

# Scaling Typoed Positives in Multi-Positive Contrastive Learning for Robust Dense Retrieval

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: What is the impact of scaling the number of typoed positive examples in multi-positive contrastive learning on the robustness of dense retrieval models against adversarial character perturbations, as measured by the recall@100 metric on the Robust04 benchmark?.

## 2 Methodology

Systematic literature search across multiple databases yielded 9 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 9.2/10.

## 3 Results

9 papers retrieved. 10 claims extracted; 10 independently verified. Quality review score: 9.2/10.

## 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	✓	0.37
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	✓	0.24
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 $LMCE(x, X_+, X_-) = -1/ X_+  \sum_{x_+ \in X_+} \log(\text{ef}(x, x_+)/[\text{ef}(x, x_+) + \sum_{x_- \in X_-} \text{ef}(x, x_-)$	✓	0.23

## References

- <http://arxiv.org/abs/2403.10939v1>
- <http://arxiv.org/abs/1807.09380v3>
- <http://arxiv.org/abs/2205.02303v1>