DRAMA: Diverse Augmentation from Large Language Models Towards Smaller Generalizable Dense Retrievers

Anonymous ACL submission

Abstract

Large language models (LLMs) have demonstrated strong effectiveness and robustness when fine-tuned as dense retrievers. However, their large parameter size presents significant computational challenges at inference time. While smaller retrievers offer better efficiency, they often fail to generalize effectively with limited supervised fine-tuning data. In this work, we introduce DRAMA, a training framework that leverages LLMs to train smaller generalizable dense retrievers. In particular, we adopt pruned LLMs as the backbone and train on diverse LLM-augmented data in a single-stage contrastive learning setup. Experiments show that DRAMA offers better multilingual and long-context capabilities than traditional encoder-based retrievers, and achieves strong effectiveness across multiple tasks and languages.[1]

1 Introduction

Recent advancements in large language models (LLMs) have demonstrated their effectiveness and robustness in text retrieval tasks (Muennighoff et al., 2024; Sun et al., 2023; Li et al., 2024; BehnamGhader et al., 2024; Lee et al., 2025). Directly fine-tuning advanced billion-parameter LLMs with available annotated data can generate significantly higher zero-shot effectiveness than fine-tuning a pre-LLM-era smaller model with only a few hundred million parameters (Ma et al., 2024; Luo et al., 2024). However, the large parameter size of LLMs brings non-negligible inference-time compute costs, such as encoding large-scale corpora and increased query latency. For example, using Llama3.1$_{8B}$ as the backbone increases the inference cost around 40$\times$ compared to a dense retriever based on BERT.

In this work, we holistically explore how to effectively leverage large language models to create smaller retrievers, in terms of both data and model backbone, to develop generalizable yet efficient dense retrievers with fewer than 1B parameters.

Although several works have discussed using LLMs for retrieval data augmentation, such as directly generating training triplet (Wang et al., 2024b) or using LLM to mine positive and negative documents from a real corpus (Lee et al., 2024), the effectiveness of these methods has not been thoroughly compared under standardized conditions. We comprehensively study the effectiveness of multiple methods of LLM data augmentation with a controlled setup: using the same models and corpora across different data creation methods and only relying on open-sourced models and open-access data. Specifically, we utilize LLM retrievers (based on Llama3.1-$_{8B}$) and Insturct-LLM (based on Llama3.3$_{70B}$-Instruct) to generate augmentation data. This includes lower computational cost approaches such as generating cropped sentences as queries and using an LLM retriever to mine positive and negative documents over a corpus, as well as higher computational cost methods that further utilize Instruct-LLM to generate queries and provide relevance judgment as a listwise reranker. We investigate the effectiveness of various combinations of these diverse LLM augmentations, providing high-quality augmented training data for English and multilingual retrieval.

Existing work on training smaller dense retriever models is mostly based on pretrained language models with encoder-only architecture, either continuously pretrain pre-LLM-era models like BERT or XLM-RoBERTa-Large (Wang et al., 2023; Chen et al., 2024) or more recently using higher quality corpora to pretrain from scratch with modern model optimizations (Warner et al., 2024). We instead propose to leverage LLMs as the backbone for smaller dense retrievers by pruning the decoder-only LLM into a small size and serving as initialization for the text encoder. Specifically, we further prune

[1] DRAMA checkpoints are available at `<anonymized>`.

Llama3.2$_{1B}$ (which is pruned from Llama3.1$_{8B}$) into 0.1B (BERT-base) and 0.3B (XLM-RoBERTa-Large), while preserving multilingual and long-context capability. We demonstrate that pruned decoder-only models perform well as retrievers, by simply turning on the bi-directional attention during retriever training. This offers a more flexible pathway to creating smaller dense retrievers with arbitrary sizes while still leveraging pretrained LLM weights, making smaller retrievers compatible with current and future LLM advancements.

Combining LLM-based data augmentation and backbones, we introduce a single-stage training framework:DRAMA (smaller Dense Retriever from diverse LLM AugMentAtion). Our smaller retriever models achieve strong effectiveness on BEIR (Thakur et al., 2021), MIRACL (Zhang et al., 2023), and multiple multilingual retrieval tasks on MTEB (Muennighoff et al., 2022). These results demonstrate that our training framework produces models that excel in generalization across diverse English retrieval tasks and exhibit strong multilingual effectiveness, showing the potential for unified smaller retrievers that perform effectively across tasks and languages.

In summary, our contributions are as follows:

- We investigate diverse methods for leveraging LLMs to generate data augmentation for training smaller models, analyzing their individual and combined effectiveness.
- We prune LLMs to derive smaller decoder-only language models as backbones for retrievers, demonstrating their advantages in effectiveness and length extrapolation compared to pre-LLM-era models.
- Our training framework produces a series of multilingual and generalizable smaller retrievers, highlighting the benefits of aligning smaller retriever training with ongoing advancements in LLMs.

2 Related Work

2.1 Robust Dense Retrieval

Dense Passage Retrieval (Karpukhin et al., 2020) utilizes a pre-trained language model such as BERT (Devlin et al., 2019), to encode text into dense vectors and conduct passage retrieval as a nearest neighbor search. This approach has shown strong in-domain effectiveness compared to traditional lexical retrievers such as BM25 (Robertson and Zaragoza, 2009). However, dense retrievers have been found to struggle with generalization when applied to out-of-domain retrieval tasks (Thakur et al., 2021). To address this issue, various works have aimed to improve the generalization of dense retrievers through continuous pre-training tailored for retrieval tasks. Works such as Condenser (Gao and Callan, 2021), RetroMAE (Xiao et al., 2022), and SimLM (Wang et al., 2023) have enhanced the dense representation of BERT via customized architectures during language modeling. Other works, including Contriever (Izacard et al., 2022), GTE (Li et al., 2023), E5 (Wang et al., 2024a) have further adapted two-stage contrastive learning. These models are first trained with unsupervised or weakly supervised large-scale contrastive learning, followed by supervised contrastive learning with available relevance-judged data (Nussbaum et al., 2024; Yu et al., 2024). CDE (Morris and Rush, 2024) further proposes a two-stage model architecture that integrates corpus-level information into document embeddings.

2.2 LLM for Text Ranking

On the other hand, recent large language models have shown strong potential in relevance modeling for text ranking. Finetuning LLM as dense retriever models have shown significantly stronger effectiveness across various tasks and languages compared to smaller ones (Wang et al., 2024b; Muennighoff et al., 2024; Springer et al., 2024; Li et al., 2024). For example, RepLlama (Ma et al., 2024), which uses straightforward supervised fine-tuning based on the Llama2-7B model, outperforms previous smaller retriever models that were based on multi-stage continuous pre-training, with a lower training cost. This demonstrates the data efficiency and naturally strong generalization of LLM-based retrievers (Luo et al., 2024). Moreover, instruction-following LLMs have also shown strong effectiveness when directly prompted as rerankers (Ma et al., 2023; Sun et al., 2023). Reflecting the excel relevance understanding of large language models for retrieval. In this work, we aim to leverage the characteristics of LLM-based ranking methods that are data-efficient and generalizable, shifting their high inference time costs into training time costs as data augmentation.

2.3 Data Augmentation for Retriever

InPars (Bonifacio et al., 2022) and Promptagator (Dai et al., 2023) generate synthetic queries that align with given documents sampled from the

task corpus, creating training data for retrieval corpora with limited human queries and judgments. DRAGON (Lin et al., 2023) enhances the robustness of dense retrievers by employing sentence cropping as pseudo-queries and generating augmented data based on retrieval results from multiple retrievers (e.g., sparse, multi-vector models). With the emergence of LLMs, Mistral-E5 (Wang et al., 2024b) directly prompts an LLM to generate synthetic query-positive-negative triplets, using them as augmentation data to train a 7B LLM retriever across diverse text embedding tasks. Gecko (Lee et al., 2024) takes a different approach by leveraging real documents: it generates synthetic queries from sampled real documents, retrieves top candidate passages, and uses an LLM to rerank them in pointwise way. While these methods introduce various strategies for data augmentation in retrievers, they have not been systematically compared within a single framework where LLMs and corpora are controlled for fair comparison. We explore various types of LLM-based data augmentation and evaluate their individual and combined effectiveness.

2.4 Multilingual Retriever

Multilingual capabilities are crucial for effective retrieval systems. While numerous multilingual retrievers have been developed (Izacard et al., 2022; Wang et al., 2024c; Zhang et al., 2024; Chen et al., 2024), they often face a trade-off between achieving strong performance in multilingual retrieval across various languages and preserves good English generalization performance on English retrieval. While concurrent work ArcticEmbV2 (Yu et al., 2024) also aims to have strong effectiveness in both English and multilingual, they follow the previous training paradigm that firstly pretrain the model with contrastive learning over weakly supervised data pairs and then followed by supervised fine-tuning. In our work, we address this challenge from a different view, by conducting data augmentation from LLM and using pruned LLM as the backbone of smaller retriever.

3 Method

3.1 Data Augmentation for Contrastive Dense Retriever Training

Given a query q, a positive document D^+ relevant to the query, and a set of hard negative documents $\{D_{\text{HN}}\}$ that are similar to the positive document but are not highly relevant to the query, a dense retriever model is trained using the InfoNCE loss (van den Oord et al., 2019) as follows:

$$\mathcal{L}(q, D^+, \{D_{\text{N}}\}) = -\log p(D = D^+ \mid q)$$
$$= -\log \frac{\exp(\text{Sim}(q, D^+)/\tau)}{\sum\limits_{D_i \in \{D^+\} \cup \{D_{\text{N}}\}} \exp(\text{Sim}(q, D_i)/\tau)},$$

where $\{D_{\text{N}}\}$ is the union of the hard negative documents $\{D_{\text{HN}}\}$ for each query and in-batch negative documents, which are positive or hard negatives from other queries in the same training batch. The similarity $\text{Sim}(Q, D)$ is commonly computed as the cosine similarity between the embedding vectors of the query and document.

Data augmentation for dense retrieval focuses on creating triplets of queries q, positive documents D_{P}, and hard negative documents $\{D_{\text{HN}}\}$. In this work, we make the following assumptions regarding available resources for data augmentation:

- **Initial Supervised Data** (D_{sft}): A commonly accessible general-domain retrieval dataset.
- **Large Retrieval Model** (LLM_{Ret}): An LLM-based retrieval model, fine-tuned on D_{sft}.
- **Instruction-following LLM** (LLM_{Inst}): An LLM with strong instruction-following capability that can generate synthetic data reflecting its relevance preferences.
- **Large Corpus** (C): A diverse or multilingual document corpus that serves as the basis for synthetic query generation and relevance assessment.

With the above assumption, we explored various ways of utilizing LLM to conduct data augmentation for smaller retrievers, ranging from lower to higher computational costs for data creation.

3.1.1 Data Augmentation via Llama-3.1$_{\text{8B}}$ Retriever

Given an LLM-based retriever model, one of the simplest approaches to data augmentation, without relying on even larger LLMs, is to enable the smaller retriever to learn from the relevance preferences of the 8B embedding model LLM_{emb}. Inspired by methods such as SPAR (Chen et al., 2022) and DRAGON (Lin et al., 2023), we begin with the corpus C. For each document in C, we perform random sentence cropping to extract a smaller segment, which is treated as pseudo-query q. These

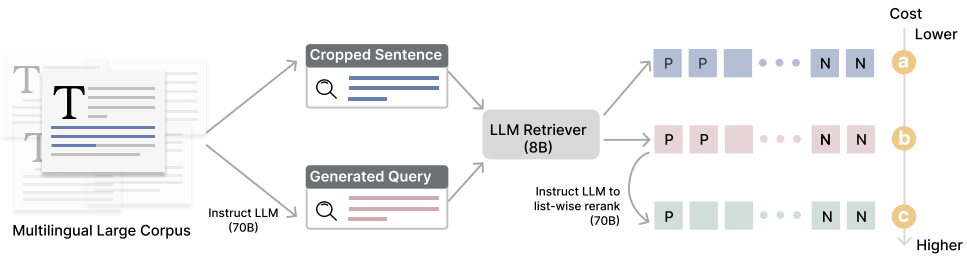

Figure 1: Methods to create data augmentation for smaller retriever with LLMs: (a) Using cropped sentences as queries, selecting the top-ranked documents from top-k retrieval as positives and the remaining as hard negatives. (b) Replacing cropped sentences with synthetic queries generated by prompting instruction-following LLM. (c) Refining retrieval results from the LLM retriever using an instruction-following LLM as a listwise reranker.

pseudo-queries, along with the full corpus, are encoded using the 8B retriever model. Retrieval is then conducted for each pseudo-query q to identify the top-k candidate documents. Among these candidates, the top $[1, m]$ documents are regarded as positive D^+, while the top $[k-n, k]$ documents are designated as hard negatives D_{HN}. The process is illustrated in Figure 1.a. In this work, we set $k = 50, m = 10, n = 20$.

3.1.2 Synthetic Queries from Llama-3.3$_{70\text{B}}$-Instruct

The availability of instruction-following LLMs, such as Llama-3.3$_{70\text{B}}$-Instruct, enables the generation of synthetic queries that are more similar to real queries compared to those from random sentence cropping. For each document in the corpus C, we prompt the LLM to generate a synthetic query q. Similar to the above process, these LLM-generated queries are fed into the 8B LLM$_{\text{Ret}}$ to perform retrieval. Based on the retrieval results, we can identify positive documents and hard negative documents for the synthetic queries as illustrated in Figure 1.b.

3.1.3 LLM Ranking Preference from Llama-3.3$_{70\text{B}}$-Instruct

Instead of relying solely on the relevance preferences of the 8B embedding model, which are influenced by its fine-tuning on supervised data D_{sft}, the instruction-following LLM such as Llama-3.3$_{70\text{B}}$-Instruct can be further leveraged to refine relevance judgments. Specifically, we prompt the LLM to perform listwise reranking of the top-k candidates retrieved for each synthetic query, as illustrated in Figure 1.c. In this process, the LLM provides its relevance judgments by reranking the candidates. The top-1 candidate after reranking is treated as the positive document D^+, while the top $[k-n, k]$ candidates from the reranked list are designated as hard negatives D_{HN}. In our experiments, we set $k = 20, n = 10$. This listwise reranking approach aligns more closely with how humans select the most relevant one among multiple candidates.

In practice, having the data augmentation from LLM listwise rerank can further improve the LLM$_{\text{Ret}}$ by combining the augmented data with the initial supervised data D_{sft}. We sampled LLM listwise rerank augmented data as the same amount of D_{sft} to re-train the LLM$_{\text{Ret}}$. The effectiveness of this operation is further analyzed in Section. 6.1.

3.1.4 Triplet Generation from Llama-3.3$_{70\text{B}}$-Instruct

Another approach to leverage the LLM's relevance preferences for data augmentation is to directly prompt the LLM to generate triplets consisting of a query, a positive document, and a hard negative document. This approach does not rely on a pre-existing corpus to provide seed documents. Following Mistral-E5 (Wang et al., 2024b), but adhering to our controlled data augmentation framework (i.e., creating the same amount of augmentation data with the same LLM), we first prompt the LLM to brainstorm $|C|$ retrieval tasks. Each task includes a retrieval scenario t, a query q, and its context. Based on the task and query, the LLM is then prompted to generate a corresponding positive document and a hard negative document. While this method appears promising in theory, our experiments revealed that purely synthetic triplet data generated in this manner does not substantially improve the training of smaller retriever models. Detailed analyses can be found in Section 6.1.

3.2 Pruning

Previous pre-LLM-era retriever models predominantly utilized encoder-only architectures, such as BERT-base for English retrieval and XLM-RoBERTa-Large for multilingual retrieval. In

this work, in addition to leveraging LLMs for data augmentation, we investigate whether recent decoder-only LLMs can provide better backbones for smaller retriever models. We perform structured pruning on an LLM to obtain models with non-embedding parameter sizes of 0.1B and 0.3B, making them comparable to BERT-base and XLM-RoBERTa-Large, respectively. Specifically, we initialize the pruning process with Llama3.2_{1B}, itself a pruned version of Llama3.1_{8B}. Following the methodology from ShearedLlama (Xia et al., 2024), the pruning process is performed in two stages. In the first stage, a parameter mask is learned to selectively prune the model. This is followed by a continuous pretraining stage to recover the performance of the pruned model. Pruning from an LLM offers several potential advantages compared to training traditional pre-trained language models. First, it allows us to leverage the latest advancements in LLMs, which are trained on large-scale, high-quality datasets and exhibit strong generalization and multilingual capabilities. Secondly, it supports longer contexts than earlier models, allowing for improved handling of retrieval scenarios requiring extended input sequences. Thirdly, the pruning process provides the flexibility to tailor model sizes based on specific deployment needs.

4 Experiment Setup

4.1 Finetuning Data

Controlling the supervised fine-tuning data is critical for ensuring a fair comparison across methods when studying the generalizability of retrieval models. BEIR (Thakur et al., 2021) was originally designed for zero-shot evaluation, encouraging the use of MS MARCO Passage Retrieval as the sole fine-tuning dataset. However, many recent retrievers incorporate supervised data from the evaluation tasks, making the evaluation not entirely zero-shot. To balance fairness in assessing model generalization while maintaining adequate baselines for comparison, we follow the fine-tuning data setup of E5 (Wang et al., 2024a). This setup includes general-domain retrieval datasets but not include fine-tuning data for domain-specific retrieval tasks such as financial QA or scientific document retrieval. For our experiments, we use the open-source replication of the E5 fine-tuning data (Li et al., 2024).

4.2 Data Augmentation

For the LLM retriever model LLM_{ret}, we initialize it with Llama3.1_{8B} and first fine-tune it following the training recipe of RepLlama (Ma et al., 2024) for one epoch on the MS MARCO Passage Ranking training set (Bajaj et al., 2018). We then further fine-tune it on the aforementioned E5 fine-tuning data to obtain an LLM retriever focusing on English retrieval. We train another multilingual LLM retriever by continuous fine-tuning of the MS MARCO-trained LLM retriever using only the MIRACL (Zhang et al., 2023) training data. This allows us to better study generalization in the multilingual retrieval setting.

For the large corpus C used in English data augmentation, we sample 25M documents from a diverse open web-crawled dataset. For multilingual augmentation, we use a combination of multilingual Wikipedia and a multilingual web-crawled corpus covering 19 non-English languages, with each corpus containing 25M documents. In both cases, we segment documents into text chunks of up to 256 tokens.

4.3 Pruning

We prune Llama3.2_{1B} into 0.1B and 0.3B models using 25B tokens in total covering English and 19 non-English languages from web-crawled corpora. The pruned models support a maximum context length of 8,192 tokens.

4.4 Training

The full training data for the smaller retriever models consists of: (1) LLM augmented data based on cropped sentences. (2) 25M LLM retriever augmented data based on generated queries. (3) 25M Inst-LLM listwise reranker augmented data based on generated queries. These three types of data augmentation are applied to all sources, including English web-crawl corpora, multilingual Wikipedia, and multilingual web-crawl corpora (denoted as enWeb, mWiki, and mWeb respectively). The sampling ratio of augmented data across these three sources is 2:1:1.

We train the model with each query paired with one positive document and seven hard negative documents for the 0.1B and 0.3B models and three hard negative documents for the 1B model. We adopt the Matryoshka Representation Learning (MRL) during training to enable flexible dimensionality choice (Kusupati et al., 2022). See B for the details

Method	Non-Emb. Param.	Repre. Dim.	Contra. Pretrain.	Data Aug.	Multi. Lang.	English	Multilingual			
						BEIR (13)	MIRACL (18)	MTEB-FR (5)	MTEB-ZH (8)	MTEB-DE (4)
BM25	-	-	×	×	✓	43.7	38.5	-	-	-
Contriever	86M	768	✓	×	×	47.5	-	-	-	-
DRAGON	86M	768	×	✓	×	50.2	-	-	-	-
E5-v2-base	86M	768	✓	×	×	51.9	-	-	-	-
bge-base-en-v1.5	86M	768	✓	×	×	55.0	-	-	-	-
mE5-base	86M	768	✓	×	✓	50.2	60.1	45.4	61.6	49.2
mGTE-Dense	113M	768	✓	×	✓	54.3	62.1	50.6	**72.0**	49.1
ArcticEmb-v2-M	113M	768	✓	×	✓	56.9	59.2	53.7	55.7	55.0
DRAMA$_{0.1B}$	113M	768	×	✓	✓	56.9	70.4	52.1	61.7	55.1
E5-large-v2	303M	1024	✓	×	×	52.1	-	-	-	-
bge-large-en-v1.5	303M	1024	✓	×	×	56.1	-	-	-	-
mE5-large	303M	1024	✓	×	✓	52.9	65.4	47.7	63.7	50.4
mE5-Inst	303M	1024	✓	✓	✓	54.1	66.0	49.9	64.2	52.5
M3-BGE-Dense	303M	1024	✓	×	✓	50.0	69.2	48.6	65.6	50.4
ArcticEmb-v2-L	303M	1024	✓	×	✓	57.2	64.9	54.5	63.6	**55.9**
DRAMA$_{0.3B}$	265M	1024	×	✓	✓	58.0	71.4	54.8	63.0	55.6
Gecko	1B	768	✓	✓	✓	58.0	56.2	-	-	-
DRAMA$_{1B}$	1B	2048	×	✓	✓	**59.1**	**71.7**	**57.6**	63.7	56.2
DRAMA$_{1B}$ (768d)	1B	768	×	✓	✓	58.5	70.9	56.5	62.8	55.8
MistralE5	7B	4096	×	✓	✓	59.0	62.2	-	-	-

Table 1: Effectiveness of DRAMA compared to baseline methods (measured in nDCG@10). For each method, we indicate the number of non-embedding parameters, the text embedding dimensionality, whether contrastive pretraining is needed, whether data augmentation is applied during supervised fine-tuning, and whether the retriever supports multilingual retrieval. The notation (x) after a dataset name indicates the average value across x subsets within the dataset. Detailed results for each subset are provided in the D. We highlight the highest score for each dataset in bold and the highest score within each parameter level with an underscore. The notation (768d) indicates that we use the first 768 dimensions of representations from DRAMA$_{1B}$, as our model is trained with MRL.

of DRAMA with different dimensionality.

4.5 Evaluation

Our main evaluations are conducted on BEIR (Thakur et al., 2021) and MIRACL (Zhang et al., 2023), to assess the generalization of dense retrievers and multilingual retrieval capability. To further analyze the generalization of multilingual retrievers, we also evaluate on retrieval subsets of MTEB-FR (Ciancone et al., 2024), MTEB-ZH (Xiao et al., 2024) and MTEB-DE. To assess the effectiveness of long-context retrieval, which benefits from pruning an LLM, we evaluate on MDLR (Chen et al., 2024), a benchmark for long-context multilingual retrieval across 13 languages. We use nDCG@10 as the metrics for all evaluations.

4.6 Baseline

We select representative baselines with similar retrieval task training data settings, as described in Sec. 4.1. The major baselines include Contriever (Izacard et al., 2022), DRAGON (Lin et al., 2023), E5 (Wang et al., 2024a), BGE (Xiao et al., 2024), mE5 (Wang et al., 2024c), BGE-M3 (Chen et al., 2024), mGTE (Zhang et al., 2024), ArcticEmbV2 (Yu et al., 2024), Gecko (Lee et al., 2024), and MistralE5 (Wang et al., 2024b).

5 Results

5.1 Generalization of Smaller Retrievers

Table 1 shows the performance of our DRAMA variants on both English and multilingual retrieval tasks. The results indicate that DRAMA is a strong and generalizable retriever at different model sizes. For example, DRAMA$_{0.1B}$ achieves an nDCG@10 of 56.9 on BEIR, on par with ArcticEmb-v2-M, and outperforms other English-only and multilingual retrievers. When scaling up to DRAMA$_{0.3B}$, the score increases to 58.0, outperforming ArcticEmb-v2-L by 0.8 points and matching Gecko, which is a much larger 1B-parameter model. Beyond English retrieval, DRAMA exhibits strong multilingual capabilities. On MIRACL, all DRAMA variants (from 0.1B to 1B) outperform previous best models like M3-BGE-Dense, while also maintaining strong English retrieval performance. This suggests that DRAMA works well across different languages without losing effectiveness in English.

As discussed by (Lin et al., 2023), there is often a trade-off between in-domain and out-of-domain retrieval performance. While DRAMA achieves very high in-domain multilingual effectiveness—for example, DRAMA$_{0.1B}$ is 5.5 points higher than ArcticEmb-v2-L on MIRACL, it still maintains strong zero-shot retrieval performance in multi-

Method	Param.	L-CPT.	L-FT.	Max Len	MLDR Avg
BM25	-	×	×	∞	53.6
mE5-large	303M	×	×	512	34.2
M3-BGE-Dense	303M	✓	×	8192	45.0
ArcticEmb-v2-M	113M	×	×	8192	34.0
DRAMA$_{0.1B}$	113M	×	×	8192	47.1
DRAMA$_{0.3B}$	265M	×	×	8192	48.8
DRAMA$_{1B}$	1B	×	×	128k	54.8
M3-BGE-Dense	303M	✓	✓	8192	52.5
mGTE-Dense	113M	✓	✓	8192	56.6
DRAMA$_{0.1B}$-MLDR	113M	×	✓	8192	60.2
DRAMA$_{0.3B}$-MLDR	265M	×	✓	8192	58.9
DRAMA$_{1B}$-MLDR	1B	×	✓	128k	62.3

Table 2: Effectiveness of DRAMA on the multilingual long-context retrieval task. L-CPT: Model has seen long-context data during contrastive pretraining. L-FT: Model has seen long-context data during supervised fine-tuning. Max Len: Maximum input length supported.

lingual settings like MTEB-FR. On MTEB-ZH, DRAMA performs slightly lower than ArcticEmb-v2, but the difference is within 1 point. Overall, these results suggest DRAMA is generalizable across retrieval tasks and languages.

5.2 Effectiveness in Long Context Retrieval

Pruning an recent LLM to create smaller retriever backbones offers two key advantages in functionality. First, it helps preserve multilingual capability. Most existing retrievers at the 0.1B parameter scale use `bert-base-uncased` as their backbone. While these models achieve strong performance in English retrieval, they do not support multilingual retrieval. By pruning an LLM instead, we achieve strong English retrieval effectiveness while retaining its multilinguality with only a small amount of multilingual web data (less than 10B tokens).

Second, as recent LLMs are designed to handle long contexts, pruning an LLM as the retriever backbone allows better long-context retrieval capabilities. Table 2 shows that even though DRAMA's fine-tuning data does not include MLDR training data, and DRAMA is not trained with text beyond 256 tokens, it still performs well in length extrapolation. For example, DRAMA$_{0.1B}$ achieves an nDCG@10 of 46.8 on MLDR, despite never being trained on long-context retrieval data. Comparing DRAMA$_{0.1B}$ to M3-BGE-Dense, which was trained with long-context data during contrastive pretraining but not fine-tuned on MLDR, DRAMA outperforms it by 2.1 points. This demonstrates the advantage of using a pruned LLM, which inherently supports longer contexts.

It is also important to note that BM25, a traditional lexical retrieval method, performs well in long-context retrieval. However, after further fine-tuning DRAMA on MLDR training data, it surpasses BM25 and other methods that have MLDR in training data. This result shows the potential of further adapting DRAMA to long-context multilingual retrieval tasks.

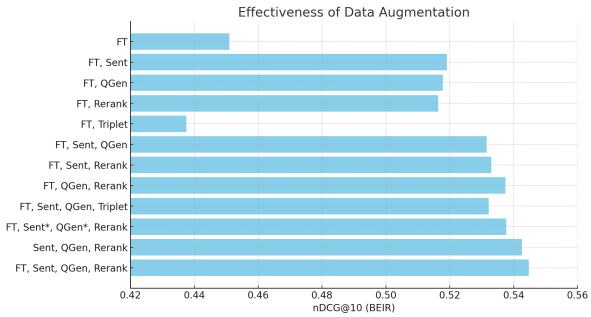

Figure 2: Effectiveness of different data augmentation combinations. The model is trained based on 0.1B backbone, using only the English data augmentation and with 1 hard negative per query.

6 Analysis and Ablation Study

6.1 Effectiveness of Data Augmentation

Figure 2 illustrates the effectiveness of different data augmentation combinations. First, we observe that directly fine-tuning the model without data augmentation results in poor generalization performance. Incorporating any form of LLM-based data augmentation significantly improves BEIR performance, with one exception: directly prompting Llama3.3$_{70B}$-Instruct to generate fully synthetic triplets (queries, positive documents, and negative documents) does not yield meaningful improvements. This suggests that training a smaller retriever model benefits more from using real documents. Moreover, combining multiple types of data augmentation further enhances effectiveness beyond using any single augmentation method alone. The highest performance is achieved when all three types of data augmentation are combined. Notably, when all augmentation strategies are applied together, the importance of fine-tuning data is diminishing, showing the effectiveness of our data augmentation approach. The data point noted by [FT, Sent*, QGen*, Rerank] shows the performance of using LLM$_{Ret}$ without further improvement from LLM listwise rerank augmentation. Its lower effectiveness compared to the final combination underscores that incorporating LLM-based rerank augmentation enhances the performance of LLM$_{Ret}$ and further improving the effectiveness of the smaller retriever model. In addition, we study

Backbone	Param.	BEIR
BERT	0.1B	53.50
ModernBERT	0.1B	54.22
Llama3.2$_{1B \to 0.1B}$	0.1B	54.47
XLM-RoBERTa-Large	0.3B	54.74
Llama3.2$_{1B \to 0.3B}$	0.3B	56.14

Figure 3: Effectiveness of using pruned Llama3.2 as smaller retriever backbone compares to pre-LLM-era or recent encoder-only backbone. The models are trained using only the English data augmentation and with 1 hard negative per query.

Model Size	Attention	Pooling	BEIR
0.1B	Bi-direction	Mean	54.47
	Bi-direction	EOS	54.37
	Uni-direction	Mean	53.88
	Uni-direction	EOS	53.58
0.3B	Bi-direction	Mean	56.14
	Bi-direction	EOS	55.85
	Uni-direction	Mean	55.18
	Uni-direction	EOS	54.79

Figure 4: Impact of different attention and pooling mechanisms for the smaller retriever. The model is trained using only the English data augmentation and with 1 hard negative per query.

the effectiveness of multilingual data mixture in Appendix A.

6.2 Effectiveness of Model Backbone

In Table 3, we compare the effectiveness of using a pruned Llama model as the retriever backbone against pre-LLM-era encoder-only models. At the 0.1B scale, the pruned model outperforms BERT by approximately 1 point on average across BEIR. Similarly, at the 0.3B scale, the pruned model surpasses XLM-RoBERTa-Large by about 1.5 points. This demonstrates the effectiveness of using pruned-decoder-only LLM as a retriever backbone for text encoding tasks. Additionally, the 0.1B pruned model performs slightly better than ModernBERT, a recently developed encoder-only model. However, unlike ModernBERT, our approach retains multilingual support and leverages existing LLM pretraining, dropping the need to train the backbone from scratch.

6.3 Attention and Pooling Mechanism

In Table 4, we analyze how the attention mechanism and pooling strategy affect retrieval performance when training the pruned model as a text encoder. It shows that bi-directional attention outperforms uni-directional attention. While mean pooling yields higher scores than last-token pooling, the impact of the attention mechanism is greater than that of the pooling strategy. Even with massive augmented training data, uni-directional attention remains a limiting factor. However, simply enabling bi-directional attention allows the small decoder-only model to function more effectively.

Backbone	MIRACL-de	MIRACL-yo	MTEB-pl
1B $\to$ 0.1B	45.48	68.77	32.38
1B $\to$ 0.3B	55.83	83.85	36.85
1B	58.20	76.20	51.08

Figure 5: Cross-lingual generalization performance of models trained with English data augmentation, evaluated on zero-shot languages. DE and YO are seen during the pruning stage, while PL is unseen. For MTEB-pl, results are averaged over 11 retrieval tasks.

6.4 Cross-lingual Generalization

In Table 5, we analyze how our model generalizes to zero-shot languages. The models are trained using English data augmentation and evaluated on languages that were not explicitly included in the fine-tuning stage. First, we examine German (de), a higher-resource language. The results show a clear trend where zero-shot effectiveness improves as the model size increases, suggesting that scaling up enhances cross-lingual generalization. For Yoruba (yo), an interesting pattern emerges: the 0.3B pruned model outperforms the larger 1B model. This may be due to the fact that the 1B model was not well-trained in Yoruba. The pruning stage of our approach includes yo data, leading to stronger performance in this language. In contrast, Polish (pl), which was not covered in either the fine-tuning or pruning stages, shows a noticeable performance gap compared to the 1B model. This shows the importance of including a language during pruning, as exposure at this stage significantly benefits zero-shot retrieval effectiveness.

7 Conclusion

We introduced DRAMA, a training framework that leverages LLMs for diverse data augmentation and pruned LLMs as backbones to train smaller, generalizable dense retrievers. DRAMA achieves strong effectiveness across English and multilingual retrieval tasks. By shifting the computational costs of LLM ranking methods from inference to smaller retriever training, our approach offers a scalable solution for practical deployment.

Limitations

While DRAMA achieves strong retrieval effectiveness across English and multilingual tasks, several areas remain open for further investigation.

Firstly, the scope of language support. As observed in Section 6.4, including a language during the pruning stage is crucial for enabling the smaller model to generalize well to that language. While the 0.1B and 0.3B variants of DRAMA covers 20 languages, expanding this coverage could improve performance for low-resource languages that lack sufficient contrastive learning data. A more comprehensive pruning strategy, incorporating additional languages, would likely enhance zero-shot multilingual retrieval.

Another limitation lies in the amount of supervised fine-tuning data. To maintain a fair evaluation of generalization, we followed the E5 fine-tuning setup, which does not include domain-specific retrieval tasks such as financial and medical. However, incorporating a broader range of supervised datasets could further improve retrieval performance across diverse domains.

Additionally, DRAMA is trained with up to 256 context length by default. Although it demonstrates strong zero-shot extrapolation in long-context retrieval, it is worth more exploration on how to better integrate the long-context training data into the data augmentation mixing with shorter-context data efficiently. One possible approach is to organize training batches based on context length (Chen et al., 2024).

Besides, DRAMA follows a single-stage training approach, where the model is directly fine-tuned from a pruned LLM. While this simplifies the pipeline and produces strong generalization, it remains an open question whether combining with multi-stage pertaining (Yu et al., 2024) or recently proposed multi-stage distillation (Zhang et al., 2025) will help further improve the effectiveness of DRAMA.

Finally, DRAMA focused on retrieval tasks. Many recent models additionally optimize for broader text embedding tasks such as clustering and classification as well as instruction following retrieval. We leave further integrate supervised fine-tuning data and LLM data augmentation for these tasks into DRAMA training framework as future work.

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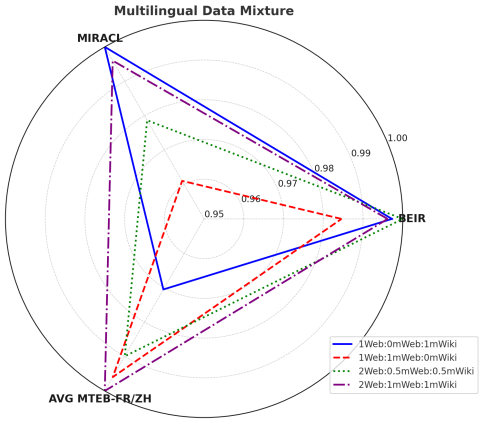

Figure 6: Effectiveness of different mixture ratios of English and multi-lingual data augmentation ratio for the data source of Web, mWeb and mWiki. The model is trained based on 0.1B backbone with 1 hard negative per query.

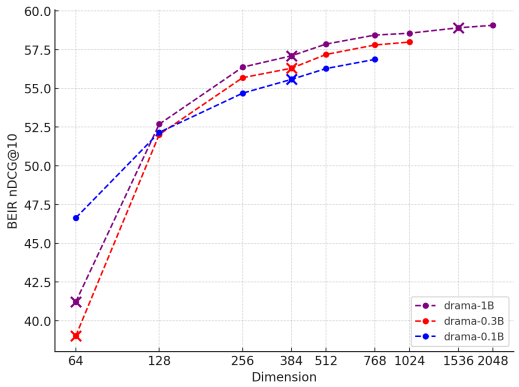

Figure 7: Effectiveness of DRAMA across different text representation dimensions. Points marked with × indicate dimensionalities that were not explicitly optimized in the MRL process.

Appendix A Multilingual Data Balance

Figure 6 illustrates how different mixtures of data sources affect effectiveness across English retrieval, in-domain multilingual retrieval, and multilingual generalization. We observe that excluding mWeb negatively impacts multilingual generalization, likely due to overfitting on the Wikipedia corpus. Conversely, excluding mWiki leads to a drop in in-domain multilingual retrieval effectiveness. However, mixing both mWiki and mWeb enables strong performance across both in-domain effectiveness and multilingual generalization. Additionally, we find that maintaining a 1:1 balance between English and multilingual data yields better overall performance than doubling the proportion of English data. While increasing the English proportion slightly improves BEIR effectiveness, it significantly weakens multilingual retrieval performance. Overall, using a 1:1 ratio of English to multilingual data and incorporating augmentation data from both Wikipedia and web-crawled multilingual sources achieves the best trade-off, covering the largest area in the radar chart and ensuring robust performance across retrieval tasks.

Appendix B Matryoshka Representation Learning

In Figure 7, we compare the effectiveness of DRAMA variants across different dense representation dimensionalities. For dimensions larger than 256, the trend of model size scaling is clear—larger model achieves higher effectiveness. Additionally, text representations largely retain their effectiveness compared to using the full-dimensionality representation. However, at 128 dimensions, the scaling trend is not guaranteed. At 64 dimensions, the 0.1B model outperforms both the 0.3B and 1B models, likely because 64 dimensions were not a target setting during MRL training for the larger models. In contrast, for dimensions 384 and 1536, despite also not being target dimensions for MRL, the effectiveness is well preserved. This observation raises the importance of considering the range of target dimensionalities during MRL training to ensure effectiveness at test time.

Appendix C Detailed Training Setup

Model License: Our LLM retriever is trained based on Llama3.1-8B follows Llama 3.1 Community License Agreement. Data augmentation based on Inst-LLM is based on Llama3.3-70B-Instruct follows Llama 3.3 Community License Agreement. Our backbone model is pruned based on Llama3.2-1B, following Llama 3.2 Community License Agreement.

Languages: For pruning and data augmentation, our web crawl text corpora cover the following 20 languages: English, Arabic, Bengali, Spanish, Persian, Finnish, French, Hindi, Indonesian, Japanese, Korean, Russian, Swahili, Telugu, Thai, Chinese, German, Yoruba, Italian, Portuguese.

Training: The models are trained using the `dpr-scale`[2] codebase on 32 A100 GPUs over approximately two days. The training configurations for different model sizes are as follows:

[2] https://github.com/facebookresearch/dpr-scale

DRAMA$_{0.1B}$: Batch size of 2048, with each query paired with seven hard negatives. DRAMA$_{0.3B}$: Batch size of 1024, with each query paired with seven hard negatives. DRAMA$_{1B}$: Batch size of 256, with each query paired with three hard negatives. All three variants are trained for 200,000 steps.

Appendix D Detailed Evaluation Results

We use the `tevatron` codebase to evaluate BEIR and MIRACL. For retrieval tasks in MTEB-FR/ZH/DE, we utilize the `mteb` codebase. For BEIR and MIRACL, we set the maximum context length as 512 for both query and document following previous works. For baselines, we adopt BEIR and MIRACL scores directly from the original works. In MLDR, we reference baseline results from the mGTE work for mE5, BGE-M3, and mGTE. For Arctic-Embedding, we conduct the MLDR evaluation ourselves. While some MTEB scores are reported in previous works, we observe version changes in certain datasets within MTEB-FR. To ensure consistency, we re-evaluate MTEB-FR/ZH/DE baselines ourselves. We set the maximum context length as 1024 following (Zhang et al., 2024).

The full evaluation results are presented in Table 3, Table 4, Table 5, Table 6, Table 7, and Table 8.

Method	Param.	CPT	Multi.	Avg	BEIR (nDCG@10)												
					TREC-COVID	NF Corpus	Sci Fact	SCI DOCS	FiQA	Argu Ana	Touche-2020	DB Pedia	Climate-FEVER	FEVER	NQ	Hotpot QA	Quora
BM25	-	×	✓	43.7	59.5	32.2	67.9	14.9	23.6	39.7	44.2	31.8	16.5	65.1	30.5	63.3	78.9
Contriever	86M	✓	×	47.5	59.6	32.8	67.7	16.5	32.9	44.6	23.0	41.3	23.7	75.8	49.8	63.8	86.5
DRAGON	86M	×	×	50.2	75.9	33.9	67.9	15.9	35.6	46.9	26.3	41.7	22.7	78.1	53.7	66.2	87.5
E5-v2-base	86M	✓	×	51.9	69.6	35.4	71.9	18.7	39.9	44.5	26.4	42.2	26.6	85.0	58.2	69.2	86.6
bge-base-en-v1.5	86M	✓	×	55.0	78.1	37.4	74.0	21.7	40.6	63.6	25.7	40.8	31.2	86.3	54.1	72.6	88.9
mE5-base	86M	✓	✓	50.2	69.7	32.5	69.3	17.2	38.2	44.2	21.4	40.4	23.9	79.4	60.0	68.6	87.6
mGTE-Dense	113M	✓	✓	54.3	57.4	36.7	73.4	18.3	63.0	58.4	22.8	40.1	34.8	92.1	58.1	63.0	88.0
ArcticEmb-v2-M	113M	✓	✓	56.9	80.3	35.9	71.8	20.3	44.0	58.0	29.8	43.9	38.3	91.6	64.6	72.4	88.7
DRAMA$_{0.1B}$	113M	×	✓	56.9	83.3	36.9	75.7	19.1	44.2	54.8	29.1	44.8	38.0	89.4	60.8	74.9	88.3
E5-large-v2	303M	✓	×	52.1	66.5	37.1	72.2	20.5	41.1	46.4	20.7	44.0	22.2	82.8	63.4	73.1	86.8
bge-large-en-v1.5	303M	✓	×	56.1	74.8	38.1	74.6	22.6	45.0	63.5	24.8	44.1	36.6	87.2	55.0	74.1	89.1
mE5-large	303M	✓	✓	52.9	71.3	34.0	70.4	17.5	43.8	54.4	23.4	41.3	25.7	82.8	64.1	71.2	88.2
mE5-Inst	303M	✓	✓	54.1	82.0	35.5	71.9	18.7	47.7	58.4	27.2	38.4	29.9	78.0	57.8	69.3	89.1
M3-BGE-Dense	303M	✓	✓	50.0	55.6	31.4	64.4	16.4	41.3	54.0	22.6	39.8	24.2	81.4	60.6	69.4	88.6
ArcticEmb-v2-L	303M	✓	✓	57.2	83.9	35.3	70.6	20.2	45.5	59.2	29.5	43.4	43.5	91.9	63.7	68.2	89.0
DRAMA$_{0.3B}$	265M	×	✓	58.0	83.8	37.9	76.1	19.7	46.9	54.1	28.1	47.7	41.9	89.5	64.1	75.6	88.4
Gecko	1B	✓	✓	58.0	82.6	40.3	75.4	20.4	59.2	62.2	25.9	47.1	33.2	87.0	61.3	71.3	88.2
DRAMA$_{1B}$	1B	×	✓	59.1	85.8	37.6	77.9	20.7	50.6	53.5	29.6	50.0	38.7	89.9	67.3	77.4	88.7
DRAMA$_{1B}$(768d)	1B	×	✓	58.4	85.2	37.1	77.5	20.7	50.2	53.1	29.0	49.2	37.9	89.5	66.5	75.5	88.5
MistralE5	7B	×	✓	59.0	87.2	38.6	76.4	16.3	56.6	61.9	26.4	48.9	38.4	87.8	63.5	75.7	89.6

Table 3: Full BEIR evaluation of DRAMA.

Method	Param.	MIRACL (nDCG@10)																		
		Avg	ar	bn	en	es	fa	fi	fr	hi	id	ja	ko	ru	sw	te	th	zh	de	yo
BM25	-	38.5	48.1	50.8	35.1	31.9	33.3	55.1	18.3	45.8	44.9	36.9	41.9	33.4	38.3	49.4	48.4	18.0	22.6	40.6
mE5-base	86M	65.4	76.0	75.9	52.9	52.9	59.0	77.8	54.5	62.0	52.9	70.6	66.5	67.4	74.9	84.6	80.2	56.0	56.4	56.5
mGTE-Dense	113M	62.1	71.4	72.7	54.1	51.4	51.2	73.5	53.9	51.6	50.3	65.8	62.7	63.2	69.9	83.0	74.0	60.8	49.7	58.3
ArcticEmb-v2-M	113M	59.2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
DRAMA$_{0.1B}$	113M	70.4	80.5	74.5	56.3	61.4	62.8	78.9	62.2	61.9	58.0	74.2	70.5	72.3	77.1	81.5	80.4	64.8	62.3	88.5
mE5-large	303M	60.1	71.6	70.2	51.2	51.5	57.4	74.4	49.7	58.4	51.1	64.7	62.2	61.5	71.1	75.2	75.2	51.5	43.4	42.3
mE5-Inst	303M	66.0	76.8	73.9	51.5	53.7	59.4	77.3	53.7	60.3	52.1	69.0	65.3	67.9	72.5	83.4	78.6	56.2	55.5	81.5
M3-BGE-Dense	303M	69.2	78.4	80.0	56.9	56.1	60.9	78.6	58.3	59.5	56.1	72.8	69.9	70.1	78.7	86.2	82.6	62.7	56.7	81.8
ArcticEmb-v2-L	303M	64.9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
DRAMA$_{0.3B}$	265M	71.4	81.4	77.2	58.5	62.4	63.7	79.9	62.4	64.8	58.3	75.6	70.0	73.6	78.1	81.8	81.4	65.1	63.4	87.2
Gecko	1B	56.2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
DRAMA$_{1B}$	1B	71.7	81.1	76.6	58.4	62.2	64.5	80.9	62.8	65.7	58.7	76.4	69.3	74.6	77.6	80.6	81.8	68.2	63.9	88.1
MistralE5	7B	62.2	73.3	70.3	57.3	52.2	52.1	74.7	55.2	52.1	52.7	66.8	61.8	67.7	68.4	73.9	74.0	54.0	54.0	58.8

Table 4: Full MIRACL evaluation of DRAMA.

Method	Param.	L-CPT.	L-FT.	Max Len	MLDR (nDCG@10)													
					Avg	ar	de	en	es	fr	hi	it	ja	ko	pt	ru	th	zh
BM25	-	×	×	∞	53.6	45.1	52.6	57.0	78.0	75.7	43.7	70.9	36.2	25.7	82.6	61.3	33.6	34.6
mE5-large	303M	×	×	512	34.2	33.0	26.9	33.0	51.1	49.5	21.0	43.1	29.9	27.1	58.7	42.4	15.9	13.2
M3-BGE-Dense	303M	✓	×	512	45.0	37.9	43.3	41.2	67.7	64.6	32.0	55.8	43.4	33.1	67.8	52.8	27.2	18.2
DRAMA$_{0.1B}$	113M	×	×	8192	46.8	40.0	46.2	39.7	74.4	73.2	25.6	56.2	42.0	35.9	69.7	57.8	29.3	18.9
DRAMA$_{0.3B}$	265M	×	×	8192	46.8	39.3	47.1	39.9	74.8	72.3	26.9	60.5	41.0	32.8	70.7	55.9	31.4	16.4
DRAMA$_{1B}$	1B	×	×	128k	54.7	49.1	54.1	50.9	80.3	77.1	37.7	67.6	51.6	43.5	77.2	61.7	35.9	24.4
M3-BGE-Dense	303M	✓	✓	512	52.5	47.6	46.1	48.9	74.8	73.8	40.7	62.7	50.9	42.9	74.4	59.5	33.6	26.0
mGTE-Dense	113M	✓	✓	512	56.6	55.0	54.9	51.0	81.2	76.2	45.2	66.7	52.1	46.7	79.1	64.2	35.3	27.4
DRAMA$_{0.1B}$-MLDR	113M	×	✓	8192	60.2	60.6	55.3	56.6	84.0	81.3	43.6	72.2	55.9	48.7	82.3	73.8	38.8	29.1
DRAMA$_{0.3B}$-MLDR	265M	×	✓	8192	58.9	58.2	53.1	57.0	83.1	81.0	39.9	71.0	54.9	47.5	80.8	71.8	39.2	28.7
DRAMA$_{1B}$-MLDR	1B	×	✓	128k	62.3	59.9	58.2	62.1	84.6	81.6	49.2	77.6	57.9	52.7	84.3	70.8	43.7	32.9

Table 5: Full MLDR evaluation of DRAMA.

Method	Param.	MTEB-FR-Retrieval (nDCG@10) Avg	AlloprofRetrieval	BSARDRetrieval	MintakaRetrieval	SyntecRetrieval	XPQARetrieval
mE5-base	86M	45.4	34.4	18.8	31.0	82.9	59.6
mGTE-Dense	113M	50.6	49.4	19.1	34.7	82.6	67.4
ArcticEmb-v2-M	113M	53.7	54.6	18.4	31.4	89.8	74.4
DRAMA$_{0.1B}$	113M	52.1	51.9	24.7	26.7	85.5	71.5
mE5-large	303M	47.7	39.3	21.4	34.2	82.4	61.3
mE5-Inst	303M	49.9	51.4	24.3	30.3	86.2	57.4
M3-BGE-Dense	303M	48.6	48.3	16.6	22.9	84.5	70.9
ArcticEmb-v2-L	303M	54.5	53.9	21.9	30.7	88.5	77.3
DRAMA$_{0.3B}$	265M	54.8	55.8	26.6	28.8	89.9	72.8
DRAMA$_{1B}$	1B	57.6	55.9	29.9	37.5	91.6	72.9

Table 6: Full MTEB-FR-Retrieval evaluation of DRAMA.

Method	Param.	MTEB-ZH-Retrieval (nDCG@10) Avg	Cmedqa	Covid	Du	Ecom	Medical	MMarco	T2	Video
mE5-base	86M	61.6	27.2	73.5	81.7	54.2	48.4	76.0	70.8	61.3
mGTE-Dense	113M	72.0	43.8	81.0	87.5	64.8	61.9	79.4	84.7	72.8
ArcticEmb-v2-M	113M	55.7	19.7	72.2	68.4	48.6	38.3	71.2	71.3	56.1
DRAMA$_{0.1B}$	113M	61.7	21.2	78.4	74.9	57.9	42.4	76.2	76.4	66.0
mE5-large	303M	63.7	28.7	75.6	85.3	54.7	51.5	79.2	76.1	58.2
mE5-Inst	303M	64.2	33.9	76.1	85.2	53.7	56.2	78.6	82.9	47.2
M3-BGE-Dense	303M	65.6	33.8	78.3	84.0	58.5	54.2	77.3	81.5	57.0
ArcticEmb-v2-L	303M	63.6	27.8	78.8	78.4	56.4	51.1	78.4	79.7	58.6
DRAMA$_{0.3B}$	265M	63.0	21.2	78.4	74.9	57.9	42.4	76.2	76.4	66.0
DRAMA$_{1B}$	1B	63.7	23.6	76.1	77.8	60.1	45.8	79.4	79.0	67.8

Table 7: Full METB-ZH-Retrieval evaluation of DRAMA.

Method	Param.	MTEB-DE-Retrieval (nDCG@10) Avg	GerDaLIR	GermanDPR	GermanQuAD-Retrieval	XMarket
mE5-base	86M	49.2	6.9	79.6	93.9	16.3
mGTE-Dense	113M	49.1	9.4	80.0	91.1	16.0
ArcticEmb-v2-M	113M	55.0	16.1	81.8	94.4	27.6
DRAMA-0.1B	113M	55.1	15.4	82.8	95.9	26.2
mE5-large	303M	50.4	6.5	82.9	94.6	17.5
mE5-Inst	303M	52.5	10.7	79.4	94.5	25.3
M3-BGE-Dense	303M	50.4	10.9	82.5	95.1	13.1
ArcticEmb-v2-L	303M	55.9	17.5	83.7	95.2	27.0
DRAMA-0.3B	265M	55.6	15.7	82.6	96.4	27.7
DRAMA-1B	1B	56.2	15.3	84.4	97.1	28.0

Table 8: Full MTEB-DE-Retrieval evaluation of DRAMA.