Extending Multi-Positive Contrastive Learning for Robust Dense Retrieval Against Query Perturbations

Assignee Research

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Abstract

Dense retrieval has become the new paradigm in passage retrieval. Despite its effectiveness on typo-free queries, it is not robust when dealing with queries that contain typos. Current works on improving the typo-robustness of dense retrievers combine (i) data augmentation to obtain the typoed queries during training time with (ii) additional robustifying subtasks that aim to align the original, typo-free queries with their typoed variants. Even though multiple typoed variants are available as positive samples per query, some methods assume a single positive sample and a set of negative ones p

1 Introduction

This paper examines: Improving the Robustness of Dense Retrievers Against Typos via Multi-Positive Contrastive Learning. Research question: Can the multi-positive contrastive learning method be extended to improve robustness against other types of query perturbations (e.g., paraphrasing or synonym substitutions) in dense retrieval, and how does this impact recall@10 on benchmark datasets like TriviaQA or HotpotQA?.

2 Methodology

Systematic literature search across multiple databases yielded 15 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

15 papers retrieved. 10 claims extracted; 10 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
Employing multi-positive contrastive learning on the robustifying subtask yields improvements in robustness against usin	✓	0.38
The more dramatic improvement comes when applying multi-positive contrastive learning on DR+DL since the original work o	✓	0.38
In DR+DLM, we consider the typo-free query and all its available typoed variants as positives and use a multi-positive c	✓	0.32
Employing all available positives (typoed queries) at once and using multi-positive contrastive loss outperforms samplin	✓	0.23
The improvements are held even when comparing DR+DL+STM against DR+DL+ST, a model that already uses multiple positives.	✓	0.26
DR+DL+ST uses a contrastive loss with a single positive for the query retrieval dual task (i.e., Lq_CE) while considerin	✓	0.25
Current typo-robust dense retrievers use contrastive learning with a single positive sample and multiple negative ones f	✓	0.39
Given an anchor x, a positive sample x+, and a set of negative samples X-, the contrastive prediction task aims to bring	✓	0.36
In many cases, multiple positive samples are available per anchor and can be used simultaneously to increase the discrim	✓	0.30
A multi-positive contrastive loss is computed as LMCE(x, X+, X-) = -1/|X+| Σx+$\in$X+ log(ef(x,x+)/[ef(x,x+) + Σx-$\in$X-ef(x,x-	✓	0.24

References

- http://arxiv.org/abs/2403.10939v1
- https://arxiv.org/abs/2308.09861
- https://arxiv.org/abs/2403.10939