Scaling WEAM-Aligned Model Size for Zero-Shot Cross-Lingual Image-Text Retrieval Performance

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. Research question: What is the effect of scaling the WEAM-aligned model size on the zero-shot cross-lingual image-text retrieval performance, as measured by recall@K and throughput on the LAION-5B dataset?.

2 Methodology

Systematic literature search across multiple databases yielded 6 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

6 papers retrieved. 18 claims extracted; 16 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 Cross-lingual Test Dataset is called XTD10.	✓	0.19
Metric learning is used to project samples from different modalities into a common semantic representation space.	✓	0.16
Multi-lingual metric learning methods minimize distance between image and caption pairs as well as multi-lingual pairs o	✓	0.24
Images are used as pivots to perform metric learning, allowing text in one language to be independent of the other langu	✓	0.16
Visual object detection and multi-head attention are used to selectively align salient visual objects with textual phras	✓	0.16
Language-independent text encoders align different languages to a common sentence embedding space using shared weights.	✓	0.27
The baseline method used is from Portaz et al., 2019, which follows a zero-shot approach but on a word level.	✓	0.22
Datasets like Yoshikawa et al., 2017; Li et al., 2018; Elliott et al., 2016; Grubinger et al., 2006; Wu et al., 2017 pro	✓	0.37
The Massively Multilingual Image Dataset initiative focuses on parallel data for 100 languages but is word-level concept	✓	0.20
MSCOCO 2014 and XTD10 are used for testing, and Multi30K dataset is used for experiments.	✓	0.21
The train-val-test split for MSCOCO2014 is provided in Rajendran et al., 2016.	✓	0.27
The test set is converted into 1K image-text pairs by sampling the longest caption for each image.	×	0.14
The model is trained with only English language text-image pairs using metric learning.	✓	0.17
English text training data is converted into its cross-lingual embedding space for initialization.	✓	0.18
A pre-trained image embedding model like ResNet is assumed to exist.	✓	0.18
The image embedding extraction model is kept frozen and no trainable layers are added on the visual side.	×	0.13
The last average pooled layer of the pre-trained ResNet152 architecture is used as the image embedding of size 2048.	✓	0.21
Two state-of-the-art cross-lingual models, LASER and mUSE, are experimented with for sentence-level embeddings.	✓	0.20

References

- http://arxiv.org/abs/2012.05107v1
- http://arxiv.org/abs/2210.08402v1
- http://arxiv.org/abs/2109.07622v1