The Journal of Open Source Software

DeBIR: A Python Package for Dense Bi-Encoder Information Retrieval

Vincent Nguyen [1,2], **Sarvnaz Karimi** [2], **and Zhenchang Xing** [1,2]

1 Australian National University, School of Computing **2** Commonwealth Scientific and Industrial Research Organisation, Data61

DOI: 10.xxxxxx/draft

Software

- Review
- Repository
- Archive

Editor: Open Journals

Reviewers:

- @openjournals

Submitted: 01 January 1970
Published: unpublished

Summary

Information Retrieval (IR) is the task of retrieving documents given a query or information need. These documents are retrieved and ranked based on a relevance function or relevance model such as Best-Matching 25 (Robertson et al., 1995). Although deep learning has been successful in other computer science fields, such as computer vision (Krizhevsky et al., 2012; Szegedy et al., 2014) and natural language processing (Devlin et al., 2019; Lee et al., 2019; Yang Liu & Lapata, 2019), success in information retrieval was limited in the literature due to comparisons against weak baselines (Yang et al., 2019). However, in 2019 (**lin-neural-recentation?**), deep learning in information retrieval could surpass less computationally intensive keyword-based statistical models in terms of retrieval effectiveness, sparking the field of dense retrieval. Dense retrieval is the task of retrieving documents given a query or information need using a dense vector representation of the query and documents. The dense vector representation is obtained by passing the query and documents through a neural network. The neural network is usually a pre-trained language model such as BERT (Devlin et al., 2019) or RoBERTa (Yinhan Liu et al., 2019). The dense query vector representation is then used to retrieve documents using a similarity function such as cosine similarity.

Unlike statistical learning, tuning deep learning retrieval methods is often costly and time-consuming. This cost makes it essential to automate much of the training, tuning and evaluation processes efficiently.

DeBIR is a library for facilitating dense retrieval research, primarily focusing on bi-encoder dense retrieval where query and documents dense vectors are generated separately (Reimers & Gurevych, 2019). It allows for expedited experimentation in dense retrieval research by reducing boilerplate code through an interchangeable pipeline API and code extendability through the inheritance of general classes. It further abstracts standard training loops and hyperparameter tuning into easy-to-define configuration files. This library is aimed at helping practitioners, researchers and data scientists experimenting with bi-encoders by providing them with dense retrieval methods that are easy to use out of the box but also have additional extendability for more nuanced research. Furthermore, our pipeline runs asynchronously to reduce I/O performance bottlenecks, facilitating faster experiments and research.

A brief summary of the pipeline stages (Figure 2) is:

1. Configuration based on TOML files; these are loaded in a class factory to create pipeline objects.
2. An executor object takes in a query builder object. The purpose of the query builder object is to define the mapping of the documents and which parts of the query to use for query execution.
3. The executor object asynchronously executes the queries.

4. Finally, an evaluator object uses the results to list metrics defined by a configuration file against an oracle test set.

This pipeline is condensed into a single class that can be built from a configuration file.

Statement of Need

Dense retrieval has been popular in Information Retrieval for some time (Guo et al., 2017; Hui et al., 2017; Yin et al., 2015). In the early 2000s, there had been considerable stagnation in retrieval effectiveness as there needed to be stronger baselines (Armstrong et al., 2009) when proposing new methods. This stagnation repeated with the rise of deep learning, where retrieval performance was again compared against weaker baselines and was not significantly stronger than older non-deep learning statistical models, such as a well-tuned BM25 model (Yang et al., 2019).

However, this was later recanted when transformer models could be used fine-tuned on Natural Language Inference tasks or ms-marco as a cross-encoder (where a query and document pair are encoded at ranking time) (Lin, 2019), significantly overtaking even the best BM25 models.

Today, there are generally two classes of dense retrieval models for IR: the cross-encoder, which encodes queries and documents at query time and the bi-encoder, which can encode documents at index time and queries at query time. The cross-encoder is generally more effective than the bi-encoder model for retrieval. However, this increased effectiveness requires a more substantial computation and can be a bottleneck in production systems. Therefore, a less expensive model such as BM25 is typically used to retrieve smaller candidate lists (first-stage retrieval) for second-stage retrieval re-ranking by a cross-encoder.

However, bi-encoders are more effective than BM25 and can complement BM25 for ranking (Nguyen et al., 2022). Therefore, a gap in the literature in IR is to replace BM25 first-stage retrieval with a bi-encoder or used as the only ranking system in the pipeline if query speed is needed. However, current libraries don't address this use case as it requires integration with the indexing and querying pipeline of the search engine.

DeBIR is a library that mainly facilitates bi-encoder research (where query and document can be encoded independently) and provides base classes with flexible functionality through inheritance. Although we provide cross-encoder re-rankers for feature completeness, the library's priority is facilitating bi-encoder research. The strength of bi-encoders lies in the offline indexing of dense vectors. These vectors can then be used for first-stage retrieval and potentially passed to a second-stage retrieval system such as a cross-encoder. Bi-encoders can be used as the sole retrieval system when there is a lack of training data (Nguyen et al., 2022) and, therefore, can be more useful in areas such as biomedical IR, where training data is scarce. Cross-encoders, however, require large amounts of training data for effectiveness.

The DeBIR library exposes an API for commonly used functions for training, hyper-parameter tuning (Figure 2) and evaluation of transformer-based models. The pipeline can be broken up into multiple stages: parsing, query building, query execution, serialization and evaluation (Figure 1). Furthermore, we package our caching mechanism for the expensive encoding operations to speed up the pipeline during repeated experimentation.

Although similar libraries exist, such as sentence-transformers (Reimers & Gurevych, 2019), openNIR(MacAvaney, 2020), they have less of a focus on the early stages of the dense retrieval pipeline. This stage involves indexing the textual data from the corpora and indexing dense vector representations, which is only helpful for bi-encoder type models over the traditional cross-encoder and is thus not typically explored by other libraries. Other limitations include a lack of extendability that restrict the users' options for training customization (we provide base classes that can be inherited) or that the library is tailored to general-purpose machine learning rather than informational retrieval.

This library will help facilitate early-stage dense retrieval and rapid experimentation research with bi-encoders, which other libraries have yet to explore. Our library is also flexible enough for second-stage retrieval using cross-encoders from this library or other libraries. Furthermore, we will continue to improve this tool.

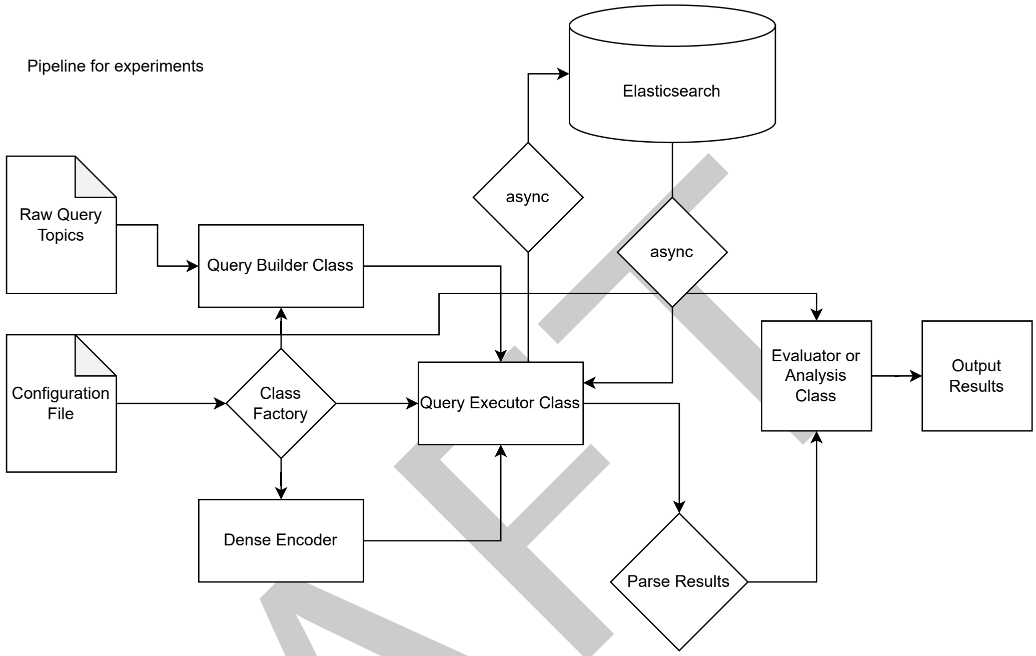

Figure 1: Standard flow of the DeBIR query/evaluation loop.

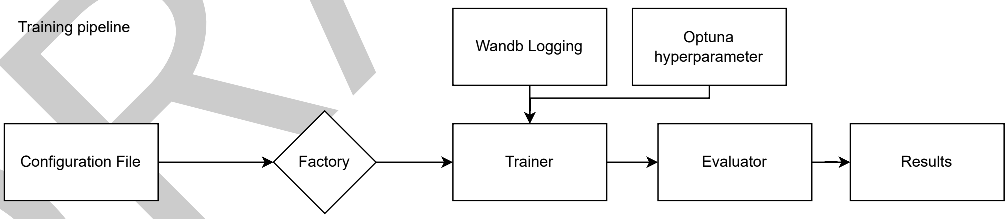

Figure 2: Standard flow of the DeBIR training loop.

Acknowledgments

The DeBIR library uses sentence-transformers, hugggingface's transformers and datasets, allRank, optuna, elasticsearch and trectools python packages.

This search is supported by CSIRO Data61, an Australian Government agency through the Precision Medicine FSP program and the Australian Research Training Program. We extend thanks to Brian Jin (Data61) for providing a code review.

Examples

Pipeline

The pipeline is a single class that can be built from a configuration file. The configuration file is a TOML file that defines the pipeline stages and their parameters. The pipeline is built

The Journal of Open Source Software

using a class factory that takes in the configuration file and creates the pipeline stages. The pipeline stages are then executed in order.

```python
from debeir.interfaces.pipeline import NIRPipeline
from debeir.interfaces.callbacks import (SerializationCallback,
                                         EvaluationCallback)
from debeir.evaluation import Evaluator

p = NIRPipeline.build_from_config(config_fp="./tests/config.toml",
                                  engine="elasticsearch",
                                  nir_config_fp="./tests/nir_config.toml")

# Optional callbacks to serialize to disk
serial_cb = SerializationCallback(p.config, p.nir_settings)

# Or evaluation
evaluator = Evaluator.build_from_config(p.config, metrics_config=p.metrics_config)
evaluate_cb = EvaluationCallback(evaluator,
                                 config=p.config)

p.add_callback(serial_cb)
p.add_callback(evaluate_cb)

# Asynchronously execute queries
results = await p.run_pipeline()

# Post processing of results can go here
```

Training a model

```python
import wandb

from debeir.training.hparm_tuning.trainer import SentenceTransformerTrainer
from debeir.training.hparm_tuning.config import HparamConfig
from sentence_transformers import evaluation

# Load a hyper-parameter configuration file
hparam_config = HparamConfig.from_json(
        "./configs/training/submission.json"
)

# Integration with wandb
wandb.wandb.init(project="My Project")

# Create a trainer object
trainer = SentenceTransformerTrainer(
    dataset=get_dataset(), # Specify some dataloading function here
    evaluator_fn=evaluation.BinaryClassificationEvaluator,
    hparams_config=hparam_config,
    use_wandb=True
)

# Foward parameters to underlying SentenceTransformer model
trainer.fit(
    save_best_model=True,
    checkpoint_save_steps=179
```

```
)
```

Hyperparameter tuning

```python
from sentence_transformers import evaluation
from debeir.training.hparm_tuning.optuna_rank import (run_optuna_with_wandb,
                                                     print_optuna_stats)
from debeir.training.hparm_tuning.trainer import SentenceTransformerHparamTrainer
from debeir.training.hparm_tuning.config import HparamConfig

# Load a hyper-parameter configuration file with optuna parameters
hparam_config = HparamConfig.from_json(
   "./configs/hparam/trec2021_tuning.json"
)

trainer = SentenceTransformerHparamTrainer(
   dataset_loading_fn=data_loading_fn,
   evaluator_fn=evaluation.BinaryClassificationEvaluator,
   hparams_config=hparam_config,
)

# Run optuna with wandb integration
study = run_optuna_with_wandb(trainer, wandb_kwargs={
    "project": "my-hparam-tuning-project"
})

# Print optuna stats and best run
print_optuna_stats(study)
```

More information on the library is found on the github page, DeBeIR . Any feedback and suggestions are welcome at issues .

References

Armstrong, T., Moffat, A., Webber, W., & Zobel, J. (2009). Improvements that don't add up: Ad-hoc retrieval results since 1998. *CIKM*, 601–610.

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *Proceedings of the Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 4171–4186. https://doi.org/10.18653/v1/N19-1423

Guo, J., Fan, Y., Ai, Q., & Croft, B. (2017). A deep relevance matching model for ad-hoc retrieval. *Computing Research Repository*, *abs/1711.08611*, 55–64. http://arxiv.org/abs/1711.08611

Hui, K., Yates, A., Berberich, K., & Melo, G. de. (2017). A position-aware deep model for relevance matching in information retrieval. *Computing Research Repository*, *abs/1704.03940*. http://arxiv.org/abs/1704.03940

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. In F. Pereira, C. J. C. Burges, L. Bottou, & K. Q. Weinberger (Eds.), *Advances in neural information processing systems 25* (pp. 1097–1105). Curran Associates, Inc.

Lee, J., Yoon, W., Kim, S., Kim, D., Kim, S., So, C. H., & Kang, J. (2019). BioBERT: a pre-trained biomedical language representation model for biomedical text mining. *Bioinformatics*, *36*(4), 1234–1240. https://doi.org/10.1093/bioinformatics/btz682

Lin, J. (2019). Neural hype, justified! A recantation. *ACM SIGIR Forum*, *53*. http://sigir.org/wp-content/uploads/2019/december/p088.pdf

Liu, Yang, & Lapata, M. (2019). Text summarization with pretrained encoders. *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, 3730–3740. https://doi.org/10.18653/v1/D19-1387

Liu, Yinhan, Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., & Stoyanov, V. (2019). RoBERTa: A robustly optimized BERT pretraining approach. *Computing Research Repository*, *abs/1907.11692*. http://arxiv.org/abs/1907.11692

MacAvaney, S. (2020). OpenNIR: A complete neural ad-hoc ranking pipeline. *Proceedings of the 13th International Conference on Web Search and Data Mining*, 845–848. https://doi.org/10.1145/3336191.3371864

Nguyen, V., Rybinski, M., Karimi, S., & Xing, Z. (2022). Search like an expert: Reducing expertise disparity using a hybrid neural index for COVID-19 queries. *Journal of Biomedical Informatics*, *127*, 104005. https://doi.org/https://doi.org/10.1016/j.jbi.2022.104005

Reimers, N., & Gurevych, I. (2019). Sentence-BERT: Sentence embeddings using Siamese BERT-networks. *EMNLP*, 3982–3992. https://doi.org/10.18653/v1/D19-1410

Robertson, S., Walker, S., Jones, S., Hancock-Beaulieu, M., & Gatford, M. (1995, January). Okapi at TREC-3. *TREC*. https://trec.nist.gov/pubs/trec3/t3/_proceedings.html

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., & Rabinovich, A. (2014). Going deeper with convolutions. *IEEE Conference on Computer Vision and Pattern Recognition*, 1–9. https://doi.org/10.1109/CVPR.2015.7298594

Yang, W., Lu, K., Yang, P., & Lin, J. (2019). Critically examining the" neural hype" weak baselines and the additivity of effectiveness gains from neural ranking models. *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, 1129–1132. https://dl.acm.org/doi/10.1145/3331184.3331340

Yin, W., Schütze, H., Xiang, B., & Zhou, B. (2015). ABCNN: Attention-based convolutional neural network for modeling sentence pairs. *Computing Research Repository*, *abs/1512.05193*. http://arxiv.org/abs/1512.05193