MixGR: Enhancing Retriever Generalization for Scientific Domain through Complementary Granularity

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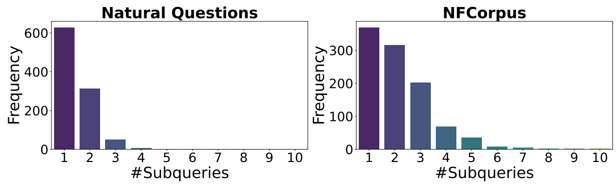
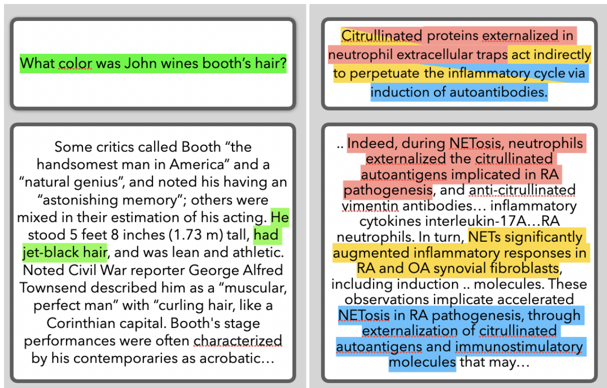
Abstract

Recent studies show the growing significance of document retrieval in the generation of LLMs within the scientific domain by bridging their knowledge gap. However, dense retrievers often struggle with domain-specific retrieval and complex query-document relationships, particularly when query segments correspond to various parts of a document. To alleviate such prevalent challenges, this paper introduces `MixGR`, which improves dense retrievers' awareness of query-document matching across various levels of granularity in queries and documents using a zero-shot approach. `MixGR` fuses various metrics based on these granularities to a united score that reflects a comprehensive query-document similarity. Our experiments demonstrate that `MixGR` outperforms previous document retrieval by 22.6% and 10.4% on nDCG@5 with unsupervised and supervised retrievers, respectively, averaged on queries containing multiple subqueries from four scientific retrieval datasets. Moreover, the efficacy of two downstream scientific question-answering tasks highlights the advantage of `MixGR` to boost the application of LLMs in the scientific domain.



(a) Subquery distribution of general and scientific queries: scientific queries, e.g., NFCorpus (Boteva et al. 2016, *Right*), demonstrate a more diverse range of subqueries per query than general queries, e.g., Natural Questions (Kwiatkowski et al. 2019, *Left*).



(b) Comparison between general and scientific query-doc retrieval: compared with the general query-doc retrieval exemplified by NQ (Kwiatkowski et al. 2019, *Left*), the scientific query-doc retrieval exemplified by SciFact (Wadden et al. 2020, *Right*) demonstrates that one query can be decomposed to multiple subqueries, which can be mapped to different parts of documents.

Figure 1: Scientific document retrieval is shown to be more complicated than general domains.

1 Introduction

Recent advances in Large Language Models (LLMs) have significantly impacted various scientific domains (Zhang et al., 2022; Touvron et al., 2023; Birhane et al., 2023; Grossmann et al., 2023). However, LLMs are notorious for their tendency to produce hallucinations, producing unreliable outputs (Ji et al., 2023). To address this, Retrieval-Augmented Generation (RAG; Lewis et al. 2020) has been developed to address this issue by incorporating external knowledge during the generation.

Though notable for accessing external and relevant knowledge, dense retrievers face specific challenges in the scientific domain: (1) *Domain-specific* nature: dense retrievers are typically trained on the general corpus such as Natural Questions (NQ; Kwiatkowski et al. 2019). However, scientific domains differ notably, e.g., the terminology and the pattern of queries as shown in Figure 1a. (2) *Complexity* of scientific documents: they are long, structured (Erera et al., 2019) and contain complex relationships between arguments (Stab et al., 2014). Figure 1a demonstrates that scientific queries tend to contain more subqueries than those in general domains. This indicates that subqueries within a single query may align with different parts of a document (doc), resulting in complex interactions between queries and documents (Figure 1b).

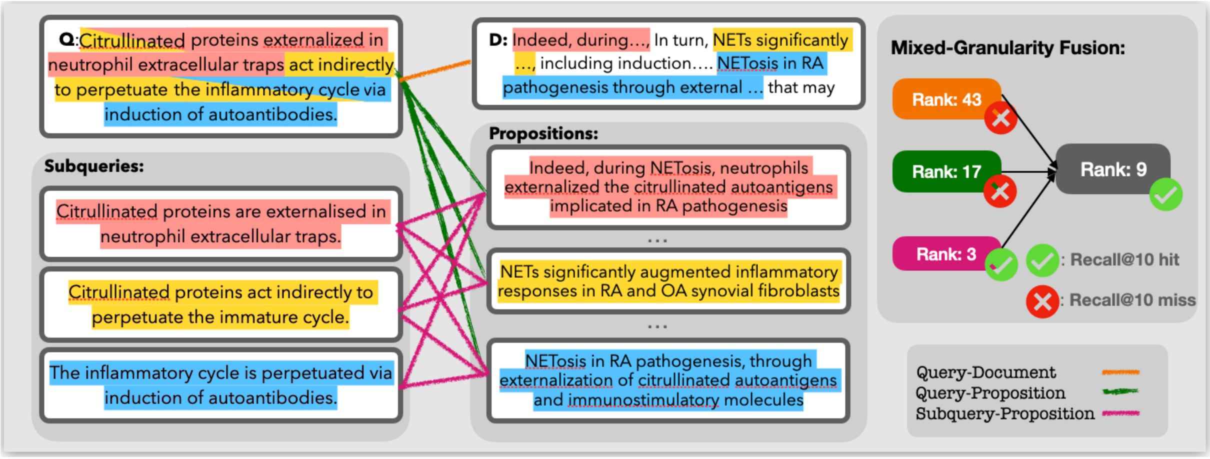


Figure 2: The illustration of `MixGR`: Both queries and documents (e.g., the query-doc pair from SciFact in Figure 1b) are decomposed into subqueries and propositions, respectively, each containing distinct semantic components. Starting from the original queries and documents along with their decomposed elements, metrics from various granularity combinations are fused into a single integrated score.

Such complexity poses significant challenges for dense retrievers (Lupart et al., 2023). Addressing these challenges requires specific training on the scientific corpus. However, this is often hindered by the necessity of extensive annotations (Wadden et al., 2020) and extra computation (Wang et al., 2021a).

In this study, we introduce a novel **zero-shot** approach that effectively adapts dense retrievers to scientific domains. This method specifically addresses the complexities arising from the composition of scientific queries and their consequent intricate relationships with documents. Inspired by Chen et al. (2023), showing that finer units improve retrievers' generalization to rare entities, we incorporate more granular retrieval units, specifically propositions (prop), to address domain-specific challenges as shown in Figure 2. Given the complexity between scientific queries and documents (Figure 1b), we also consider finer units within queries–subqueries–to measure query-doc similarity at a finer granularity. This metric captures the similarity between subqueries and propositions, moving beyond simple point similarity between query-doc vectors. Given a query, the distribution of corresponding information within a document is unknown. Additionally, our empirical analysis reveals that similarities at various granularities provide complementary insights. Therefore, for each query-doc pair, we fuse the metrics from these granularities to a unified score, termed **Mix**ed-**G**ranularity **R**etrieval as `MixGR`, as depicted in Figure 2.

We conducted document retrieval experiments on four scientific datasets using six dense retrievers, comprising two unsupervised and four supervised models. Our results demonstrate that `MixGR` markedly surpasses previous query-doc retrieval methods. Notably, we recorded an average improvement of 22.6% for unsupervised retrievers and 10.4% for supervised retrievers in terms of nDCG@5 for queries involving multiple subqueries. Furthermore, documents retrieved via `MixGR` substantially enhance the performance of downstream scientific QA tasks, underscoring their potential utility for RAG within scientific domains.

Our contributions are three-fold:

- We identify the challenges within scientific document retrieval, i.e., domain shift and query-doc complexity. We initiate retrieval with mixed granularity within queries and documents to address these issues;
- We propose `MixGR`, which further incorporates finer granularities within queries and documents, computes query-doc similarity over various granularity combinations, and fuses them as a united score. Our experiments across four datasets and six dense retrievers empirically reveal that `MixGR` significantly enhances existing retrievers on the scientific document retrieval and downstream QA tasks;
- Further analysis demonstrates the complementarity of metrics based on different granularities and the generalization of `MixGR` in retrieving units finer than documents.

2 Preliminary and Related works

Generalization of Dense Retrievers Dense retrievers generally employ a dual-encoder framework (Yih et al., 2011; Reimers and Gurevych, 2019) to separately encode queries and documents into compact vectors and measure relevance using a non-parametric similarity function (Mussmann and Ermon, 2016). However, the simplicity of the similarity function (e.g., cosine similarity) can restrict expressiveness, leading to suboptimal generalization in new domains such as scientific fields that differ from original training data (Thakur et al., 2021). To improve dense retrievers' adaptability across tasks, researchers have used data augmentation (Wang et al., 2022; Lin et al., 2023; Dai et al., 2023), continual learning (Chang et al., 2020; Sachan et al., 2021; Oguz et al., 2022), and task-aware training (Xin et al., 2022; Cheng et al., 2023). However, these methods still require training on domain-specific data, incurring additional computational costs. This work focuses on *zero-shot* generalization of dense retrievers to scientific fields by incorporating multi-granularity similarities within queries and documents.

Granularity in Retrieval For dense retrieval, the selection of the retrieval unit needs to balance the trade-off between completeness and compactness. Coarser units, like documents or fixed-length passages, theoretically encompass more context but may introduce extraneous information, adversely affecting retrievers and downstream tasks (Shi et al., 2023; Wang et al., 2023). Conversely, finer units like sentences are not always self-contained and may lose context, thereby hindering retrieval (Akkalyoncu Yilmaz et al., 2019; Yang et al., 2020). Additionally, some studies extend beyond complete sentences; for example, Lee et al. (2021a) use phrases as learning units to develop corresponding representations. Meanwhile, ColBERT (Khattab and Zaharia, 2020) addresses token-level query-doc interaction but is hampered by low efficiency.

Chen et al. (2023) propose using *propositions* as retrieval units, defined as atomic expressions of meaning (Min et al., 2023). These units are contextualized and self-contained, including necessary context through decontextualization, e.g., coreference resolution (Zhang et al., 2021). Proposition retrieval improves retrieval of documents with long-tail information, potentially benefiting domain-specific tasks. This motivates the use of propositions as retrieval units for scientific document retrieval. Furthermore, we extend fine granularity to queries and enhance the query-doc similarity measurement, moving from a point-wise assessment between two vectors to integrating multiple query-doc granularity combinations.

Fusion within Retrieval Each type of retriever, sparse or dense, has its own strength and can be complementary with each other. Based on this insight, previous studies have explored the fusion of searches conducted by different retrievers as a zero-shot solution for domain adaptation (Thakur et al., 2021). A common method involves the convex combination, which linearly combines similarity scores (Karpukhin et al., 2020; Wang et al., 2021b; Ma et al., 2021). However, this approach is sensitive to the weighting of different metrics and score normalization, which complicates configuration across different setups (Chen et al., 2022).

In this work, we enhance retrieval by integrating searches across various query and document granularity levels for a given retriever. To avoid the limitations of convex combination, we use Rank Reciprocal Fusion (RRF; Cormack et al. 2009), a robust, non-parametric method (Chen et al., 2022), to aggregate these searches.

3 `MixGR`: Mix-Granularity Retrieval

3.1 Finer Units in Queries and Documents

We first decompose queries and documents into atomic units, i.e., subqueries and propositions, respectively. A proposition (or subquery) should meet the following three principal criteria (Min et al., 2023):

- Each proposition conveys a distinct semantic unit, collectively expressing the complete meaning.
- Propositions should be atomic and indivisible.
- According to Choi et al. (2021), propositions should be contextualized and self-contained, including all necessary text information such as resolved coreferences for clear interpretation.

Here, we employ an off-the-shelf model, *propositioner*,[1] for decomposing queries and documents (Chen et al., 2023). This model is developed by distilling the decomposition capacities of GPT-4 (Achiam et al., 2023) to a Flan-T5-Large model

[1] https://huggingface.co/chentong00/propositionizer-wiki-flan-t5-large

	Query	Document
Accuracy (%)	96.3	94.7
IAA (%)	92.0	89.0

Table 1: Human-evaluated accuracy of query/document decomposition by *propositioner* (Chen et al., 2023).

(Chung et al., 2024) using Wikipedia as the corpus. We sample decomposition results from 100 queries and 100 documents from the datasets in §4.1 and manually label the correctness of decomposition as shown in Table 1. This model is shown to effectively decompose queries and documents into atomic units within scientific domains. Please see Appendix B for further details.

3.2 Multi-Granularity Similarity Calculation

Given these various granularities including queries, subqueries, documents and propositions, we extend the query-doc similarity metrics to include measurements across different combinations of granularities as depicted in Figure 2.

Notations The sets of queries and documents are denoted as $\mathcal{Q}$ and $\mathcal{D}$, respectively. Given a retriever s, the similarity between a query $\mathrm{q} \in \mathcal{Q}$ and a document $\mathrm{d} \in \mathcal{D}$ is denoted as $s(\mathrm{q}, \mathrm{d})$. A document d can be decomposed to N propositions, i.e., $\mathrm{d} = [d_1, ..., d_N]$. And a query q can be decomposed to M subqueries, i.e., $\mathrm{q} = [q_1, ..., q_M]$.

Query-doc $s_{q\text{-}d}$: The direct and original similarity between q and d is $s_{q\text{-}d}(\mathrm{q}, \mathrm{d}) \equiv s(\mathrm{q}, \mathrm{d})$.

Query-prop $s_{q\text{-}p}$: Recent works (Chen et al., 2023) determine query-doc similarity by calculating the maximum similarity between the **query** and individual **propositions** within the document (Lee et al., 2021b; Chen et al., 2023). The computation of this metric, denoted as $s_{q\text{-}p}$, is as follows:

$$s_{q\text{-}p}(\mathrm{q}, \mathrm{d}) = \max_{i=1,\dots,N} \{s(\mathrm{q}, d_i)\}. \quad (1)$$

Subquery-prop $s_{s\text{-}p}$: Considering that different parts of a query may be captured by various propositions within a document shown in Figure 1b, we further assess query-doc similarity by analyzing the relationships between **subqueries** and individual **propositions**. The similarity between a query and a document can be defined as the average similarity across subqueries, calculated by identifying the maximum similarity between one subquery and each proposition, in analogy to MaxSim in ColBERT (Khattab and Zaharia, 2020). This metric, represented by $s_{s\text{-}p}$, is calculated as:

$$s_{s\text{-}p}(\mathrm{q}, \mathrm{d}) = \frac{1}{M} \sum_{i=1}^{M} \max_{j=1,\dots,N} \{s(q_i, d_j)\}. \quad (2)$$

3.3 Rank Reciprocal Fusion

We then use RRF to fuse these metrics across different query and document granularities:

$$s_f(\mathrm{q}, \mathrm{d}) = \frac{1}{1 + r_{q\text{-}d}(\mathrm{q}, \mathrm{d})} + \frac{1}{1 + r_{q\text{-}p}(\mathrm{q}, \mathrm{d})} + \frac{1}{1 + r_{s\text{-}p}(\mathrm{q}, \mathrm{d})}, \quad (3)$$

where $r_{q\text{-}d}$, $r_{q\text{-}p}$, $r_{s\text{-}p} \in \mathbb{R}_{\geq 0}$ signify the rank of the retrieve results by $s_{q\text{-}d}$, $s_{q\text{-}p}$, and $s_{s\text{-}p}$, respectively. Technically, we retrieve the top-k results $R^k_{q\text{-}d}$, $R^k_{q\text{-}p}$, and $R^k_{s\text{-}p}$ by $s_{q\text{-}d}$, $s_{q\text{-}p}$, and $s_{s\text{-}p}$, respectively, where k is set 200 empirically. When a query-doc pair $(\mathrm{q}', \mathrm{d}')$ in one retrieval result does not exist in the other sets (e.g., $(\mathrm{q}', \mathrm{d}') \in R^k_{q\text{-}d}$ but $(\mathrm{q}', \mathrm{d}') \notin R^k_{q\text{-}p}$), we will calculate the missing similarity (e.g., $s_{q\text{-}p}(\mathrm{q}', \mathrm{d}')$) before aggregation.

4 Experimental Setting

4.1 Scientific Retrieval Datasets

We evaluate our approach on four different scientific retrieval tasks, including NFCorpus (Boteva et al., 2016), SciDocs (Cohan et al., 2020), SciFact (Wadden et al., 2020), and SciQ (Welbl et al., 2017), as shown in Table 4 in Appendix A. We employ the *propositioner* released by Chen et al. (2023) mentioned in §3.1 to break down both queries and documents to atomic units. As we focus with priority on query-doc complexity in scientific domains, we report the experiments and analysis on the subset of the queries which contain multiple subqueries.

4.2 Dense Retrievers

We evaluate the performance of six off-the-shelf dense retrievers, both supervised and unsupervised. Supervised retrievers are trained using human-labeled query-doc pairs in general domains,[2] while unsupervised models do not require labeled data. These retrievers encode the queries and index the corpus at both document and proposition levels:

[2]The supervised retrievers used in our experiment have not been trained on these four datasets.

Retriever	Setup	NFCorpus ND@5	NFCorpus ND@20	SciDocs ND@5	SciDocs ND@20	SciFact ND@5	SciFact ND@20	SciQ ND@5	SciQ ND@20	Avg. ND@5	Avg. ND@20
Unsupervised Dense Retrievers											
SimCSE	$s_{q\text{-}d}$	16.2	13.3	7.6	9.7	27.1	31.2	62.3	67.3	28.3	30.4
	$s_{q\text{-}p}$	20.0	16.4	8.2	11.1	32.8	37.2	75.6	78.5	34.1	35.8
	$s_{s\text{-}p}$	**22.8**	**18.3**	7.3	10.5	32.7	36.9	80.9	83.2	35.9	37.2
	`MixGR`	22.3	18.1	**9.1**	**12.2**	**34.8**	**39.8**	**84.0**	**85.5**	**37.5** (+32.5%)	**38.9** (+28.0%)
Contriever	$s_{q\text{-}d}$	42.2	34.9	13.5	18.5	64.5	68.5	67.2	70.0	46.9	48.0
	$s_{q\text{-}p}$	43.0	35.5	14.5	19.4	64.0	68.9	79.7	81.0	50.3	51.2
	$s_{s\text{-}p}$	41.4	34.9	13.5	18.3	63.2	67.5	83.6	84.6	50.4	51.3
	`MixGR`	**44.0**	**37.1**	**15.5**	**20.7**	**66.4**	**71.0**	**85.2**	**86.7**	**52.8** (+12.6%)	**53.9** (+12.3%)
Supervised Dense Retrievers											
DPR	$s_{q\text{-}d}$	25.1	20.7	7.3	10.4	31.8	37.7	60.6	64.1	31.2	33.2
	$s_{q\text{-}p}$	25.2	20.6	7.8	10.6	36.1	40.5	63.6	67.9	33.2	34.9
	$s_{s\text{-}p}$	26.5	21.4	6.4	10.0	37.1	41.3	67.7	70.7	34.4	35.9
	`MixGR`	**27.7**	**22.9**	**8.2**	**11.5**	**39.4**	**43.6**	**73.6**	**76.1**	**37.2** (+19.2%)	**38.5** (+16.0%)
ANCE	$s_{q\text{-}d}$	29.9	24.4	9.3	13.1	41.5	45.3	66.4	69.1	36.8	38.0
	$s_{q\text{-}p}$	29.4	24.0	9.2	12.9	43.3	46.4	62.3	66.4	36.0	37.4
	$s_{s\text{-}p}$	30.3	24.5	7.5	11.9	43.5	47.3	66.1	69.1	36.9	38.2
	`MixGR`	**31.9**	**25.9**	**9.6**	**14.1**	**46.8**	**49.9**	**74.4**	**76.8**	**40.7** (+10.6%)	**41.7** (+9.7%)
TAS-B	$s_{q\text{-}d}$	42.3	34.1	13.8	19.3	60.1	65.6	84.8	86.3	50.2	51.3
	$s_{q\text{-}p}$	42.5	34.4	14.3	18.1	60.7	64.4	85.6	86.3	50.8	50.8
	$s_{s\text{-}p}$	40.9	33.1	12.6	17.2	61.7	65.0	85.3	86.6	50.1	50.5
	`MixGR`	**43.6**	**35.2**	**14.0**	**19.6**	**62.7**	**66.9**	**90.5**	**91.0**	**52.7** (+5.0%)	**53.2** (+3.7%)
GTR	$s_{q\text{-}d}$	42.1	34.1	**13.6**	18.9	58.3	62.2	83.3	84.4	49.3	49.9
	$s_{q\text{-}p}$	42.3	34.4	13.2	18.0	60.6	63.3	85.8	86.5	50.5	50.6
	$s_{s\text{-}p}$	41.5	33.6	11.6	16.2	58.4	62.0	88.5	89.0	50.0	50.2
	`MixGR`	**43.3**	**35.6**	**13.6**	**19.2**	**60.9**	**64.5**	**92.9**	**93.0**	**52.7** (+6.9%)	**53.1** (+6.4%)

Table 2: Document Retrieval Performance (nDCG@k = 5, 20 in percentage, abbreviated as ND@k): We evaluated four distinct scientific retrieval datasets using two unsupervised and four supervised retrievers. The retrieval results were compared among various metrics: $s_{q\text{-}d}$ (previous query-doc similarity), $s_{q\text{-}p}$ (Chen et al., 2023), $s_{s\text{-}p}$, and `MixGR`, as detailed in §3.2. **Bold** presents the best performance across the metrics, while underline denotes the second-best performance. `MixGR` outperforms all three other metrics, where the percentage in parentheses indicates the relative improvement compared with $s_{q\text{-}d}$.

- SimCSE (Gao et al., 2021) employs a BERT-base (Devlin et al., 2019) encoder trained on randomly selected unlabeled Wikipedia sentences.
- Contriever (Izacard et al., 2022) is an unsupervised retriever evolved from a BERT-base encoder, contrastively trained on segments from unlabelled web and Wikipedia documents.
- DPR (Karpukhin et al., 2020) is built with a dual-encoder BERT-base architecture, finetuned on a suite of open-domain datasets with labels, such as SQuAD (Rajpurkar et al., 2016).
- ANCE (Xiong et al., 2021) mirrors the configuration of DPR but incorporates a training scheme of Approximate Nearest Neighbor Negative Contrastive Estimation (ANCE).
- TAS-B (Hofstätter et al., 2021) is a dual-encoder BERT-base model distilled from ColBERT on MS MARCO (Nguyen et al., 2016).
- GTR (Ni et al., 2022) is a T5-base encoder, focusing on generalization, pre-trained on unlabeled QA pairs, and fine-tuned on labeled data including MS MARCO.

More details on retrievers and experimental setups are presented in Appendices C and D.

4.3 Document Retrieval Evaluation

We assess the performance of `MixGR` in the task of document retrieval. Due to input length limitations for retrievers (Karpukhin et al., 2020), we divide each document into fixed-length chunks of up to 128 words. In practice, for `MixGR` and baselines, we identify the retrieved chunks, map them back to their original documents, and return the top-k documents. We use Normalised Cumulative Discount Gain (nDCG@k) as the evaluation metrics for document retrieval. Unlike Recall@k, which only indicates the presence of golden documents in the retrieved list, nDCG@k also accounts for both the ranking of retrievals and the relevance judgment of golden documents (Thakur et al., 2021). The baselines will be the metrics containing the homogeneous granularity introduced in the previous section, i.e., $s_{q\text{-}d}$, $s_{q\text{-}p}$ and $s_{s\text{-}p}$.

4.4 Downstream QA Evaluation

As previously mentioned, scientific documents are vital for LLMs due to the rapid advancements in science and the limited availability of such content in training datasets. To better understand how `MixGR` enhances downstream QA tasks, we implement the *retrieval-then-read* approach on two datasets SciQ and SciFact. We retrieve and rank the top-k documents based on scores, $s_{q\text{-}d}$ and `MixGR`, then concatenate them to form the context. During our evaluations, we limit the number of document chunks retrieved to 1 and 3—thus, only the top k documents are injected into the reader model. We assess the performance by measuring the Exact Match (EM) rate—the proportion of responses where the predicted answer perfectly aligns with the reference answer (Kamalloo et al., 2023), denoted as EM@k. Specifically, we utilize LLama-3-8B-Instruct [3] (Touvron et al., 2023) as the reader model. We take the original query-doc retrieval setup, i.e., retrieval based on $s_{q\text{-}d}$, as the baseline. Please refer to Appendix E for more details.

5 Results

This section analyzes the impact of mixed-granularity retrieval on document retrieval and downstream applications. We highlight the effectiveness of our proposed fine-grained and mixed-granularity approaches in enhancing performance across various metrics.

5.1 Document Retrieval

Table 2 reports the results of document retrieval. We observe that retrieval by `MixGR` outperforms all single-granularity retrieval with both unsupervised and supervised dense retrievers in most cases.

With unsupervised retrievers, `MixGR` significantly outperforms the query-doc similarity, $s_{q\text{-}d}$, across all four datasets. There is an average nDCG@5 improvement of +9.2 and +5.9 (32.5% and 12.6% relatively) for SimCSE and Contriever, respectively.

With supervised retrievers, improvements associated with `MixGR` are also observed, although they are not as significant as with unsupervised retrievers. This indicates that `MixGR` effectively narrows the distributional gap between dense retrievers and scientific domains.

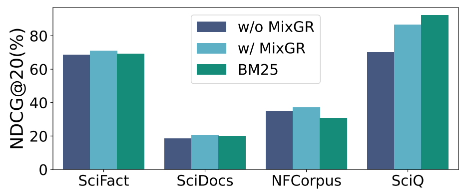


Figure 3: Comparison between BM25 and Contriever (w/ and w/o `MixGR`) on nDCG@20: Contriever w/ `MixGR` outperforms BM25 in three out of four datasets.

Unsupervised retrievers benefit more from `MixGR` than supervised ones. Remarkably, with `MixGR`, the unsupervised retriever Contriever outperforms supervised models, as evidenced by its superior average results across four datasets. This result is particularly significant given that Contriever typically underperforms compared to TAS-B and GTR when evaluated using traditional query-document similarity measures. Additionally, the study (Thakur et al., 2021) reveals that sparse retrievers like BM25 often excel over dense retrievers in domain-specific retrieval tasks. As shown in Figure 3, Contriever outperforms BM25 in three out of four datasets when applied with `MixGR`. Similarly, SimCSE also outperforms DPR under the `MixGR` scheme. These findings emphasize the substantial enhancements that `MixGR` contributes to unsupervised retrievers within scientific domains.

Finer granularity helps retrieval more. Among three metrics within `MixGR`, the subquery-proposition measurement $s_{s\text{-}p}$ shows a distinct advantage over the other two, as highlighted by the underlined results in Table 2. The original query-doc metric, $s_{q\text{-}d}$, outperforms the subquery-proposition measurement only when using the retriever TAS-B. These findings corroborate and expand upon Chen et al. (2023), suggesting that finer query-doc similarity measurement significantly improves document retrieval performance.

5.2 Downstream QA Tasks

Table 3 reports the results of scientific question answering when the documents retrieved by `MixGR` are fed into LLMs, i.e. the readers. It is observed that EM scores achieved with `MixGR` generally surpass those of the baseline across two datasets, six dense retrievers, and multiple numbers of input documents. This underscores the effectiveness

[3] https://huggingface.co/meta-llama/Meta-Llama-3-8B-Instruct

Setup		SciFact EM@1	SciFact EM@3	SciQ EM@1	SciQ EM@3
Unsupervised Dense Retrievers					
SimCSE	$s_{q\text{-}d}$	**50.0**	61.6	54.7	58.2
	`MixGR`	48.3	**62.8**	**61.3**	**66.4**
Contriever	$s_{q\text{-}d}$	63.4	**75.6**	53.9	63.3
	`MixGR`	**64.0**	70.9	**61.7**	**66.0**
Supervised Dense Retrievers					
DPR	$s_{q\text{-}d}$	51.2	59.9	52.0	57.4
	`MixGR`	**51.7**	**65.7**	**57.4**	**62.5**
ANCE	$s_{q\text{-}d}$	51.7	65.1	52.7	59.4
	`MixGR`	**57.6**	**69.2**	**54.7**	**62.9**
TAS-B	$s_{q\text{-}d}$	62.8	74.4	60.5	66.4
	`MixGR`	**62.2**	**70.3**	**64.5**	**67.6**
GTR	$s_{q\text{-}d}$	61.0	72.1	59.8	64.8
	`MixGR`	**62.8**	**73.8**	**64.1**	**66.0**

Table 3: Scientific Question Answering on SciFact and SciQ using Llama-3-8B-Instruct (Touvron et al., 2023): the top-1 and 3 document chunks retrieved by retrievers, following the metrics $s_{q\text{-}d}$ and `MixGR`, were fed into the reader. **Bold** indicates the better performance.

of `MixGR` in enhancing the performance of downstream QA tasks.

6 Analysis

In this section, we explore the complementary advantages of various similarity metrics across multiple granularities within `MixGR` through an ablation study. Although the finer-granularity metric, $s_{s\text{-}p}$, generally enhances performance as previously discussed, it can occasionally result in degradation when compared to original query-document similarity $s_{q\text{-}d}$. We identify specific conditions under which the finer-granularity metric offers greater benefits. Previous works (Chen et al., 2023) primarily explored multiple granularities in *documents*. We conduct a control experiment to highlight the significance of incorporating multiple granularities in *queries* in the `MixGR` framework, which also validate the generalization of `MixGR` on the retrieval units finer than documents.

6.1 Ablation Study

In our ablation study, we conducted a systematic evaluation of the impact of various granularity measures—$s_{q\text{-}d}$ (query-doc similarity), $s_{q\text{-}p}$ (query-prop similarity), and $s_{s\text{-}p}$ (subquery-prop similarity)—on the performance of six retrievers. By individually omitting each of these measures from the calculation of `MixGR` as defined in Equation 3, we assessed the significance of each granularity level. Specifically, the extent of performance degradation upon removal of a measure indicates its importance; greater degradation suggests higher importance of that particular granularity metric.

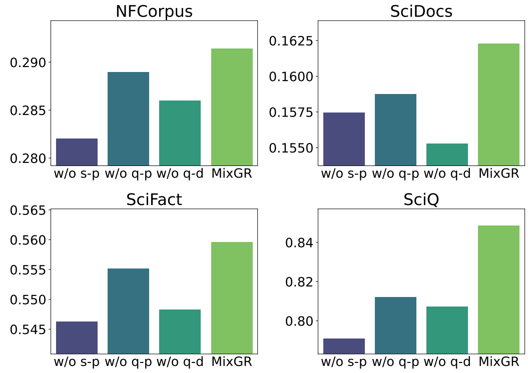


Figure 4: Ablation study of `MixGR` on the nDCG@20 metrics averaged on six retrievers: `MixGR` achieves optimal performance when combining these three metrics, indicating their complementary nature.

As illustrated in Figure 4, the nDCG@20 performance declined across all three setups and datasets, demonstrating that the metrics are complementary to each other. The degree of performance degradation varied across different configurations, highlighting the importance of each granularity measure. Notably, the most significant declines in performance consistently occurred in configurations excluding $s_{q\text{-}d}$ and $s_{s\text{-}p}$. This observation suggests that $s_{q\text{-}p}$, while beneficial, is the *least* critical measure for retrieval tasks in scientific domains. Please refer to Table 6 in Appendix F.1 for detailed results.

6.2 When is finer granularity beneficial?

Therefore, to more effectively compare the impacts of $s_{q\text{-}d}$ and $s_{s\text{-}p}$, we categorized the *correctly* retrieved pairs (complex query, [4] doc) by `MixGR` in SciFact, using SimCSE, into two distinct groups:

- $r_{q\text{-}d} \succ r_{s\text{-}p}$: The query-doc rank of $s_{q\text{-}d}$ is higher than the subquery-prop rank of $s_{s\text{-}p}$;
- $r_{q\text{-}d} \prec r_{s\text{-}p}$: The query-doc rank of $s_{q\text{-}d}$ is lower than the subquery-prop rank of $s_{s\text{-}p}$.

Upon analyzing the number of propositions in documents, a significant pattern emerges: based on the distributions present in Figure 5, the number of propositions in $r_{q\text{-}d} \prec r_{s\text{-}p}$ is generally higher than in $r_{q\text{-}d} \succ r_{s\text{-}p}$. This underscores the importance of incorporating finer units within documents, especially for those containing more propositions, and suggests potential degradation in dense retrievers

[4] We refer *complex query* as the query containing no fewer than three subqueries.

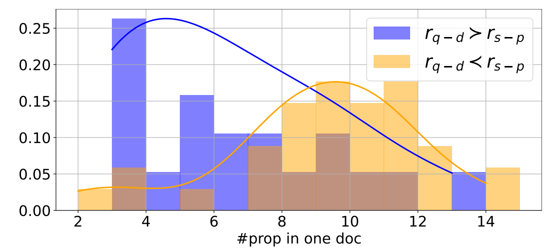


Figure 5: Distribution of proposition number within documents in two sets. There are more propositions within document when $r_{q\text{-}d} \prec r_{s\text{-}p}$ than $r_{q\text{-}d} \succ r_{s\text{-}p}$.

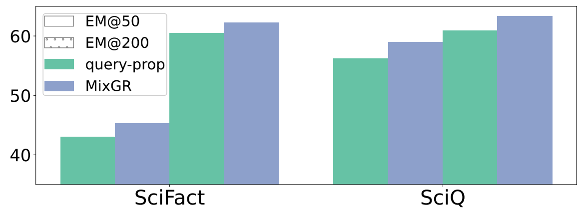


Figure 6: Proposition retrieval with `MixGR`: We evaluate Exact Match of LLama-3-8B-Instruct on SciFact and SciQ with the first 50 and 200 words of propositions, i.e., EM@50 and EM@200, retrieved by SimCSE as the context. Please refer to Table 7 for other retrievers in Appendix F.2.

when handling such documents. For other retrievers' results, please refer to Appendix F.3.

6.3 `MixGR` on Proposition Retrieval

Previous sections present the effectiveness of `MixGR` on scientific document retrieval. While previous works (Chen et al., 2023) focus on finer document granularity, we specifically assess `MixGR` on the proposition as the retrieval units. This controlled study highlights the benefits of `MixGR`, which incorporates different granularities within queries and documents, in general text retrieval beyond document-level granularity.

For a given query q and a proposition p, the conventional similarity is denoted by $s^p_{q\text{-}p} \equiv s(\mathrm{q}, \mathrm{p})$. When the query is further broken down into multiple sub-queries, we introduce a finer granularity measure, $s^p_{s\text{-}p}$, which is defined as the maximum similarity between these sub-queries and the proposition. $s^p_{s\text{-}p}$ is mathematically defined as follows:

$$s^p_{s\text{-}p}(\mathrm{q}, \mathrm{p}) = \max_{i=1,\ldots,M} \{s(q_i, \mathrm{p})\}. \quad (4)$$

Therefore, the merged score by RRF, $s^p_f(\mathrm{q}, \mathrm{p})$, is calculated as:

$$s^p_f(\mathrm{q}, \mathrm{p}) = \frac{1}{1 + r^p_{q\text{-}p}(\mathrm{q}, \mathrm{p})} + \frac{1}{1 + r^p_{s\text{-}p}(\mathrm{q}, \mathrm{p})}, \quad (5)$$

where $r^p_{q\text{-}p}$ and $r^p_{s\text{-}p}$ signify the rank of the retrieve results by $s^p_{q\text{-}p}$ and $s^p_{s\text{-}p}$, respectively.

Following $s^p_{q\text{-}p}(\mathrm{q}, \mathrm{p})$ and $s^p_f(\mathrm{q}, \mathrm{p})$, we input the first 50 and 200 words in propositions retrieved with SimCSE on SciFact and SciQ into the reader LLama-3-8B-Instruct. This process adheres to the same setups outlined in §4.4. As shown in Figure 6, the performance advance observed with mixed-granularity retrieval on propositions, compared to the original query-prop similarity, demonstrates the effectiveness of using mixed-granularity in retrieval. This substantiates the generalizability of `MixGR` beyond document-level granularity. Please refer to Appendix F.2 for details.

6.4 Prospect: Adaptive `MixGR`

Here, we outline potential future research directions. In §6.1, we observed the complementary nature of retrieval results achieved using different granularities. Additionally, as discussed in §6.2, we noted a distinct pattern where retrieval guided by a specific granularity outperforms others. These findings indicate that metrics based on different granularities each have relatively distinct strengths in specific contexts, presenting opportunities for further exploration. Unlike the non-parametric method of fusion by RRF, which overlooks the relative importance of components, an adaptive approach could enhance fusion and, consequently, improve retrieval performance with dense retrievers–a prospect we aim to explore in future research.

7 Conclusion

In this work, we identify key challenges for dense retrievers in scientific document retrieval, namely domain shift and query-document complexity. In response, we propose a zero-shot approach, `MixGR`, that utilizes atomic components in queries and documents to calculate their similarity with greater nuance. We then use Rank Reciprocal Fusion (RRF) to integrate these metrics, modeling query-doc similarity at different granularities into a unified score that enhances document retrieval.

Our experiments demonstrate that `MixGR` significantly enhances the existing dense retriever on document retrieval within the scientific domain. Moreover, `MixGR` has proven beneficial for downstream applications such as scientific QA. The analysis reveals a synergistic relationship among the components of `MixGR`, and suggests evolving our non-parametric fusion framework into a more general method as a future research direction.

Limitation

Our work explores retrieval guided by an integral metric that incorporates various levels of granularity. We identify several limitations in our approach: (1) *Coverage of Retrievers*: Our study categorizes dense retrievers into supervised and unsupervised models, yet all utilize a dual-encoder structure. Future studies could include a more diverse array of retriever architectures. (2) *Coverage of Domains*: While our main focus is on the scientific domain, and we extend to three additional domains in Appendix G, there are still many domains we have not explored. (3) *Languages*: Our research is limited to an English corpus. The applicability of `MixGR` in multilingual contexts also deserves further validation and exploration.

Ethical Statements

We foresee no ethical concerns and potential risks in our work. All of the retrieval models and datasets are open-sourced, as shown in Table 10 in Appendix H. The LMs we applied are also publicly available. Given our context, the outputs of LLMs should be insensitive.

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Appendix

A Datasets

Different from the setup of the original dataset, we split one document into several chunks with a maximum of 128 words. This is because some dense retrievers such as DPR (Karpukhin et al., 2020) have the requirement of maximum input. Too long inputs will be overflow, leading to the loss of information. The chunk selected can be used to locate the document in the original dataset during the evaluation. Specifically, for SciQ, we reformulate the dataset from a QA task to a retrieval task. Originally, this task aims to answer scientific questions given the context. We collect the contexts in training, validation and test sets as the corpus.

Also, we will explain our motivation of focusing the queries containing subqueries:

- Chen et al. (2023) have studied the advantage of using propositions, i.e., the atomic units within documents, as the retrieval units given a complete query. And `MixGR` will not affect the retrieval results of single-subquery queries.

- In this work, we highlight the advantages of mixed-granularity retrieval that incorporates finer units in both queries and documents. Queries containing multiple subqueries are particularly well-suited to our research problem, as they will have different combinations with the documents.

Statistic	**NFCorpus** (Boteva et al., 2016)	**SciDocs** (Cohan et al., 2020)	**SciFact** (Wadden et al., 2020)	**SciQ** (Welbl et al., 2017)
#Query	1 016	1 000	1 109	884
#Multi-semantics queries	647	206	283	256
#Subqueries	3 337	522	614	874
#Documents	3 633	25 657	5 183	12 241
#Propositions	67 110	351 802	87 190	91 635

Table 4: Statistics for the NFCorpus, SciDocs, SciFact, and SciQ datasets.

B Query and Document Decomposition

Here, we will complement the necessary information regarding the query and document decomposition.

B.1 Subquery and Proposition Examples

Here, we present examples of subqueries and propositions decomposed from the documents. The example is the decomposition of the example in Figure 1.

Query: Citrullinated proteins externalized in neutrophil extracellular traps act indirectly to perpetuate the inflammatory cycle via induction of autoantibodies.

- Subquery-0: Citrullinated proteins are externalized in neutrophil extracellular traps.
- Subquery-1: Citrullinated proteins act indirectly to perpetuate the inflammatory cycle.
- Subquery-2: The inflammatory cycle is perpetuated via induction of autoantibodies.

Document: RA sera and immunoglobulin fractions from RA patients with high levels of ACPA and/or rheumatoid factor significantly enhanced NETosis, and the NETs induced by these autoantibodies displayed distinct protein content. Indeed, during NETosis, neutrophils externalized the citrullinated autoantigens implicated in RA pathogenesis, and anti-citrullinated vimentin antibodies potently induced NET formation. Moreover, the inflammatory cytokines interleukin-17A (IL-17A) and tumor necrosis factor-α (TNF-α) induced NETosis in RA neutrophils. In turn, NETs significantly augmented inflammatory responses in RA and OA synovial fibroblasts, including induction of IL-6, IL-8, chemokines, and adhesion molecules. These observations implicate accelerated NETosis in RA pathogenesis, through externalization of citrullinated autoantigens and immunostimulatory molecules that may promote aberrant adaptive and innate immune responses in the joint and in the periphery, and perpetuate pathogenic mechanisms in this disease.

- Proposition-0: RA sera and immunoglobulin fractions from RA patients with high levels of ACPA and/or rheumatoid factor significantly enhanced NETosis.
- Proposition-1: NETs induced by these autoantibodies displayed distinct protein content.
- Proposition-2: During NETosis, neutrophils externalized the citrullinated autoantigens implicated in RA pathogenesis.
- Proposition-3: Anti-citrullinated vimentin antibodies potently induced NET formation.
- Proposition-4: Interleukin-17A (IL-17A) and tumor necrosis factor- (TNF-) induced NETosis in RA neutrophils.
- Proposition-5: NETs significantly augmented inflammatory responses in RA and OA synovial fibroblasts.
- Proposition-6: NETs inducing IL-6, IL-8, chemokines, and adhesion molecules occurred in RA and OA synovial fibroblasts.
- Proposition-7: These observations implicate accelerated NETosis in RA pathogenesis.
- Proposition-8: NETosis externalizes citrullinated autoantigens and immunostimulatory molecules.
- Proposition-9: NETosis may promote aberrant adaptive and innate immune responses in the joint and in the periphery.
- Proposition-10: NETosis may perpetuate pathogenic mechanisms in RA.

B.2 Remarks on *Propositioner*

During our manual check on the decomposition results of *propositioner* (Chen et al., 2023), we find the following potential flaws.

(1) Wrong logic during decomposition:

Query: Identification of Design Elements for a Maturity Model for Interorganizational Integration: A Comparative Analysis
→ *Subqueries*: ['Identification of Design Elements for a Maturity Model for Interorganizational Integration.', 'A Comparative Analysis is used for identifying design elements.']

(2) Hallucination:

Query: Bigger ocean waves and waves that carry more sediment cause a greater extent of what?
→ *Subqueries*: ['Bigger ocean waves cause a greater extent of erosion.', 'Waves that carry more sediment cause a greater extent of erosion.']

(3) Information loss:

Query: The reduction was 1.6 ± 1.6 in controls. ...
→ *Subqueries*: ['The reduction in migraine headache was 1.6 1.6 in controls.', ...]

We find that the proposition will convert the questions to declarative sentences during decomposition. This may stem from the fact that its training corpus is Wikipedia, where a small portion of sentences are questions. Still, we find that *propositioner* can still decompose question-style queries, as shown in the following example:

Query: What is the purpose of bright colors on a flower's petals?
→ *Subqueries*: ["The purpose of bright colors on a flower's petals is unknown."]

B.3 Human Evaluation on Query and Document Decomposition

As mentioned in §3.1, we evaluate the decomposition outputs by *propositioner* (Chen et al., 2023), 100 samples for both query and document decomposition. Concretely, we ask three students at the post-graduate levels to evaluate the results, who are paid above the local minimum hourly wage. The instruction is shown below:

Propositions in documents (or subqueries in queries) are defined as follows:

- Each proposition conveys a distinct semantic unit, collectively expressing the complete meaning.
- Propositions should be atomic and indivisible.
- According to Choi et al. (2021), propositions should be contextualized and self-contained, including all necessary text information such as coreferences for clear interpretation.

Given the document (query) and the corresponding propositions (subqueries) generated by the model, please check whether the document (query) has been correctly decomposed.
Please write *1* as correct, and *0* as incorrect.

C Retrievers Models

Table 5 presents the dense retrievers applied in the experimental section, i.e., §4.

D Offline Indexing

The `pyserini` and `faiss` libraries were employed to convert retrieval units into embeddings. We leveraged GPUs for encoding these text units in batches with a batch size of 64 and a floating precision

Model	HuggingFace Checkpoint
SimCSE (Gao et al., 2021)	`princeton-nlp/unsup-simcse-bert-base-uncased`
Contriever (Izacard et al., 2022)	`facebook/contriever`
DPR (Karpukhin et al., 2020)	`facebook/dpr-ctx_encoder-multiset-base`
	`facebook/dpr-question_encoder-multiset-base`
ANCE (Xiong et al., 2021)	`castorini/ance-dpr-context-multi`
	`castorini/ance-dpr-question-multi`
TAS-B (Hofstätter et al., 2021)	`sentence-transformers/msmarco-distilbert-base-tas-b`
GTR (Ni et al., 2022)	`sentence-transformers/gtr-t5-base`

Table 5: Model checkpoints released on HuggingFace. For DPR and ANCE, two different models encode the context and query.

f16. Following the preprocessing of these embeddings, all experiments conducted involved the utilization of an exact search method for inner products using `faiss.IndexFlatIP`,

E Downstream Tasks

The templates of LLama for downstream QA tasks, i.e., SciFact and SciQ, are listed as follows. For SciQ, we convert it from multiple choice question answering to open question answering.

> Given the knowledge source: *context* \\n Question: *query* \\n Reply with one phrase. \\n Answer:

As SciFact is a fact-checking task, we here check whether LLMs can predict the relationship between the context and the claim. The template of SciFact is shown as follows:

> Context: {*context*} \\n Claim: {*query*} \\n For the claim, the context is supportive, contradictory, or not related? \\n Options: (A) Supportive (B) Contradictory (C) Not related \\n Answer:")

F Detailed Results

F.1 Ablation Study

As discussed in §6.1, we remove the component, i.e., query-doc similarity, query-prop similarity, or subquery-prop similarity, and assess the corresponding performance compared with `MixGR`. In Table 6, it is observed that `MixGR` outperforms all its components.

F.2 `MixGR` for Propositional Retrieval

Here, we evaluate `MixGR` on the retrieval units beyond documents, e.g., propositions, which Table 7 present. We observe that `MixGR` can outperform the previous document retrieval based on the similarity between query and proposition, on proposition retrieval, as discussed in §6.3.

F.3 Advantageous pattern for finer granularity measurement

In Table 8, we can notice the average number of propositions in $r_{q\text{-}d} \prec r_{s\text{-}p}$ is more than $r_{q\text{-}d} \succ r_{s\text{-}p}$. This shows that the finer granularity can better deal with the documents with more propositions than the original query-document simillarity.

G `MixGR` for Other Domains

Our work provides a comprehensive analysis of the impact of `MixGR` on scientific text retrieval, considering both the variety of datasets and the use of dense retrievers. The applicability of `MixGR` to other domains remains an open question. We explore this by conducting document retrieval experiments on three distinct datasets: ConditionalQA (Sun et al., 2022), FiQA (Maia et al., 2018), and Arguana (Wachsmuth et al., 2018), which belong to the domains of law, finance, and argumentation, respectively.

Retriever	Setup	NFCorpus		SciDocs		SciFact		SciQ		Avg.	
		ND@5	ND@20	ND@5	ND@20	ND@5	ND@20	ND@5	ND@20	ND@5	ND@20
Unsupervised Dense Retrievers											
SimCSE	w/o $s_{s\text{-}p}$	19.6	16.0	8.7	11.5	32.3	37.0	76.1	78.0	34.2	35.6
	w/o $s_{q\text{-}p}$	21.4	17.4	8.5	11.6	33.1	37.4	77.9	79.6	35.2	36.5
	w/o $s_{q\text{-}d}$	22.8	18.6	8.5	11.9	33.9	39.0	80.7	82.2	36.5	37.9
	`MixGR`	22.3	18.1	9.1	12.2	34.8	39.8	84.0	85.5	37.5	38.9
Contriever	w/o $s_{s\text{-}p}$	43.6	36.2	14.8	20.0	65.6	69.9	78.0	80.1	50.5	51.5
	w/o $s_{q\text{-}p}$	43.0	36.6	14.6	20.1	66.3	70.8	81.6	83.3	51.4	52.7
	w/o $s_{q\text{-}d}$	43.2	36.3	14.7	20.0	65.0	69.5	83.3	84.8	51.6	52.6
	`MixGR`	44.0	37.1	15.5	20.7	66.4	71.0	85.2	86.7	52.8	53.9
Supervised Dense Retrievers											
DPR	w/o $s_{s\text{-}p}$	26.5	21.9	8.2	11.2	35.0	40.8	66.6	69.9	34.1	35.9
	w/o $s_{q\text{-}p}$	27.5	22.8	7.5	11.2	38.3	42.4	71.0	73.1	36.1	37.4
	w/o $s_{q\text{-}d}$	26.6	22.2	8.0	11.2	38.0	42.1	69.5	72.2	35.5	36.9
	`MixGR`	27.7	22.9	8.2	11.5	39.4	43.6	73.6	76.1	37.2	38.5
ANCE	w/o $s_{s\text{-}p}$	30.7	25.2	10.0	13.7	45.8	48.9	69.0	72.0	38.9	40.0
	w/o $s_{q\text{-}p}$	32.0	26.2	9.0	13.4	46.8	50.4	71.3	73.9	39.8	41.0
	w/o $s_{q\text{-}d}$	30.8	25.1	8.8	13.4	44.9	48.6	67.8	70.1	38.1	39.3
	`MixGR`	31.9	25.9	9.6	14.1	46.8	49.9	74.4	76.8	40.7	41.7
TAS-B	w/o $s_{s\text{-}p}$	42.9	34.7	13.8	19.2	61.4	66.7	86.7	87.0	51.2	51.9
	w/o $s_{q\text{-}p}$	42.9	34.9	13.8	19.6	63.2	67.3	88.3	88.8	52.1	52.7
	w/o $s_{q\text{-}d}$	42.7	34.5	13.6	18.8	62.1	65.3	85.2	85.9	50.9	51.1
	`MixGR`	43.6	35.2	14.0	19.6	62.7	66.9	90.5	91.0	52.7	53.2
GTR	w/o $s_{s\text{-}p}$	43.2	35.2	13.4	18.9	60.9	64.5	87.2	87.5	51.2	51.5
	w/o $s_{q\text{-}p}$	43.0	35.5	13.8	19.5	60.6	64.7	88.4	88.5	51.4	52.0
	w/o $s_{q\text{-}d}$	42.4	34.9	12.6	18.0	61.5	64.4	89.0	89.3	51.4	51.6
	`MixGR`	43.3	35.6	13.6	19.2	60.9	64.5	92.9	93.0	52.7	53.1

Table 6: Ablation study (nDCG@k = 5, 20 in percentage, abbreviated as ND@k): We evaluated four distinct scientific retrieval datasets using two unsupervised and four supervised retrievers. The retrieval results were compared using various metrics: `MixGR` w/o $s_{s\text{-}q}$, `MixGR` w/o $s_{q\text{-}p}$, `MixGR` w/o $s_{s\text{-}p}$, and `MixGR`, as detailed in §3.

The results are detailed in Table 9. We observe that `MixGR`'s benefits are considerably more limited, or even negative, outside the scientific context. This disparity may be attributed to the varying degrees of alignment between the domain-specific characteristics of each field and the training corpus of the dense retrievers. Or, *propositioner* can not perform well in these domains. Such findings further underscore the potentially distinct domain-specific nature of scientific document retrieval.

H Licences of Scientific Artifacts

	Setup	SciFact		SciQ	
		EM@50	EM@200	EM@50	EM@200
Unsupervised Dense Retrievers					
SimCSE	$s_{q\text{-}d}$	43.0	60.5	56.2	60.9
	MixGR	**45.3**	**62.2**	**59.0**	**63.3**
Contriever	$s_{q\text{-}d}$	**49.4**	67.4	56.2	**62.9**
	MixGR	47.7	**71.5**	**57.4**	62.5
Supervised Dense Retrievers					
DPR	$s_{q\text{-}d}$	49.4	56.4	55.5	60.2
	MixGR	**52.3**	**59.9**	**59.0**	**60.9**
ANCE	$s_{q\text{-}d}$	**47.1**	61.6	53.9	**60.5**
	MixGR	45.9	**66.9**	**55.5**	59.8
TAS-B	$s_{q\text{-}d}$	50.0	**69.8**	56.2	60.9
	MixGR	**52.3**	68.0	**58.2**	**62.9**
GTR	$s_{q\text{-}d}$	41.9	**66.3**	60.2	63.7
	MixGR	**45.9**	63.4	**60.9**	**65.2**

Table 7: Scientific Question Answering (Exact Match) was conducted using LLama-3 (Touvron et al., 2023) with propositions retrieved by six retrievers. Here, EM@50 and EM@200 have been reported, where the first 50 and 200 words are fed into the reader models. **Bold** indicates superior performance, and it is observed that retrieval using MixGR on proposition units generally outperforms the baseline.

Model	Avg. #prop in $r_{q\text{-}d} \prec r_{s\text{-}p}$	Avg. #prop in $r_{q\text{-}d} \succ r_{s\text{-}p}$
SimCSE	9.06	6.32
Contriever	8.25	7.24
ANCE	8.12	8.15
DPR	8.54	7.88
GTR	8.45	6.79
TAS-B	8.00	7.52

Table 8: Average number of propositions in two sets of document for different retrievers, i.e., $r_{q\text{-}d} \prec r_{s\text{-}p}$ and $r_{q\text{-}d} \succ r_{s\text{-}p}$. We can notice the average number of propositions in $r_{q\text{-}d} \prec r_{s\text{-}p}$ is more than $r_{q\text{-}d} \succ r_{s\text{-}p}$. This shows that the finer granularity can better deal with the documents with more propositions.

Retriever	Setup	Arguana		ConditionalQA		FiQA		Avg.	
		ND@5	ND@20	ND@5	ND@20	ND@5	ND@20	ND@5	ND@20
Unsupervised Dense Retrievers									
SimCSE	$s_{q\text{-}d}$	16.4	25.9	52.3	58.0	8.4	10.9	25.7	31.6
	$s_{q\text{-}p}$	12.5	20.9	53.7	59.5	7.6	9.7	24.6	30.0
	$s_{s\text{-}p}$	6.3	12.3	42.8	50.8	9.3	11.6	19.5	24.9
	`MixGR`	12.7	22.4	57.7	63.3	10.6	13.8	27.0	33.2
Contriever	$s_{q\text{-}d}$	25.9	36.0	82.5	83.9	25.0	29.9	44.5	49.9
	$s_{q\text{-}p}$	24.8	35.9	81.8	83.5	18.8	23.1	41.8	47.5
	$s_{s\text{-}p}$	24.1	34.5	63.3	67.2	18.6	22.9	35.3	41.5
	`MixGR`	28.7	39.2	83.5	84.5	24.7	29.8	45.6	51.2
Supervised Dense Retrievers									
DPR	$s_{q\text{-}d}$	9.0	16.6	58.5	63.6	12.0	14.6	26.5	31.6
	$s_{q\text{-}p}$	8.4	16.9	60.1	64.7	8.4	10.9	25.6	30.8
	$s_{s\text{-}p}$	6.1	12.2	34.8	41.8	9.2	11.8	16.7	21.9
	`MixGR`	8.2	16.3	59.9	65.4	11.2	14.9	26.4	32.2
ANCE	$s_{q\text{-}d}$	12.0	20.5	64.2	68.0	14.6	18.2	30.3	35.6
	$s_{q\text{-}p}$	11.7	21.3	64.0	68.2	8.5	10.9	28.1	33.5
	$s_{s\text{-}p}$	10.1	18.6	41.4	48.1	8.4	11.3	20.0	26.0
	`MixGR`	12.4	21.8	66.2	69.8	12.8	16.2	30.5	36.0
TAS-B	$s_{q\text{-}d}$	27.9	37.8	75.3	77.9	26.7	31.5	43.3	49.0
	$s_{q\text{-}p}$	18.8	30.5	76.4	78.7	15.3	19.7	36.8	43.0
	$s_{s\text{-}p}$	12.9	20.8	60.8	65.2	13.9	17.8	29.2	34.6
	`MixGR`	22.6	33.6	77.7	79.2	22.8	27.9	41.1	46.9
GTR	$s_{q\text{-}d}$	31.4	40.7	79.8	82.3	34.4	39.6	48.5	54.2
	$s_{q\text{-}p}$	25.6	36.9	80.1	82.0	22.8	27.4	42.8	48.8
	$s_{s\text{-}p}$	20.4	30.0	62.9	67.7	19.6	24.2	34.3	40.6
	`MixGR`	29.4	39.4	82.4	84.1	30.8	36.1	47.5	53.2

Table 9: Comparison between `MixGR` and its components on ConditionalQA, Arguana, and FiQA. We can find that the similarity based on the finer granularity $s_{s\text{-}p}$ and `MixGR` won't bring as many benefits as their performance in the scientific domains, even the degradation.

Artifacts/Packages	Citation	Link	License
Artifacts(datasets/benchmarks).			
SciFact	(Wadden et al., 2020)	`https://huggingface.co/datasets/BeIR/scifact`	cc-by-sa-4.0
SciDocs	(Cohan et al., 2020)	`https://huggingface.co/datasets/BeIR/scidocs`	cc-by-sa-4.0
SciQ	(Welbl et al., 2017)	`https://huggingface.co/datasets/bigbio/sciq`	cc-by-nc-3.9
NFCorpus	(Boteva et al., 2016)	`https://huggingface.co/datasets/BeIR/nfcorpus`	cc-by-sa-4.0
Packages			
PyTorch	(Paszke et al., 2019)	`https://pytorch.org/`	BSD-3 License
transformers	(Wolf et al., 2019)	`https://huggingface.co/transformers/v2.11.0/index.html`	Apache License 2.0
numpy	(Harris et al., 2020)	`https://numpy.org/`	BSD License
matplotlib	(Hunter, 2007)	`https://matplotlib.org/`	BSD compatible License
vllm	(Kwon et al., 2023)	`https://github.com/vllm-project/vllm`	Apache License 2.0
Models			
LLaMA-3	(Touvron et al., 2023)	`https://huggingface.co/meta-llama/Meta-Llama-3-8B-Instruct`	LICENSE
SimCSE	(Gao et al., 2021)	`https://huggingface.co/princeton-nlp/unsup-simcse-bert-base-uncased`	MIT license
Contriever	(Izacard et al., 2022)	`https://huggingface.co/facebook/contriever`	License
DPR	(Karpukhin et al., 2020)	`https://huggingface.co/facebook/dpr-ctx_encoder-multiset-base`	cc-by-nc-4.0
ANCE	(Xiong et al., 2021)	`https://huggingface.co/castorini/ance-dpr-context-multi`	MIT license
TAS-B	(Hofstätter et al., 2021)	`https://huggingface.co/sentence-transformers/msmarco-distilbert-base-tas-b`	Apache License 2.0
GTR	(Ni et al., 2022)	`https://huggingface.co/sentence-transformers/gtr-t5-base`	Apache License 2.0

Table 10: Details of datasets, major packages, and existing models we use. The datasets we reconstructed or revised and the code/software we provide are under the MIT License.