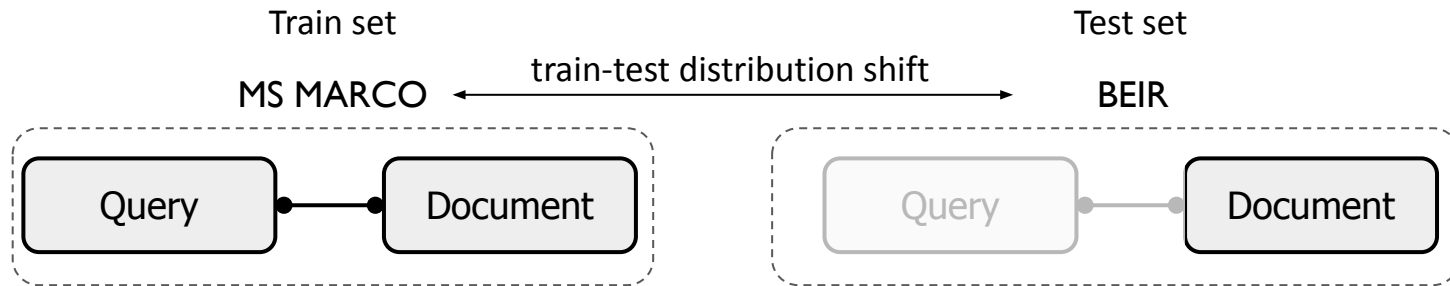


Relevance-assisted Generation for Robust Zero-shot Retrieval

Jihyuk Kim, Minsoo Kim , Joonsuk Park, Seung-won Hwang
(presenter: Jihyuk Kim)

Task: zero-shot retrieval



Relevance annotations are available for large-scale open-domain corpus



Queries and relevance annotations are often not available, for specialized domains (e.g., medical question)

→ *zero-shot retrieval*

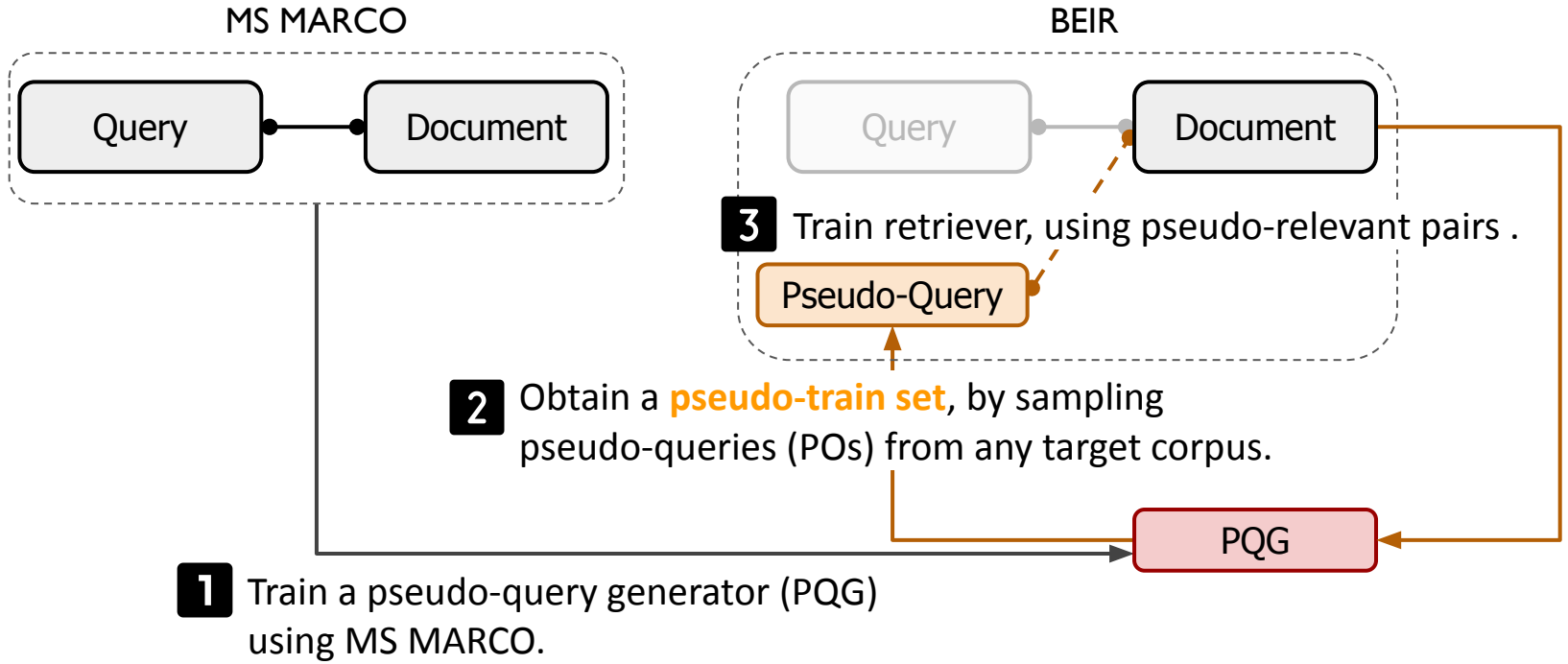
Dense retrievers do not generalize well to out-of-domain corpus.



RQ. How can we make the dense retriever domain-adaptive?

Create domain-tailored train set, via pseudo-query generation

🤔 What if we can get a training dataset for any given corpus?
💡 We can! via pseudo-query generation!



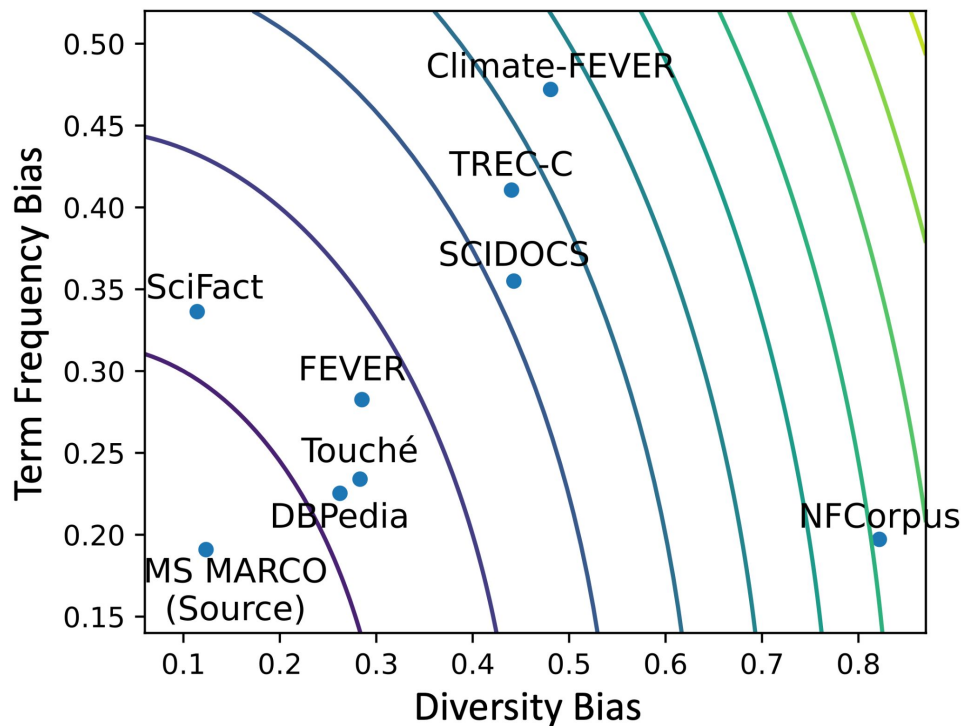
Challenge: distribution shift

❌ **Term frequency bias:**

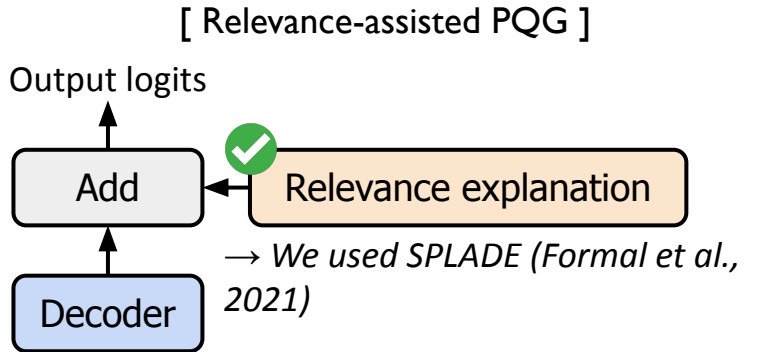
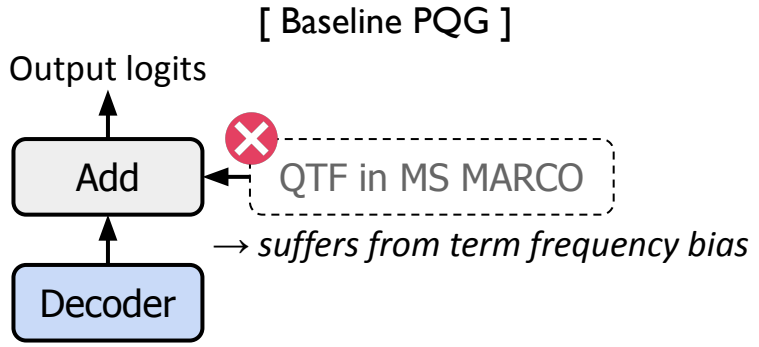
PQG fails to generate query terms, when rarely observed in MS MARCO.

❌ **Diversity bias:**

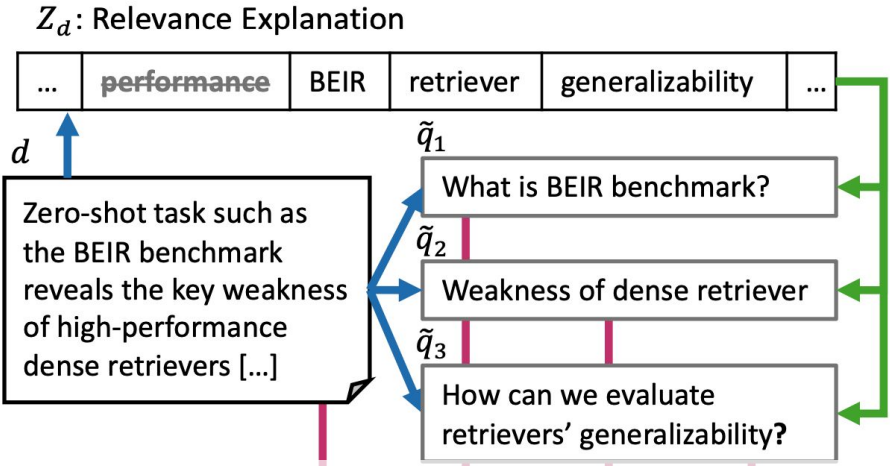
A fixed-size single dense vector cannot cover diverse topics in long documents.



Proposed solution 1. relevance-assisted PQG



Stage 1: Pseudo-query generation



Stage 2: Document Representation



(b) Relevance-aware Multi-query Domain Adaptation (RaMDA; Ours)

→ decoding → guidance → vectorization || concatenator

Proposed solution 2. multi-query vector augmentation

Hypothetical long document

... BEIR benchmark reveals the key weakness ...

dense retrievers poorly generalize to out-of-domain corpus ...

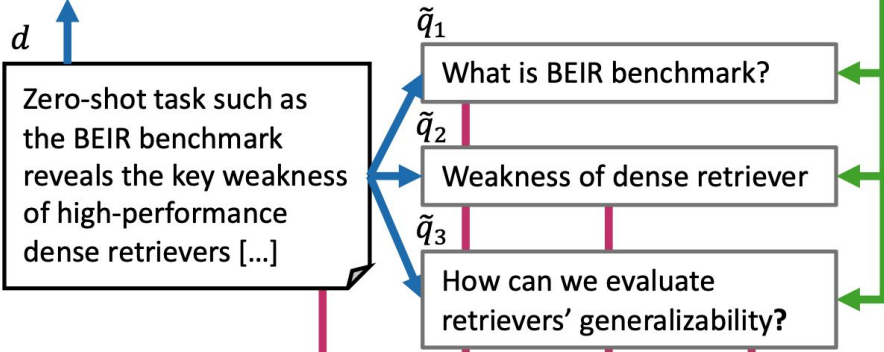
...

Out-of-domain datasets have been released, enabling evaluation generalizability ...

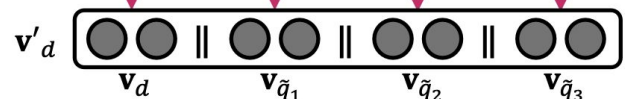
- ✓ What is BEIR benchmark?
- ✓ What are the weaknesses of dense retrievers?
- ✓ How can we evaluate the generalization ability?

Stage 1: Pseudo-query generation

Z_d : Relevance Explanation



Stage 2: Document Representation



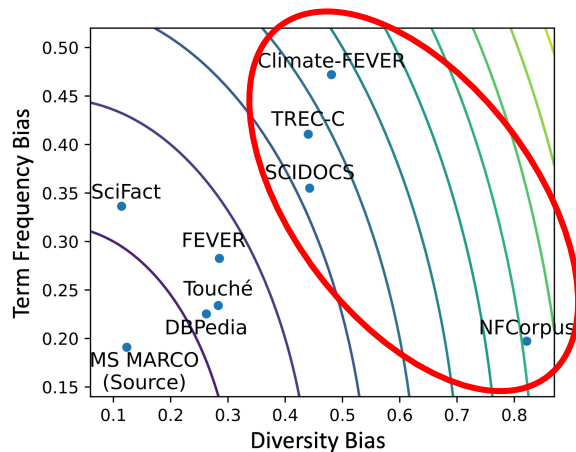
(b) Relevance-aware Multi-query Domain Adaptation (RaMDA; Ours)

→ decoding → guidance → vectorization || concatenator

Experiment

- Dataset: Four BEIR datasets, showing the largest distribution shifts from MS MARCO

- NFCorpus
- SCIDOCS
- TREC-COVID
- Climate-FEVER

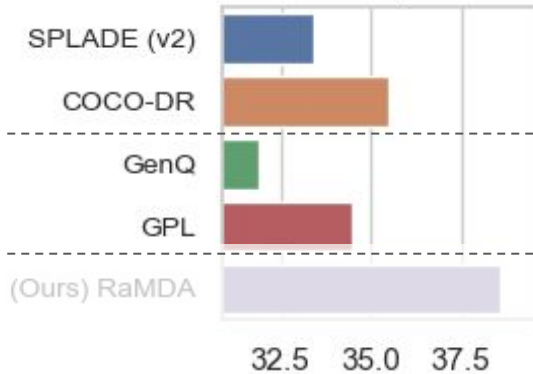


- Baseline

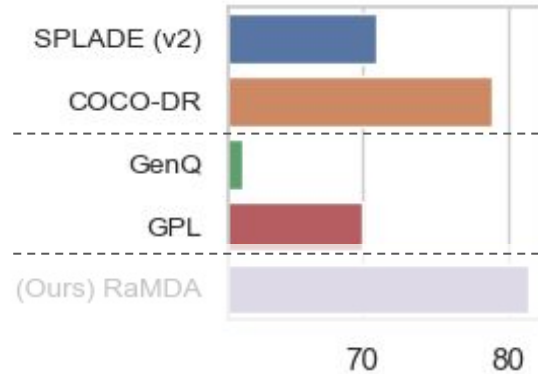
- **GenQ** generates pseudo-queries from BEIR corpus, and fine-tunes a dense retriever.
- **GPL**, building upon GenQ, additionally utilizes an expensive cross-encoder to label relevance of pseudo-queries.
- *+ domain invariant retriever*: **COCO-DR** and **SPLADE**, as state-of-the-art dense and sparse retriever, respectively.

Results

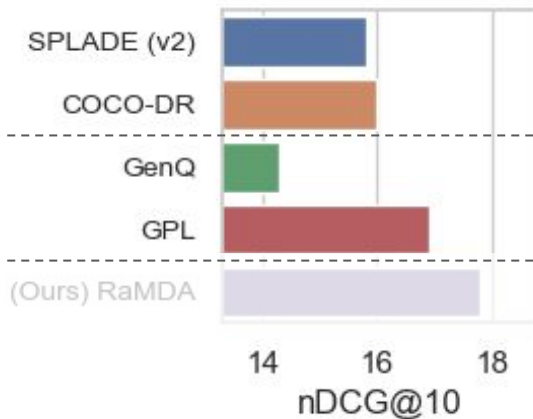
NFCorpus



TREC-COVID



SCIDOCS

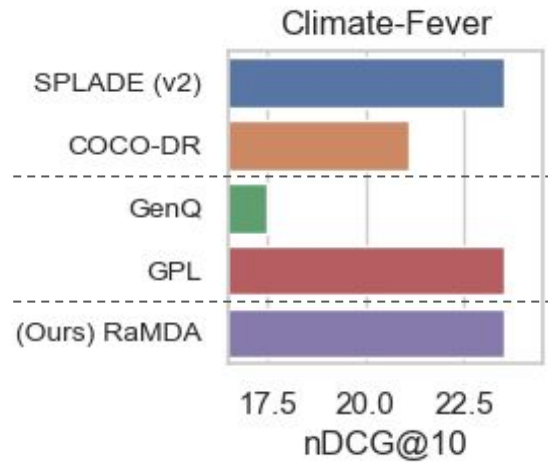
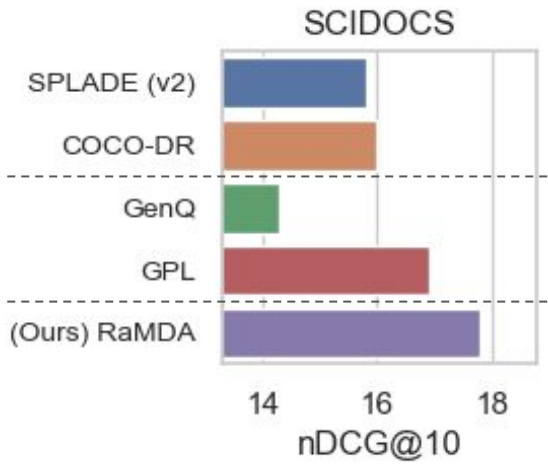
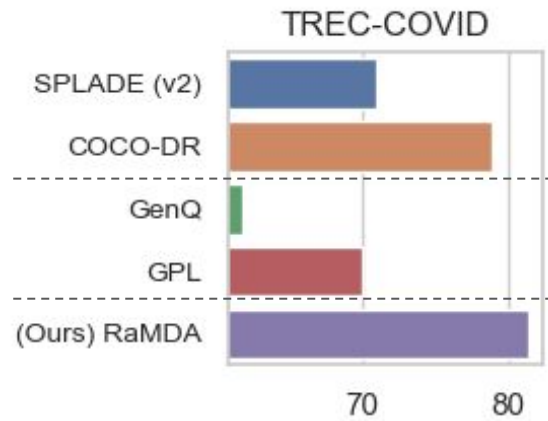
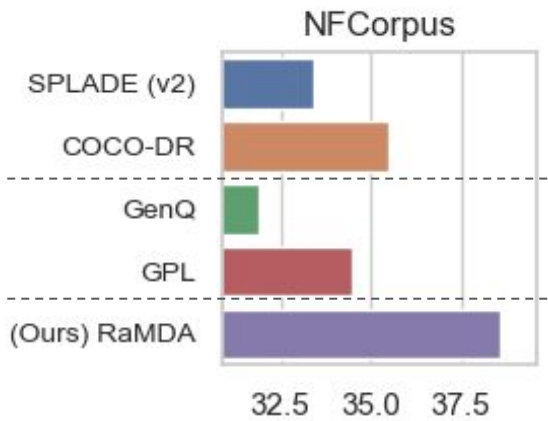


Climate-Fever



❌ Previous PQG approaches often underperform domain-invariant retrievers.

Results



✔ Our model shows better or comparable performance than all baselines.

Thank you!