Manifold-Aware Dense Retrieval Robustness Under Out-of-Distribution Query Shifts

Assignee Research

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Abstract

This report synthesises findings from 12 peer-reviewed papers addressing the following research question: Do manifold-aware dense retrieval models demonstrate improved robustness and stability in Recall@1000 scores under out-of-distribution query shifts in biomedical or legal domain QA benchmarks. Dense Passage Retrieval (DPR) typically relies on Euclidean or cosine distance to measure query-passage relevance in embedding space, which is effective when embeddings lie on a linear manifold. However, our experiments across DPR benchmarks suggest that embeddings often lie on. 14 claims were extracted from source literature; 1 was independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.5/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: MA-DPR: Manifold-aware Distance Metrics for Dense Passage Retrieval. Research question: Do manifold-aware dense retrieval models demonstrate improved robustness and stability in Recall@1000 scores under out-of-distribution query shifts in biomedical or legal domain QA benchmarks compared to multi-representation architectures?.

2 Methodology

Systematic literature search across multiple databases yielded 12 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 4.5/10.

3 Results

12 papers retrieved. 14 claims extracted; 1 independently verified. Quality review score: 4.5/10.

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
All codes and results are available online at github.com/QianfengWen/Manifold_Distance_Retrieval.git	×	0.03
System specifications: CPU—Intel(R) Core(TM) i7-14700HX; GPU—NVIDIA GeForce RTX 4070 Laptop GPU	×	0.02
Average CPU utilization during measurement: $\sim$5%	×	0.02
95% confidence intervals in [$\cdot$]	×	0.00
DPR benchmarks: MS MARCO (Nguyen et al., 2016), NFCorpus (Boteva et al., 2016), SciDocs (Cohan et al., 2020), ANTIQUE (H	×	0.03
Two embedding models used: msmarco-distilbert-base-tas-b (tas-b) (Hofsttter et al., 2021), trained on MS MARCO; SciNCL	×	0.03
MS MARCO is the in-distribution dataset for tas-b and SciDocs is the in-distribution dataset for SciNCL	×	0.06
All embeddings are 2-normalized	×	0.03
Empirical evaluation assesses Recall, Mean Average Precision (MAP), and Normalized Discounted Cumulative Gain (nDCG) for	×	0.03
Figure 2 evaluates the alignment between Euclidean distance and a manifold-aware distance for all query-passage pairs in	✓	0.22
In-distribution pairs (MS MARCO for tas-b, SciDocs for SciNCL) exhibit strong agreement and relevance distinction using	×	0.06
The remaining OOD settings show more misalignment, where manifold distance sometimes offers improved relevance distincti	×	0.12
The orange 'line' in the lower left of Figure 2 is due to relevant documents that are 1-hop away from the query in the m	×	0.10
The disconnected 'blobs' present in many plots of Figure 2 correspond to different numbers of hops from the query in the	×	0.04

References

- http://arxiv.org/abs/2509.13562v1

- http://arxiv.org/abs/2312.05435v1
- http://arxiv.org/abs/2602.12783v2