uses a shared multi-task dual-encoder training framework for several downstream tasks.	✓	0.16

References

- http://arxiv.org/abs/2012.05107v1
- http://arxiv.org/abs/2109.07622v1
- http://arxiv.org/abs/2305.05295v2