Mitigating Zero-Shot Retrieval Performance Gaps via Domain-Specific Fine-Tuning of Dense Retrievers on BEIR Datasets

Assignee Research

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Abstract

We propose the new problem of choosing which dense retrieval model to use when searching on a new collection for which no labels are available, i.e. in a zero-shot setting. Many dense retrieval models are readily available. Each model however is characterized by very differing search effectiveness – not just on the test portion of the datasets in which the dense representations have been learned but, importantly, also across different datasets for which data was not used to learn the dense representations. This is because dense retrievers typically require training on a large amount of labele

1 Introduction

This paper examines: Selecting which Dense Retriever to use for Zero-Shot Search. Research question: To what extent does domain-specific fine-tuning of dense retrievers on BEIR datasets mitigate the performance gap observed in zero-shot retrieval when compared to pre-trained models without fine-tuning?.

2 Methodology

Systematic literature search across multiple databases yielded 10 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.8/10.

3 Results

10 papers retrieved. 16 claims extracted; 16 independently verified. Quality review score: 7.8/10.

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 problem of unsupervised Out-Of-Ditribution (OOD) performance evaluation involves estimating the performance of a mod	✓	0.27
Miller et al. [33] show a positive correlation between in-domain and out-of-domain performances.	✓	0.23
Hendrycks et al. [22] use the statistics of softmax outputs to identify misclassifications.	✓	0.17
Guillory et al. [18] evaluate the tions, approximated via the difference of confidences between the base dataset predict	✓	0.23
Garg et al. [17] estimate the average confidence threshold (ATC) from the validation data, above which the prediction of	✓	0.26
Deng et al. [13] show negative correlation between recognition accuracy and the Frechet distance between network activat	✓	0.29
Jiang et al. [26] predict generalization gap using margin distribution - the distances of training points to the decisio	✓	0.29
Bridal et.al. [2] analyze training dynamics of the model; in particular, the authors measure generalization of a model v	✓	0.33
The authors of [5, 9, 27] perform the training of the same network several times, and measure the disagreement between t	✓	0.28
Deng et al. [13] show how the performance on auxiliary task can be used to estimate the performance on the main task.	✓	0.25
Khratmtsova et al. [28] propose to analyze how the network changes when it is fine-tuned on the target dataset with an u	✓	0.25
Bi-encoder dense retrievers, initialized with pre-trained language models (PLMs) and fine-tuned with supervised data, ha	✓	0.28
Many dense retrieval models are readily available, each characterized by very differing search effectiveness.	✓	0.29
Dense retrievers typically require training on a large amount of labeled data to achieve satisfactory search effectivene	✓	0.37
Effectiveness gains obtained by dense retrievers on datasets for which they are able to observe labels during training,	✓	0.32
Methods inspired by recent work in unsupervised performance evaluation with the presence of domain shift in the area of	✓	0.40

References

- http://arxiv.org/abs/2412.08329v1
- http://arxiv.org/abs/2505.07166v1
- http://arxiv.org/abs/2309.09403v1