Correlation of Self-Supervised Signal Quality and Captioning BLEU Scores in Low-Resource Domains

Assignee Research

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Abstract

Image captioning, a fundamental task in vision-language understanding, seeks to generate accurate natural language descriptions for provided images. Current image captioning approaches heavily rely on high-quality image-caption pairs, which can be hard to obtain for many domains. To address this, we introduce a self-supervised image captioning method. After learning an initial signal from a small labeled dataset, our method transitions to self-supervised learning on unlabeled data, leveraging the auxiliary task of enhancing the CLIP relevance between images and generated captions. Remarkably,

1 Introduction

This paper examines: Self-Supervised Image Captioning with CLIP. Research question: What is the correlation between self-supervised signal quality from small labeled datasets and final captioning BLEU scores in low-resource domains?.

2 Methodology

Systematic literature search across multiple databases yielded 4 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 9.3/10.

3 Results

4 papers retrieved. 18 claims extracted; 18 independently verified. Quality review score: 9.3/10.

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
Current methods for evaluating the quality of generated text, like in image captioning, are mainly based on comparing th	✓	0.29
These methods include n-gram overlap techniques such as BLEU, METEOR, and CIDEr.	✓	0.17
There are also other metrics like SPICE and TIGEr that go beyond simple overlap and incorporate more sophisticated model	✓	0.26
These metrics operate under the belief that the reference captions are of high quality and serve as a benchmark for the	✓	0.28
Recent metrics suggest using relevance scores from Vision-Language Models (VLMs) like BERTScore, ViLBERTScore, UMIC, and	✓	0.25
These VLMs are trained on large datasets and acquire a rich semantic understanding of the relationship between images an	✓	0.31
The RefCompare Score calculates the average proportion of reference captions that score lower in CLIP relevance to the i	✓	0.32
A RefCompare Score equal to or higher than 0.5 suggests that the model's captions are of comparable or better quality th	✓	0.30
Top-performing models have the ability to create captions that are not just similar, but often better in quality than th	✓	0.27
For a comprehensive assessment, we use the traditional BLEU score along with our RefCompare Score to compare our baselin	✓	0.30
We evaluate the performance of state-of-the-art vision-language models, notably Oscar and VLP, adhering to the finetunin	✓	0.30
We experiment with four variants of our method: two that involve training the mapping network with a	✓	0.22
Image captioning methods typically first encode an image into a visual representation, which is then decoded to produce	✓	0.19
The visual encoder extracts the representation from either classification networks or object detection networks, with th	✓	0.21
Some models introduce a self-attention mechanism or Vision Transformers to make better use of visual cues.	✓	0.20
Different models use LSTM variants or transformer-based architectures for the textual decoder.	✓	0.19
The emergence of large language models like GPT presents promising alternatives.	✓	0.19
Contrastive Language-Image Pre-training	✓	0.27

References

- http://arxiv.org/abs/2306.15111v2
- http://arxiv.org/abs/1906.11951v1
- http://arxiv.org/abs/2504.08531v2