BEYOND CONTENT RELEVANCE: EVALUATING INSTRUCTION FOLLOWING IN RETRIEVAL MODELS

ABSTRACT

Instruction-following capabilities in large language models (LLMs) have significantly progressed, enabling more complex user interactions through detailed prompts. However, retrieval systems have not matched these advances, most of them still relies on traditional lexical and semantic matching techniques that fail to fully capture user intent. Recent efforts have introduced instruction-aware retrieval models, but these primarily focus on intrinsic content relevance, which neglects the importance of customized preferences for broader document-level attributes. This study evaluates the instruction-following capabilities of various retrieval models beyond content relevance, including LLM-based dense retrieval and reranking models. We develop ***InfoSearch***, a novel retrieval evaluation benchmark spanning six document-level attributes: *Audience*, *Keyword*, *Format*, *Language*, *Length*, and *Source*, and introduce novel metrics – Strict Instruction Compliance Ratio (SICR) and Weighted Instruction Sensitivity Evaluation (WISE) to accurately assess the models' responsiveness to instructions. Our findings reveal that while reranking models generally surpass retrieval models in instruction following, they still face challenges in handling certain attributes. Moreover, although instruction fine-tuning and increased model size lead to better performance, most models fall short of achieving comprehensive instruction compliance as assessed by our benchmark.

1 INTRODUCTION

The advent of instruction-following in large language models (LLMs) has greatly expanded their generative capabilities (Lou et al., 2023; Brown, 2020), allowing users to express more complex intentions through detailed instructions (Touvron et al., 2023; Black et al., 2022). However, advances in retrieval systems have not kept pace with these improvements in generative models. Many retrieval systems still rely heavily on traditional lexical or semantic matching techniques (Xiong et al., 2020; Xiao et al., 2023; Wang et al., 2022), which are often too limited to fully capture user intent. As a result, while users have grown accustomed to interacting with generative models using intricate instructions (Team et al., 2023; Bai et al., 2023; Achiam et al., 2023), their sophisticated search behaviors in retrieval remains constrained-primarily centered around keyword-based queries followed by manual filtering of results to find the desired information. Several studies have started to explore instruction-aware retrievers that can interact with users as seamlessly as generative models, but they mainly focus on task-level instructions (Asai et al., 2023; Wang et al., 2023; Su et al., 2023; Peng et al., 2024), guiding retrievers with one instruction for each task. While this task-level instruction is essential for adapting a single retrieval model to multiple predefined scenarios, it falls short of meeting users' customized demands beyond standard tasks (Weller et al., 2024b).

Recently, a few works have started shifting from task-level to instance-level instructions, providing tailored instructions for each instance to better reflect customized needs (Weller et al., 2024a; Oh et al., 2024). These efforts incorporate instructions that specify which content to include or exclude, thus clarifying user intent. While they greatly enrich the diversity of instructions, their primary focus remains on *content relevance*. Typically when searching for certain documents, users care about two types of aspects: the informational content they provide and the manner in which it is presented (Taylor, 1962; Mizzaro, 1998), which involves document-level attributes such as length, language, and format. A sole focus on content relevance neglects the importance of customized preferences for broader document-level attributes.

We believe that a truly instruction-aware retrieval system must go beyond content relevance to accommodate a range of diverse, user-defined document attributes. To further research in this direction, we propose ***InfoSearch***, a novel benchmark designed to evaluate IR models based on their ability to follow customized instructions across six structured dimensions: Audience, Keyword, Format, Language, Length, and Source. These dimensions reflect a wide range of document-level features that are crucial to fulfilling user requirements beyond content relevance. In addition, we include both instructed and reversely instructed modes to evaluate the model's comprehension of instructions presented in affirmative and negative formats. Each instruction is carefully crafted and manually validated to ensure naturalness and representativeness of complex real-world scenarios.

Beyond the comprehensiveness of datasets, well-defined evaluation metrics are crucial for gaining a thorough understanding of the instruction-following capabilities of retrieval models. While traditional IR metrics like nDCG and MRR are primarily effective for assessing content relevance in ad-hoc retrieval tasks (Weller et al., 2024a), we propose new metrics specifically designed to measure the depth of instruction-following capabilities in retrieval models. By structuring the evaluation across these separate dimensions and modes, we offer a detailed analysis of how well models follow instructions on each condition, providing clearer insights into their strengths and limitations. Overall, instruction-specific fine-tuning and increased model parameters enhance the model's instruction-following capabilities and re-ranking models demonstrating greater proficiency than retrieval models in instruction-following. Nevertheless, both methods still exhibit substantial potential for improvement in satisfying our benchmark.

Our contributions can be summarized as follows:

- We propose ***InfoSearch***, an evaluation framework that covers six key dimensions: Audience, Keyword, Format, Language, Length, and Source, to assess retrieval models' ability to follow complex instructions beyond content matching.
- We introduce two novel metrics – Strict Instruction Compliance Ratio (SICR) and Weighted Instruction Sensitivity evaluation (WISE) metric, to evaluate instruction adherence both strictly and leniently.
- We evaluate 15 retrieval models, including 1 sparse retrieval method, 8 dense models, and 6 LLM-based reranking models. This extensive evaluation provides a comprehensive comparison of different methodologies, offering valuable insights into their instruction-following capabilities.

2 INFOSEARCH: CONSTRUCTION AND EVALUATION

We construct a benchmark, **In**struction-**Fo**llowing **Search** (***InfoSearch***), to evaluating the search models' ability to follow instructions. The benchmark is composed of instructional query/doc data across six dimensions and two novel metrics to measure models' responsiveness to instructions. Section §2.1 details the dimension settings and retrieval modes under the InfoSerach framework, Section §2.2 explains the dataset construction process, and Section §2.3 describes the design logic behind our proposed metrics.

2.1 DATASET FRAMEWORK

In real-world scenarios, users exhibit a wide range of complex and diverse search intentions. The use of tailored instructions can link the specific search query content to the requirements and preferences of the user. Instructions typically contain detailed information or document-level characteristics that align with user needs, aiming to enhance the precision and relevance of search results. As shown in Figure 1, we conducted an extensive analysis of real users and their underlying intentions to identify six factors (dimensions) influencing search behaviors: user background (**Audience**), specific search terms or topics (**Keyword**), preferred format for information presentation (**Format**), required response length (**Length**), language requirement (**Language**), and information origin (**Source**). To enhance the diversity of instructions across these six dimensions, we established multiple conditional branches within each dimension, allowing instructions to dynamically adapt and expand based on different conditions. Moreover, even within the same dimension and conditions, we create varied instructions using diverse wording and expressions. This approach not only enriches the dataset but also strengthens the robustness and reliability of the evaluation framework by simulating a broad range of potential user inputs.

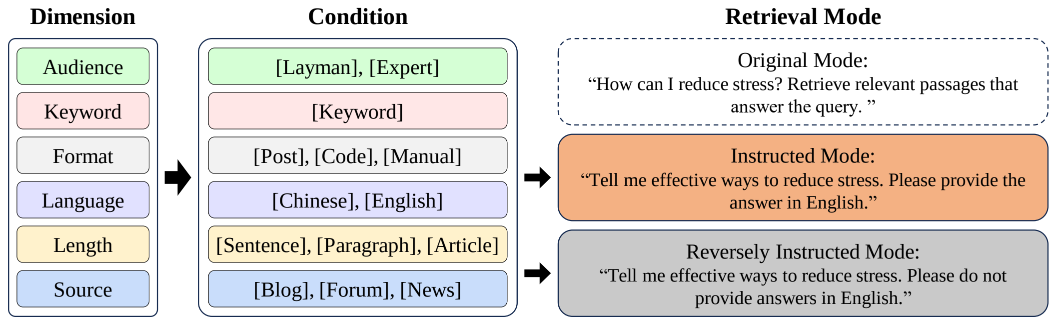


Figure 1: ***InfoSearch*** consists of six dimensions, each representing a document-level feature with values drawn from predefined conditions. Queries are paired with one dimension and evaluated in three retrieval modes based on the given instructions.

Drawing inspiration from (Zhang et al., 2024), we incorporate semantic negation into the dataset by reversing the meaning of instructions across each dimension. This approach allows each query to be associated with multiple instructions, covering various conditions and offering both positive and negative semantic contexts. This ensures that the model is exposed to three distinct retrieval modes:

- **Original Mode**: This mode serves as a baseline that evaluates the model's basic retrieval ability to find pertinent information without any specific constraints.
- **Instructed Mode**: In this mode, the model is required to find documents that are content relevant and satisfy the condition specified in the instruction.
- **Reversely Instructed Mode**: In this mode, the model is required to find documents that are content relevant and do *not* satisfy the condition specified in the instruction, which tests the model's ability to understand negation.

By integrating six dimensions and three distinct retrieval modes, we have developed the comprehensive evaluation dataset ***InfoSearch***. This dataset serves as a robust tool for systematically evaluating model's ability to interpret and respond accurately to diverse instructions during retrieval.

2.2 Construction Process

The objective of developing ***InfoSearch*** is to establish a linkage between queries and diverse instructions, ensuring that the corresponding target documents are aligned to each specific instruction. As shown in Figure 2, to achieve this, we specifically gather Question-Answer (Q-A) pairs corresponding to each dimension and expand the set of target documents by incorporating relevant content retrieved from web pages. The specific steps for constructing the framework are as follows:

- **Step 1: Condition Determination.** The query for each dimension can be diversified and expanded through various conditions, allowing the same query to correspond to different relevant documents under different conditions. Except for the Keyword dimension, the other five dimensions have fixed conditions. The condition of the Keyword dimension is the keyword in the document. Therefore, the condition of the Keyword dimension needs to be determined after filtering out the Query-Document (Q-D) pairs. To achieve this, both the query and its corresponding document were input into GPT-4, generating a unique condition for each Q-D pair.[1]
- **Step 2: Data Collection.** To ensure the naturalness of the queries and reduce production costs, we consciously integrate conditions when filtering Q-A pairs from existing datasets or web pages. For instance, in the Format dimension, due to the lack of available multi-format Q&A datasets, we selectively extract Q-D pairs from StackOverflow posts. For posts containing code and detailed official documentation responses, we use their titles as queries and the complete responses as

[1] GPT-4 occasionally selected irrelevant words, such as "and" or "what", that did not align with the user scenario when generating keyword conditions. To address this, we meticulously crafted prompt templates for condition extraction, ensuring that the conditions were both unique and representative of each document, accurately reflecting the document's core theme.

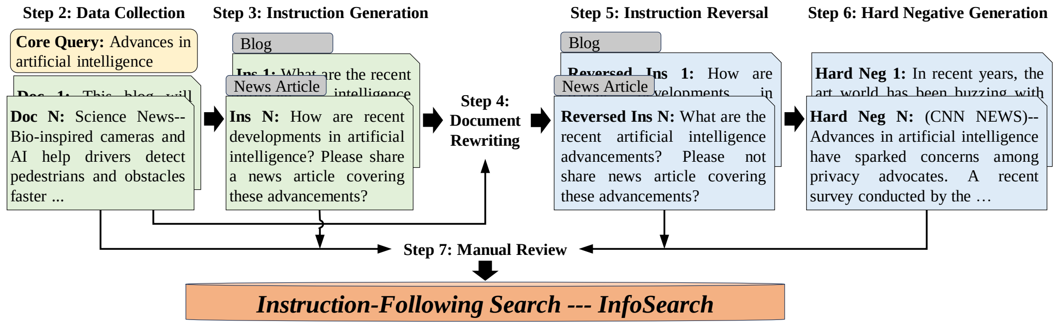


Figure 2: Overview of the dataset construction process for ***InfoSearch***.

Table 1: ***InfoSearch*** dataset statistics. $|Q|$, $|I|$ and $|R|$ represent the word lengths of the original query, instructed query and reversely instructed query respectively.

Dimension	**#** Q	**Avg** $|Q|$	**#** I	**Avg** $|I|$	**#** R	**Avg** $|R|$	**#** D
Audience	100	9.02	210	20.46	210	15.91	840
Keyword	100	6.30	288	17.90	288	18.92	1152
Format	100	9.16	300	16.65	300	19.31	1200
Language	100	8.75	200	14.09	200	15.74	800
Length	100	8.52	300	15.94	300	16.26	1200
Source	100	7.38	300	18.19	300	15.58	1200
Total	600		1598		1598		6392

documents under the [StackOverflow] condition. The pure code snippets within the answers and references to official documentation are separately extracted and used as documents under the [Code Snippet] and [Manual] conditions, respectively.

- **Step 3: Instruction Generation.** The generation of accurate and natural instructions is crucial. When searching, users tend to express their intentions using simple, naural language, so the generated instructions must remain brief and clear, closely mirroring conversational style. To achieve this, we employed words such as "smooth", "natural", and "realistic" in the prompts to guide GPT-4 in crafting instructions that emphasize not only semantic accuracy but also the emulation of authentic user. Furthermore, a two-sentence structure for the instructions, first rephrasing the query and then appending specific constraints. This structure effectively separates the core query from the conditions, enhancing the diversity of generated instructions. [2]
- **Step 4: Document Rewriting.** When the query and relevant documents fail to meet the instruction requirements, we use GPT-4 to rewrite the existing documents to generate relevant documents. In this process, we experimented with directly generating condition-satisfying documents from the query, but these often exhibited redundant expressions and inconsistent formatting. Therefore, we adjusted the existing documents, ensuring they meet the instruction requirements while preserving naturalness and authenticity in the language.
- **Step 5: Instruction Reversal.** In real retrieval, we observed that results already ranked highly tend to remain at the top even after instructions are applied. This makes it difficult to determine whether the improvement in ranking is due to the model's understanding of the instructions or simply a result of detailed keyword matching. To address this, we validate the model's comprehension of the instructions by reversing the semantic meaning of the instructions. For example, "Please answer in Chinese" is reversed to "Please do not answer in Chinese."
- **Step 6: Hard Negative Generations.** While positive documents for the same query under varying conditions may act as negative examples for one another (instruction negatives), we still need to prevent the model from relying solely on prominent features for simple retrieval, thereby neglecting the subtle relationships between the query and the documents. To address this, we

[2]For example, "What are the most effective exercises for losing weight? Please find discussions from forum posts only." This two-sentence structure ensures logical clarity and semantic coherence.

use GPT-4 to generate documents that appear to be related to the query topic but cannot actually answer the query, serving as hard negative documents (query negatives).

- **Step 7: Manual Review.** We filtered out anomalous positive documents from the outputs of 12 retrieval models, selecting those that failed to rank within the top 50 in six or more models or had a relevance score below 0.5 for the query. This process aimed to eliminate mislabeled Q-D pairs selected from other datasets or documents inaccurately retrieved through manual search. For these mismatched documents, we proceed with manual replacement.

By applying the data construction process described above, the ***InfoSearch*** benchmark comprises 600 core queries, 1,598 instructed queries, 1,598 reversely instructed queries, and 6,392 documents, as summarized in Table 1. Detailed examples of each dimension are provided in Appendix A.

2.3 Evaluation Metrics

In real applications, users typically focus only on the top K entries in search results. The relevance of these top K results not only reflects the overall performance of the model but also directly influences user experience. Moreover, when evaluating instruction-following capabilities, it is essential to assess not only the model's ranking performance on the original query but also the changes in rankings after receiving instructions. To measure instruction-following performance for retrieval models is a challenge. Two metrics were specifically proposed in previous studies for this purpose: Robustness@k (Oh et al., 2024) and p-MRR (Weller et al., 2024a). We argue that neither of them effectively reflects true instruction-following performance.

Robustness@k is designed to assess a model's performance on the same query under different instructions. Specifically, it groups instances of the same query, calculates the minimum nDCG@k score within each group, and averages the group scores to generate the overall Robustness@k score. Let $Q = \{q_1, q_2, ..., q_n\}$ be a set of queries. For each query q_i, there are m_i distinct instruction variants $\{I_{i1}, I_{i2}, ..., I_{im_i}\}$, calculate the minimum nDCG@k score across all its instruction:

$$min\text{-nDCG}(q_i) = \min_{j \in (1,2,...,m_i)} s_{ij} \tag{1}$$

where s_{ij} represents the nDCG@k score for query q_i under instruction I_{ij}. Compute the overall Robustness@k score as the average of these minimum scores across all queries:

$$Robustness@k = \frac{1}{n} \sum_{i=1}^{n} min\text{-nDCG}(q_i) \tag{2}$$

However, the Robustness@k metric oversimplifies the evaluation of a model's ability to follow instructions. ① Even if a model demonstrates strong performance across the majority of queries, a single anomalously low score can reduce the overall robustness score. ② Furthermore, focusing solely on the lowest score disregards variations in the model's responses to different instructions, thus failing to capture the overall performance trend. [3]

As for p-MRR, it is based on the MRR metric and quantifies the model's ability to follow instructions by comparing the rankings of relevant documents in the original mode and the instruction mode. The following formula is applied to calculate the score for each relevant document within a query:

$$p\text{-MRR} = \begin{cases} \frac{MRR_{og}}{MRR_{new}} - 1, & \text{if } R_{og} > R_{new} \\ 1 - \frac{MRR_{new}}{MRR_{og}}, & \text{otherwise,} \end{cases} \tag{3}$$

where MRR is mean reciprocal rank, R_{og} is the rank of the document in the original retrieval mode, and R_{new} is the new rank in the instruction mode. However, ③ p-MRR fails to distinguish the importance of ranking, neglecting to highlight the critical role that top K results play in retrieval. ④ Moreover, the linear discount mechanism of p-MRR is insufficiently sensitive to changes in higher rankings, making it ineffective in capturing subtle movements at the top. ⑤ Lastly, p-MRR demonstrates limitations when addressing special cases and extreme performances. [4]

[3]For instance, the nDCG@k scores for group A are {0.8, 0.3, 0.2}, while those for B are {0.9, 0.9, 0.2}. Although group B exhibits a better overall performance, Robustness@k assigns the same score to both groups.

[4]For example, the performance of model 1 is $R_{og} = 10$ and $R_{new} = 5$, yielding a p-MRR of -0.5, while model 2's performance is $R_{og} = 100$ and $R_{new} = 50$, resulting in a p-MRR of -0.5. Although both models receive the same score, it is evident that model 1 has a greater impact on the retrieval results.

Notation: To address these shortcomings, we define two metrics to quantify the model's responsiveness to instructions: Strict Instruction Compliance Ratio (**SICR**) and Weighted Instruction Sensitivity Evaluation (**WISE**) metric, guided by the practical demands of real-world retrieval systems. Assuming that in the original mode, the core query q has n positive documents, denoted as $\mathbf{P} = \{P_1, P_2, \ldots, P_n\}$. When it comes to the instructed mode where the core query is accompanied by a more specific instruction, there is only one unique gold document $\mathbf{P}^i$out of **P**. The remaining documents become negative. When it comes to the Reversely instructed mode, as the instruction is semantically reversed, $\mathbf{P}^i$ becomes negative. Let R_{ori}, R_{ins} and R_{rev} represent the rankings of the gold document $\mathbf{P}^i$ in original mode, instructed mode, and reversely instructed mode, respectively. Similarly, let S_{ori}, S_{ins} and S_{rev} denote the relevance score between the gold document $\mathbf{P}^i$ and the query in original mode, instructed mode, and reversely instructed mode, respectively.

Strict Instruction Compliance Ratio The **SICR** metric introduces a strict criterion for evaluating sensitivity to instructions. Ideally, for a retrieval result that strictly adheres to the instruction, the gold document's ranking and relevance score in the instructed mode should be higher than in the original mode, denoted as $(R_{ins} < R_{ori} \ \ \& \ \ S_{ins} > S_{ori})$. Simultaneously, in the reversely instruction mode, its ranking and relevance score should be lower than those in the original mode, denoted as $(R_{ori} < R_{rev} \ \ \& \ \ S_{ori} > S_{rev})$. A query that strictly satisfies these criteria is assigned a score of 1. Implementing rigorous scoring criteria ensures that all changes of relevant documents are taken into account, thereby effectively addressing the issue of low-score sensitivity (defect ①) and and incomplete evaluation (defect ②). The formula for this criterion is as follows:

$$I(q) = \begin{cases} 1, & (R_{ins} < R_{ori}) \text{ and } (S_{ins} > S_{ori}) \text{ and } (R_{ori} < R_{rev}) \text{ and } (S_{ori} > S_{rev}), \\ 0, & \text{otherwise,} \end{cases} \tag{4}$$

The SICR score is calculated as the ratio of the number of queries meeting the instruction-following criteria to the total number of queries in the test set, represented by the following formula:

$$SICR = \frac{\sum_{j=1}^{J} I(q_j)}{|Q|}, \tag{5}$$

Where $|Q|$ represents the total number of queries in the test set. This formula calculate the percentage of retrievals that strictly adhere to the specified instructions relative to the total results.

Weighted Instruction Sensitivity Evaluation The SICR metric reflect the proportion of model results that comply with instructions but lacks a detailed quantification of the degree of compliance. On this basis, the **WISE** metric relaxes the evaluation criteria by focusing only on the ranking changes, regards the results that meet $(R_{ins} \leq R_{ori} < R_{rev})$ as following the instructions, and provides more levels of rewards or penalties for the results. It can be calculated using the following formula:

$$F(q) = \begin{cases} f_{reward}(R_{ori}, R_{ins}), & \text{if } R_{ins} \leq R_{ori} < R_{rev}, \\ f_{penalty}(R_{ori}, R_{ins}), & \text{otherwise,} \end{cases} \tag{6}$$

When defining the reward component, the model is expected to comprehend and execute the instructions, effectively optimizing the rankings of the top K results accordingly. This implies that significant ranking changes within the top K results should be given greater weight to address defects ③ and ④, as these changes are more likely to be noticed and utilized by users. It is essential to consider both the absolute ranking R_{ins} and the relative ranking $(R_{ori} - R_{ins})$. To achieve this, we introduced the $\frac{1}{\sqrt{R_{ins}}}$ term, generously rewarding smaller R_{ins} values. Simultaneously, through the $(1 - \frac{R_{ori} - R_{ins}}{K})$ term, we grant higher rewards to results that demonstrate substantial ranking improvements. Additionally, a uniform value of 0.01 is assigned to results beyond the Top K. Additionally, more extreme cases are considered (defects ⑤): if a core query contains N positive documents in the original mode and meets the conditions $R_{ori} \leq N$ and $R_{ins} = 1$, it will be granted a reward of 1. This is based on the premise that, for an ideal retriever, the N positive documents would likely rank at the top in the original mode. Accordingly, results that rank higher and exhibit more significant changes should be assigned greater weight. The reward formula is defined as:

$$f_{reward} = \begin{cases} 1, & \text{if } R_{ori} \leq N \ \text{ and } \ R_{ins} = 1, \\ (1 - \frac{\sqrt{R_{ori} - R_{ins}}}{K}) \cdot \frac{1}{\sqrt{R_{ins}}}, & \text{if } R_{ori} \leq K, \\ 0.01, & \text{otherwise,} \end{cases} \tag{7}$$

where $K = 20$ signifies that our primary focus is on the top 20 retrieval results. Some of the reward values are visualized in the Figure 5.

For the penalty component, we reference the design of p-MRR, emphasizing the magnitude of the ranking drop and apply stricter penalty to golden documents with large ranking drop. However, unlike p-MRR, our R_{ins}, R_{ori}, and R_{rev} yield six possible permutations. To account for the remaining five cases aside from $(R_{ins} \leq R_{ori} < R_{rev})$, we formulated the following penalty formula: [5]

$$f_{penalty} = \begin{cases} -1, & \text{if } R_{rev} < R_{ori} < R_{ins}, \\ \frac{R_{ori}-R_{ins}}{R_{ins}}, & \text{if } R_{ori} \leq R_{ins}, \\ \frac{R_{rev}-R_{ori}}{R_{ori}}, & \text{if } R_{rev} \leq R_{ori}, \end{cases} \tag{8}$$

In summary, for a test set with J queries, the overall evaluation formula can be expressed as:

$$WISE = \frac{\sum_{j=1}^{J} F(q_j)}{J}, \tag{9}$$

3 Experiments

This section first introduces the experimental settings in §3.1, followed by a description of the overall retrieval results of different types of search models in §3.2. Lastly, it discusses models' performance across individual dimensions in §3.3.

3.1 Experimental Setup

The goal of the benchmark is to determine how effectively retrieval models adjust their retrieval behavior in response to instructions. To thoroughly assess how state-of-the-art retrieval models follow instructions, we selected **15 models** representing the four model architectures:

- **Sparse retrieval**: 1 model, BM25 (Robertson et al., 2009).
- **Dense retrieval**: 8 models, including BGE-large-v1.5 (Xiao et al., 2023), E5-large-v2 (Wang et al., 2022), Instructor-XL (Su et al., 2023), E5-Mistral (Wang et al., 2023), GritLM (Muennighoff et al., 2024), NV-Embed-v2 (Lee et al., 2024a), GTE-Qwen2 (Li et al., 2023), and SFR-Embedding-v2 (Meng et al., 2024).
- **Fine-tuned ranking models**: 3 models, including FollowIR (Weller et al., 2024a), RankVicuna (Pradeep et al., 2023a), RankZephyr (Pradeep et al., 2023b), where FollowIR is a point-wise model and the other two are list-wise.
- **Instruction-tuned generation models used for reranking**: 3 models, including Mistral-7B-Instruct-v0.2 (Jiang et al., 2023), Zephyr (Tunstall et al., 2023), and GPT-4o (Achiam et al., 2023).

For dense retrieval models, we compute the dot product between query and document vectors to determine retrieval rankings. For reranking models, the top 100 results from E5-mistral (Wang et al., 2023) are re-ranked based on the models' interpretation of the instruction. For general large language models, we use two settings: In the point-wise setting, both the query and document are inputs, with the output probabilities of *True* or *False* used as similarity scores. In the list-wise setting, following (Pradeep et al., 2023b), a list of documents is provided as a prompt (see Appendix D), and the model returns the ranked document IDs in a list.

Based on Mistral-7B-Instruct-v0.2 (Jiang et al., 2023), we conduct a specialized experiment to evaluate its zero-shot performance in three retrieval settings: dense retrieval, point-wise reranking, and list-wise reranking. Besides, we include GPT-4o as a strong baseline due to its demonstrated instruction-following capabilities and to set a high performance benchmark for all models.

[5] $R_{ori} \leq R_{ins}$ covers two cases: $(R_{ori} \leq R_{ins} \leq R_{rev})$ and $(R_{ori} \leq R_{rev} \leq R_{ins})$. Similarly, $R_{rev} \leq R_{ori}$ covers two cases: $(R_{rev} \leq R_{ori} \leq R_{ins})$ and $(R_{rev} \leq R_{ins} \leq R_{rev})$.

Table 2: Performance comparison of different retrieval models averaged over six dimensions. The last three columns display the ranking of the gold document in the original query (R_{ori}), and the relative rank change after applying the instructed and reversed instructions.

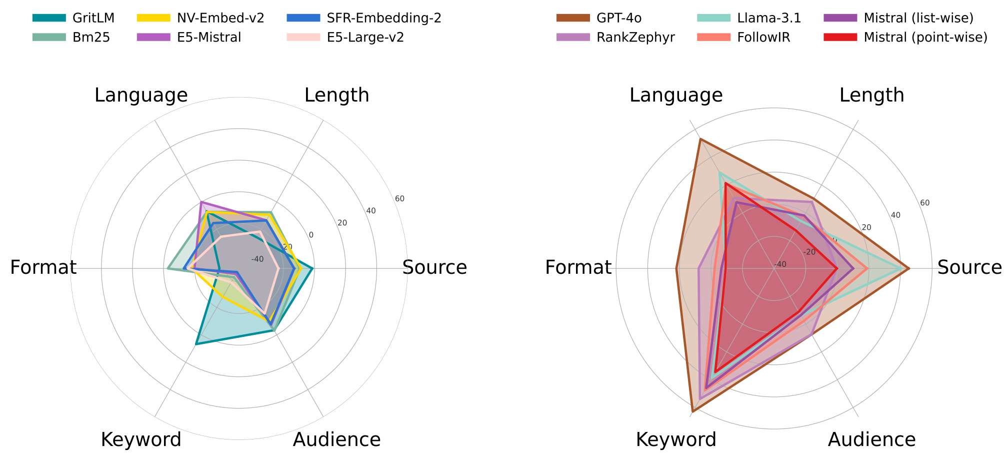
Model	nDCG@10			Robustness@10			p-MRR ↑	WISE ↑	SICR ↑	Gold Document Rank		
	Ori	Ins	Rev	Ori	Ins	Rev				R_{ori}	$R_{ins}\downarrow$	$R_{rev}\uparrow$
BM25	47.5	39.1	38.5	47.5	17.7	20.9	7.0	-12.0	0.0	18.4	18.0	18.3
Dense Retrieval												
Bge-Large-v1.5	53.2	34.9	34.9	53.2	15.8	21.0	21.3	-29.5	1.0	20.4	25.0	24.9
E5-Large-v2	60.4	52.0	49.9	60.4	26.6	30.2	5.6	-23.3	0.8	14.7	12.8	13.9
Instructor-XL	62.6	38.4	39.3	62.6	17.5	23.4	30.4	-29.8	2.7	30.5	30.5	36.3
Mistral-ins-v0.2	19.4	25.5	29.2	19.4	8.5	12.7	-32.4	-49.2	0.0	236.0	153.0	153.1
GTE-Qwen2	43.6	43.1	48.5	43.6	18.7	26.5	-21.7	-39.0	0.1	104.3	75.3	71.3
E5-Mistral-ins	78.3	64.3	66.0	78.3	41.8	46.4	4.0	-16.3	2.8	6.6	5.4	5.6
GritLM	70.8	66.2	66.3	70.8	44.2	48.3	-4.3	-11.1	6.9	14.4	5.8	8.9
SFR-Embedding-2-R	70.7	62.2	60.1	70.7	40.7	43.2	4.8	-18.1	2.1	7.4	5.7	5.6
NV-Embed-v2	69.5	54.5	52.2	69.5	33.3	36.0	17.7	-13.5	2.8	8.1	8.7	9.3
Point-wise Reranking												
Mistral-ins-v0.2	62.0	58.4	59.0	62.0	38.0	44.7	-2.3	4.1	8.1	6.5	4.7	8.8
Llama-3.1	74.8	66.8	65.4	74.8	46.1	49.2	11.5	14.4	19.3	5.4	3.7	8.2
FollowIR	72.4	66.3	65.5	72.4	46.2	50.0	4.1	13.4	12.5	5.5	3.8	7.6
List-wise Reranking												
Mistral-ins-v0.2	74.5	64.4	61.6	74.5	40.5	42.2	7.2	8.1	22.0	5.7	4.8	7.2
Zephyr-beta	70.8	55.9	58.0	70.8	32.0	36.4	1.7	-3.2	8.7	6.4	6.1	7.0
RankVicuna-v1	65.4	55.2	55.2	65.4	31.2	35.7	2.0	-6.5	5.6	7.3	6.3	7.0
RankZephyr-v1	75.0	63.5	64.7	75.0	41.8	47.5	0.7	14.5	10.5	4.5	4.4	5.4
GPT-4o	83.8	74.2	74.2	83.8	53.0	58.0	15.0	33.5	32.1	2.6	1.7	4.3

3.2 Result Overview

Table 2 provides a detailed comparison of different retrieval models across six dimensions using nDCG@10, Robustness@10, p-MRR, WISE, and SICR. The table also includes the average rankings of the golden documents in the instruction mode across the three retrieval models. Notably, almost all models achieved relatively high nDCG, indicating that relying solely on nDCG is insufficient to capture the impact of instructions on ranking changes. Although Robustness can be used for model comparison, it is unable to assess the extent of performance changes before and after instructions because the relevant documents corresponding to the three retrieval modes differ. p-MRR can partially reflect the model's responsiveness to different instructions; however, due to the limitations of this metric, the results are not expressed with sufficient accuracy. For instance, according to p-MRR evaluations, the instruction-following performance of bge-large-v.5 and Instructor models is significantly better than that of GPT-4o. Meanwhile, the WISE and SICR scores closely align with the ranking changes of the Gold Document and can clearly distinguish the instruction-following capabilities of the models as well as the performance differences between them. The results reveal distinct patterns in instruction-following performance across different model categories, which can be summarized as follows: list-wise reranking models $>$ point-wise reranking models $>$ dense retrieval models $>$ sparse retrieval models. Larger model architectures typically outperform smaller models in both WISE and SICR.

A key observation is that the WISE and SICR scores of the BM25 indicates that models relying solely on lexical matching, without any sensitivity to instruction-based retrieval or context-aware instructions, struggle to interpret and act on complex instructions. BM25's inability to adapt underscores the limitations of traditional sparse retrieval methods for instruction-following tasks.

In contrast, dense retrieval models show greater sensitivity to instructions, though their performance varies. For instance, BGE-Large-v1.5 and Instructor-XL demonstrate significant performance degradation under instructions, as reflected in their negative WISE scores. However, models like GritLM, E5-Mistral-ins and NV-Embed-v2 demonstrate greater adaptability. Notably, GritLM achieves the highest WISE and SICR score among the dense models, indicating that, benefiting from joint training on both encoding and generative tasks, GritLM is better equipped to handle complex instructions. In contrast, models primarily trained on task-specific instructions, such as BGE-Large-v1.5 and Instructor-XL, encounter difficulties when addressing a broader range of instructions.



(a) Retrieval (b) Reranking

Figure 3: Radar plots comparing the WISE scores of various models across different dimensions, highlighting the strengths and weaknesses of each model in handling different types of instructions. Among retrieval models, GritLM demonstrates the strongest instruction-following capability, while GPT-4 consistently performs the best across all dimensions in the reranking category.

Point-wise reranking models generally outperform dense retrieval models. Among them, Llama-3.1 achieves the highest WISE and SICR scores. Although it has not been fine-tuned for retrieval tasks, Llama-3.1 benefits from its extensive understanding of language, granting it some instruction-following capabilities. FollowIR also demonstrates competitiveness; by fine-tuning with content-aware instructions, FollowIR achieves comparable scores to Llama-3.1 with fewer model parameters.

Among list-wise reranking models, GPT-4o performs the best, achieving the highest scores in WISE and SICR across all models, demonstrating its exceptional capability in handling and adhering to complex instructions. Additionally, RankZephyr shows decent performance but remains closer to pointwise re-ranking models in terms of instruction following, possibly due to limitations in its training data. Although Mistral-ins-v0.2 has the second-highest SICR score after GPT-4o, its WISE score is not as remarkable, indicating that while the model can comprehend instructions, it struggles to effectively elevate the rankings of the corresponding documents.

3.3 Performance Analysis Across Dimensions

The radar plots in Figure 3 offer a visual summary of how different models perform in these dimensions, highlighting their strengths and weaknesses in instruction following. Across all models, both retrieval and reranking models show significant room for improvement. Particularly, certain dimensions – such as format and audience – consistently present challenges. Performance on these remains suboptimal, indicating that models struggle with instructions requiring specific formatting or audience adaptation. The difficulty likely arises from insufficient exposure to structured data formats such as [StackOverflow Post], [Code Snippet], or [Offical Manual], and a lack of nuanced understanding of diverse audience contexts during training.

Retrieval models show notable variability in performance across dimensions. GritLM stands out, leading in overall instruction-following ability. Retrieval models generally perform well on the language and keyword dimensions, but they struggle significantly on the format and audience dimensions. This indicates that retrieval models handle text-based instructions effectively but struggle with structural and contextual cues.

Compared to retrieval models, reranking models generally perform better across all dimensions. This improvement is particularly evident in the keyword dimension, largely because reranking models, during inference, directly verify keyword presence within the context. GPT-4 stands out in the language, source, and keyword dimensions, consistently outperforming other models. However, even top-performing models like GPT-4o face challenges with audience-related instructions. Despite the overall performance gap in the Source and Audience dimensions, RankZephyr performs comparably to GPT-4o in the length, audience, and keyword dimensions, demonstrating the effectiveness of fine-tuning for reranking tasks.

4 RELATED WORK

Dense Retrieval The development of dense retrieval models has significantly enhanced the semantic understanding and efficiency of retrieval systems. Existing dense models can be categorized into two types based on their architecture: Bidirectional Embedding Models and Decoder-only Embedding Models. Bidirectional Embedding Models are typically base on BERT (Devlin, 2018) or T5 (Raffel et al., 2020) encoders, performing general embedding tasks. Early models that base on BERT or T5 for efficient text embeddings include Sentence BERT (Reimers, 2019), SimCSE (Gao et al., 2021) and Sentence T5 (Ni et al., 2021). To better accommodate the requirements of text embeddings, researchers have pre-trained these encoders using contrastive learning (Izacard et al., 2021; Wang et al., 2022).Furthermore, these models are fine-tuned using various supervised datasets to enhance their performance in retrieval tasks or other downstream applications (Lee et al., 2024b; Li & Li, 2023). Compared to bidirectional embedding models, decoder-only embedding models initially perform relatively poorly in general embedding tasks, primarily due to their limited capacity to comprehensively capture and utilize contextual information (Brown, 2020). However, many researchers have sought to optimize these models' performance by introducing contrastive learning methods to address their deficiencies in embedding tasks (Neelakantan et al., 2022). Currently, researchers have explored not only the use of synthetic data (Wang et al., 2023) but also a hybrid strategy combining real and synthetic data (Meng et al., 2024; BehnamGhader et al., 2024), achieving significant success in text embedding tasks. Collectively, these advancements in contrastive pre-training, model scaling, and leveraging weak supervision and synthetic data significantly propel the field of retrieval.

Instruction-Following for Retrieval The notion of relevance often varies among users (Mizzaro, 1998). Consequently, queries alone may not fully address all users' information needs (Ruthven & Lalmas, 2003), while instructions can expand these intentions beyond the scope of the queries. Recent information retrieval research has recognized this and tried to train retrieval models by combining instructions with queries to enhance their instruction-following capabilities. In general, existing instruction-following models can be divided into two categories based on instruction design methods: task-aware and content-aware instruction retrieval models. TART first proposed a general retrieval system with task-level instruction, setting specific instructions for different retrieval tasks to query corresponding results (Asai et al., 2023). Subsequently, Instructor expanded the scope of instructions so that text embeddings can not only retrieve but also classify and diagnose duplicate problems (Su et al., 2023). However, these task-aware instructions are too general and lack the specificity of user instructions in real scenarios. On this basis, other researchers have developed content-level instructions. InstructIR set instructions to adapt to query-text pairs based on user background (such as work, hobbies) (Oh et al., 2024). ExcluIR set exclusionary instructions based on the content differences between query results, accounting for users' exclusionary needs in queries (Zhang et al., 2024). Similarly, FollowIR set instructions to distinguish query results by combining exclusion and inclusion (Weller et al., 2024a). However, user intentions in real scenarios involve both the internal attributes of answers (content, audience, language) and the external features of answers (format, length).

5 CONCLUSION

Despite leveraging LMs as the backbone for training retrieval models, most existing IR models cannot truly understand the instructions in query. Further, traditional score indicators(e.g., nDCG) cannot reflect whether the model has the ability to follow instructions and most existing dataset with instructions are designed with a only single dimension, so we propose ***InfoSearch*** and two novel metrics(WISE, SICR). The choice of dimensions in our dataset takes into account the instructions that users may give in actual scenarios. Additionally, our metrics consider the combined performance of the model in three modes(Original mode, Instructed mode, Reversely instructed mode), with increasing difficulty across modes as each introduces more complex challenges. We hope this work helps the future instruction-following retrieval task.

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A MORE DETAILS OF INFOSEARCH

Figure 4 illustrates the distribution of data across six dimensions in the FollowIR, InstructIR, and ***InfoSearch*** datasets. The chart highlights the varying proportions of query-document pairs based on dimensions like Audience, Keyword, Language, Length, Source, and Format. Table 3 shows the source of datasets used to collect query-document pairs for each dimension. Additionally, Table 9 to Table 14 provide specific examples from each dimension in the ***InfoSearch*** dataset.

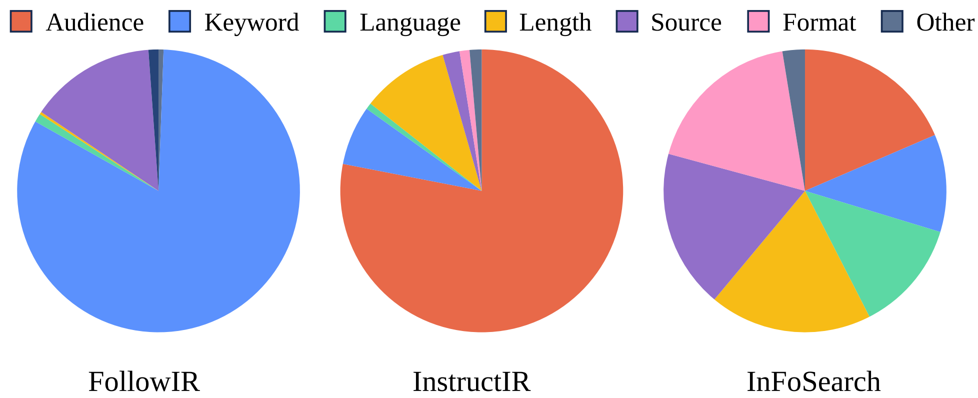

Figure 4: Comparison of the ***InfoSearch*** dataset with FollowIR and InstructIR in terms of data distribution across six dimensions.

Table 3: Structure and source of the dataset

Dimension	**Source Data**	**Condition Value**
Audience	BioASQ, scifact (Muennighoff et al., 2022)	[Layman], [Expert]
Keyword	MSMARCO (Bajaj et al., 2016)	[keyword]
Format	Stackoverflow, various office doc	[Stackoverflow Post], [Code Snippet], [Official Manual]
Language	publichealth-qa	[Chinese], [English]
Length	medical_qa (Muennighoff et al., 2022), google search	[Sentence], [Paragraph], [Article]
Source	CNN-english-news, google search	[Blog], [Forum Post], [News Article]

Table 4: Performance comparison of different retrieval models across six dimensions using the WISE and SICR metrics. The dimensions are: D1 (Audience), D2 (Keyword), D3 (Format), D4 (Language), D5 (Length), and D6 (Source). Higher scores indicate stronger instruction-following capabilities.

Model	WISe							SICR						
	D1	D2	D3	D4	D5	D6	Avg.	D1	D2	D3	D4	D5	D6	Avg.
BM25	-3.0	-42.1	-2.8	-7.2	-7.5	1.97	-12.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Dense Retrieval														
Bge-Large-v1.5	-16.8	-38.2	-42.1	-20.7	-28.6	-30.7	-29.5	0.5	0.0	0.3	2.0	1.0	2.3	1.0
E5-Large-v2	-15.6	-38.3	-15.5	-25.3	-21.6	-23.2	-23.3	1.4	0.7	0.0	0.5	0.7	1.3	0.8
Instructor-XL	-27.7	-34.7	-30.5	-20.5	-35.5	-29.8	-29.8	5.7	2.1	0.3	4.0	0.3	4.0	2.7
Mistral-ins-v0.2	-35.8	-67.8	-29.7	-31.9	-66.6	-63.3	-49.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
GTE-Qwen2	-34.0	-36.5	-44.3	-18.0	-56.4	-44.6	-39.0	0.0	0.0	0.0	0.0	0.3	0.0	0.1
E5-Mistral-ins	-7.3	-44.5	-19.9	0.1	-13.4	-13.0	-16.3	2.9	0.0	0.0	10.5	0.0	3.3	2.8
GritLM	-3.4	6.8	-36.0	-6.7	-25.8	-1.5	<u>-11.1</u>	11.4	11.8	1.3	4.5	0.3	11.7	<u>6.9</u>
SFR-Embedding-2-R	-7.8	-45.9	-13.0	-15.4	-13.5	-13.2	-18.1	2.9	1.0	2.0	1.0	1.0	4.7	2.1
NV-Embed-v2	-9.8	-27.7	-18.1	-7.3	-9.3	-8.7	-13.5	2.4	0.7	1.0	3.5	0.3	9.0	2.8
Point-wise Reranking														
Mistral-ins-v0.2	-8.9	34.5	-9.3	21.4	-12.6	-0.3	4.1	1.4	28.6	2.7	6.5	4.7	4.7	8.1
Llama-3.1	-6.2	38.7	-9.5	29.0	-5.9	40.2	<u>14.4</u>	6.2	38.3	10.0	22.0	2.7	36.7	<u>19.3</u>
FollowIR	-2.3	47.7	-2.3	20.9	-2.6	18.8	13.4	3.3	27.2	7.0	19.5	1.7	16.3	12.5
List-wise Reranking														
Mistral-ins-v0.2	-6.3	46.0	-6.6	7.6	-1.9	10.0	8.1	10.5	59.2	9.7	23.0	8.0	21.7	<u>22.0</u>
Zephyr-beta	-2.7	14.1	-13.9	-6.9	-5.7	-3.9	-3.2	1.0	27.5	8.0	10.5	2.0	3.0	8.7
RankVicuna-v1	-2.5	-8.5	-9.8	-11.8	-4.3	-2.2	-6.5	5.2	10.5	3.3	4.5	2.3	8.0	5.6
RankZephyr-v1	7.4	53.9	7.8	10.6	7.8	-0.3	<u>14.5</u>	4.3	42.5	1.0	5.5	4.3	5.3	10.5
GPT-4o	7.4	63.0	21.9	53.1	10.2	45.2	33.5	15.2	60.6	11.3	55.5	10.3	39.7	32.1

B ANALYSIS

p-MRR vs. WISE. While both metrics aim to measure models' instruction-following abilities by considering rank changes, p-MRR does not consistently reflect real performance. Many models in this study received p-MRR scores that were inconsistent with the ranking trends of the gold documents; for instance, GPT-4o scored 15.0, which was lower than both Instructor-XL and NV-Embed-v2. Eventually, most models scored even lower than BM25. This discrepancy arises because p-MRR evaluates only relative ranking changes ($R_{ins} - R_{ori}$), disregarding absolute ranking shifts (R_{ori}). In contrast, the proposed WISE metric strictly enforces instruction following standards by accounting for both absolute and relative ranking changes. GPT-4o achieved the highest WISE score, as it was able to further elevate the rankings of top golde documents when instructions were added and to lower the rankings under semantically inverse instructions ($R_{ori} = 3.51, R_{ins} < R_{ori}, R_{ori} < R_{rev}$).This makes WISE a more reliable metric for evaluating instruction-following capabilities.

Dense retrieval model vs Reranking model. Reranking models(represented by red and gray row in Table 4) significantly outperform most dense retrieval models(represented by green row in Table 4) in instruction-following tasks due to their ability to evaluate documents in relation to one another, optimizing the final ranking based on contextual relevance and nuanced understanding. By considering the entire list of retrieved documents, rerankers can effectively adjust the order based on the specific needs of the query, capturing subtle distinctions that dense retrieval models may overlook. This leads to more accurate rankings that align with user intent, especially in complex scenarios where the relationship between documents and the query is crucial for effective instruction-following. Consequently, while dense retrieval models excel in efficiently retrieving relevant documents, reranking models provide the precision necessary to enhance the overall ranking quality, resulting in superior performance in tasks requiring sophisticated language comprehension.

Point-wise reranking vs. List-wise reranking. Point-wise Ranking scores each document independently, evaluating relevance without considering the other documents in the set. Each document is treated in isolation, and the model predicts its relevance to the query. However, list-wise reranking considers the entire list of documents when making ranking decisions. Instead of scoring documents in isolation, the model looks at the relative relationships between documents in the list and ranks them in a way that optimizes the overall ranking order. List-wise ranking (represented by the gray row in Table 4) are generally better suited than point-wise ranking (represented by red row in Table 4) for instruction-following tasks because they take into account the broader context of the query and all relevant documents. When following instructions, particularly complex ones, it is essential to consider the relative importance of different documents to provide a more relevant, cohesive response. A list-wise approach is more likely to properly order documents based on their overall relevance to the instruction. Therefore, listwise rankings have the potential to achieve instruction following across different queries.

Zephyr vs. RankZephyr. RankZephyr outperforms Zephyr in both WISE and SICR because of its more sophisticated training process, better robustness to initial document order, multiple reranking passes that help correct ranking errors. Compared to Zephyr, RankZephyr learns from RankGPT, which allows it to adopt more sophisticated ranking strategies. Besides, RankZephyr benefits from multiple passes, allowing it to adjust the ranking more effectively compared to a single-pass strategy like Zephyr's, which might not optimize the ranking as thoroughly. These factors combine to ensure that RankZephyr minimizes penalties for ranking important documents too low, leading to significantly better WISE and SICR scores.

Mistral (retrieval) vs. (point-wise) vs (list-wise). Mistral-ins-v0.2 shows poor retrieval performance, highlighting its limitations in handling complex, instruction-driven ranking scenarios. Without specific training for retrieval, it fails to rank documents effectively on nuanced instructions. On the other hand, Mistral-ins-v0.2 in point-wise ranking demonstrates improved performance in both WISE and SICR, as it scores individual documents independently, allowing it to better adhere to instructions, though it lacks the depth to consider relationships between documents. However, Mistral-ins-v0.2 in list-wise ranking truly excels, as it optimizes the entire list and takes document interactions into account, enabling it to handle more sophisticated instruction-following tasks. This results in significantly better WISE and SICR scores, making list-wise Mistral-ins-v0.2 the most effective approach for instruction-following tasks where ranking coherence is critical.

C PROMPT TEMPLATES FOR CONSTRUCTING INFOSEARCH DATASET

We present the prompt that used to guide ChatGPT for generating and rephrasing task in Table 5 and Table 6.

Table 5: Prompt Templates for Generating

Task	**Prompt Template**

Generate Instruction	### TASK
	You are tasked with generating a natural query with an instruction based on the query and the condition provided by the user. You will be provided with a query and a condition and you need to:
	1. Rephrase the core query as the first sentence, making it sound like a natural human query without changing its meaning.
	2. Create a second sentence that specifies the search restriction.
	3. Ensure each sentence is smooth, concise, reasonable, natural, and realistic, mimicking a real human tone.
	
	### INPUT
	Core Query: {core query}
	Condition: {condition}
	
	### FORMATTING
	For the query with an instruction you generated, your output should be in the following format:
	{
	"core query": <str: the core query I give you >
	"condition": <str: the condition I give you >
	"query_with_instruction": <str: the query with instruction you generated >
	}

Generate Core Query	### TASK
	You excel at generating queries based on relevant documents. You will receive a document provided by the user, and your task is to create a concise query related to that document. The query must be no longer than 10 words and should summarize the core content of the document.
	
	### INPUT
	Document: {document}
	
	### FORMATTING
	For the core query you generated, your output should be in the following format:
	{
	"core query": <str: the core query you generated >
	}

Table 6: Prompt Templates for Rephrasing

Dimension	**Prompt Template**

Source	### TASK
	For a core query, I need documents from a blog, forum post, or news article. I will provide you with a core query, the corresponding document from a news article. Your task is to rewrite the document as blog and forum post content.
	
	### CAUTION
	1. For the blog you generated, you cannot use the core query as blog title directly. You need to rephrase it, but do not changed the semantics of this query. Besides, you need to give various information in the line under the title, such as the author, when it was published, the word "Blog", and the section it belongs to. All the above information must be random.
	2. For a forum post, it must be a form of discussion among multiple users. The usernames need to be random rather than use "use1", "use2" etc.
	
	### INPUT
	Core Query: {core query}
	Document: {document}
	
	### FORMATTING
	Your output should be in the following format:
	{
	"blog": <str: the blog you generated >
	"forum": <str: the forum post you generated >
	}

Audience	### TASK
	I will provide you with a core query and its corresponding document. The target audience for this document is experts. Your task is to Rewrite this document to make it easily understandable for laymen.
	
	### CAUTION
	1. Keep the semantics of the document intact.
	2. Do not use any technical jargon in the rewritten document for layman.
	
	### INPUT
	Query: {query}
	Document for expert: {expert}
	
	### FORMATTING
	Your output should be in the following format:
	{
	"query": <str: the query I give you >
	"layman": <str: the rewritten document for layman you generated >
	}

Table 7: Prompt Template for Reversing

Task	Prompt Template

Reverse Instruction	### TASK
	Your expertise lies in interpreting and transforming direct instructions into their opposite or negative forms while maintaining clarity and coherence in the transformed instructions. Your task is to reverse the instruction I give you.
	
	### CAUTION
	While reversing the instruction, ensure that the new instruction conveys the opposite meaning accurately. Please keep in mind that the transformation should remain clear and easy to understand, avoiding any ambiguity.
	
	### INPUT
	Instruction: instruction
	
	### FORMATTING
	{
	"reverse instruction": <str: the instruction your reverse >
	}

D PROMPT FOR LIST-WISE RERANKING MODELS

Table 8: Prompt for List-wise Reranking Models. The input consists of a list of documents or passages, and the model is prompted to return a ranked list of document IDs based on their relevance to the query.

TASK	Prompt Template
Rank	<|system|> You are RankGPT, an intelligent assistant that ranks passages based on their relevance to a query. <|user|> I will provide you with {num} passages, each indicated by a number identifier [ ]. Rank the passages based on their relevance to the query: {query}. [1] {passage 1} [2] {passage 2} ... [num] {passage {num}} Search Query: {query}. Rank the {num} passages above based on their relevance to the search query. The passages should be listed in descending order using identifiers. The most relevant passages should be listed first. The output format should be [ ] >[ ], e.g., [1] >[2]. Only respond with the ranking results, do not say any word or explain. <|assistant|> *Model Generation:* [9] >[4] >[20] >... >[13]

Table 9: An example in Audience dimension

Core Query	How to Prevent Heart Disease
Instructed 1	Explore effective strategies for preventing heart disease. Please explain in terms that are easy for the general public to understand.
Instructed 2	Investigate the latest preventive measures against heart disease. Make a detailed discussion suitable for a professional audience.
Reversed 1	How to Prevent Heart Disease. I'm looking for a response that is more technical than layman.
Reversed 2	How to Prevent Heart Disease. Please keep your answer simple and clear.
Document 1	To prevent heart disease, consider the following strategies : Adopt a Vegan Diet: Vegan diets, particularly those rich in soy and other plant-based proteins, can reduce the risk of cardiovascular disease. These proteins are high in non-essential amino acids, which promote glucagon activity. Glucagon helps regulate lipid levels and cholesterol synthesis, leading to healthier heart conditions. Increase Glucagon Activity: ...
Document 2	... Vegan proteins may reduce risk of cancer, obesity, and cardiovascular disease by promoting increased glucagon activity. ... glucagon promotes (and insulin inhibits) cAMP-dependent mechanisms that down-regulate lipogenic enzymes and cholesterol synthesis, while up-regulating hepatic LDL receptors and production of the IGF-I antagonist IGFBP-1. The insulin-sensitizing properties of many vegan diets–high in fiber, low in saturated fat ...

Table 10: An example in Keyword dimension

Core Query	What helps for acne?
Instructed 1	What treatments are effective for acne? Ensure your answer includes information specifically about “progesterone”.
Instructed 2	Can you tell me what helps reduce acne symptoms? Focus on the effects of “mint” in your response.
Instructed 3	What natural remedies are beneficial for managing acne? Please include details about “Chamomile”.
Reversed 1	What helps for acne? Can you provide a response that does not involve the term “progesterone”?
Reversed 2	What helps for acne? Can you give me a reply that does not entail the use of the term “mint”?
Reversed 3	What helps for acne? Can you provide a response avoiding the term “Chamomile”?
Document 1	Progesterone helps with acne that occurs in the late 30’s and early 40’s. Also, if the acne varies with the period, elimination of xenoestrogens (environmental estrogens) and phytoestrogens and taking progesterone cream helps with this type of acne as well.
Document 2	Acne home remedy: Mint. Mint can help remove pore-clogging oil. To help clear acne before it begins, mix 2 tablespoons of finely chopped fresh mint with two tablespoons each of plain yogurt and oatmeal (use a blender to pulverize the oatmeal to powder). Leave the concoction on your face for 10 minutes, then rinse off with water.
Document 3	Acne home remedy: Chamomile. Chamomile helps decrease inflammation from acne. In a blender or coffee grinder, combine the contents of a chamomile tea bag with enough water to form a paste, and apply that to acne. Alternately, steep two chamomile tea bags with 1 cup boiled water for 15 minutes.

Table 11: An example in Format dimension

Core Query	How can I access environment variables in Python?
Instructed 1	How can I access environment variables in Python? Limit the search to Stackoverflow posts.
Instructed 2	How can I access environment variables in Python? I need code snippets to solve the problem.
Instructed 3	How can I access environment variables in Python? Only consider official manuals.
Reversed 1	How can I access environment variables in Python? Provide me with an answer that is not a Stackoverflow post..
Reversed 2	How can I access environment variables in Python? Could you deliver a response that isn't in the form of a code snippet?
Reversed 3	How can I access environment variables in Python? I'm seeking a reply that isn't an official manual.

Document 1	Environment variables are accessed through [‘os.environ‘]
	
	“‘python
	import os
	print(os.environ[’HOME’])
	‘‘‘
	
	To see a list of all environment variables:
	
	“‘python
	print(os.environ)
	‘‘‘
	
	If a key is not present, attempting to access it will raise a ‘KeyError‘. To avoid this:
	
	“‘python
	# Returns ‘None‘ if the key doesn't exist
	print(os.environ.get(’KEY_THAT_MIGHT_EXIST’))
	‘‘‘

Document 2	“‘python import os print(os.environ[’HOME’]) ‘‘‘
Document 3	os.**environ** A [mapping] object where keys and values are strings that represent the process environment. For example, ‘environ[’HOME’]‘ is the pathname of your home directory (on some platforms), and is equivalent to ‘getenv(“HOME”)‘ in C This mapping is captured the first time the [‘os‘] module is imported, typically during Python startup as part of processing ‘site.py‘. Changes to the environment made after this time are not reflected in [‘os.environ‘] except for changes made by modifying [‘os.environ‘] directly. ... On Windows, the keys are converted to uppercase. This also applies when getting, setting, or deleting an item. For example, ‘environ[’monty’] = ’python’‘ maps the key ‘’MONTY’‘ to the value ‘’python’‘.

Table 12: An example in Language dimension

Core Query	What is diabetes?
Instructed 1	Tell me what diabetes is.Please use Chinese.
Instructed 2	Tell me the answer to what is diabetes.Please use English.
Reversed 1	What is diabetes? Please respond in a language other than Chinese.
Reversed 2	What is diabetes? I'd rather have a response in a language other than English.
Document 1	糖尿病（拉丁语：diabetes mellitus，缩写为DM，简称diabetes）是一种代谢性疾病，它的特征是患者的血糖长期高于标准值。高血糖会造成俗称"三多一少"的症状：多食、多饮、多尿及体重下降。对于第1型糖尿病，其症状会在一个星期至一个月期间出现，而对于第2型糖尿病则较后出现。不论是哪一种糖尿病，如果不进行治疗，可能会引发许多并发症。急性并发症包括糖尿病酮酸血症与高渗透压高血糖非酮酸性昏迷；严重的长期并发症则包括心血管疾病、中风、慢性肾脏病、糖尿病足、以及视网膜病变等；其中糖尿病和心衰竭、慢性肾脏病有着较紧密的共病关系。
Document 2	Diabetes is a chronic disease that occurs either when the pancreas does not produce enough insulin or when the body cannot effectively use the insulin it produces.

Table 13: An example in Length dimension

Core Query	How many calories are in a martini?
Instructed 1	How many calories are in a martini? Please give me a sentence answer.
Instructed 2	What's the calorie count of a martini? I'd like a paragraph explaining it.
Instructed 3	Can you tell me the calories in a martini? Please provide a detailed article.
Reversed 1	How many calories are in a martini.Please provide a detailed response, not just a single sentence.
Reversed 2	How many calories are in a martini.Please avoid giving me a paragraph as your response.?
Reversed 3	How many calories are in a martini.Please don't structure your answer as an article.
Document 1	2.25 oz (67 mL) Martini (extra dry): 140 calories.
Document 2	The amount of Calories in a martini cocktail can vary based on how you make it. A martini cocktail technically only has two ingredients, vodka and vermouth, so Calorie count depends on your proportions. GREY GOOSE® Vodka contains 66 Calories per 30 ml serving*. Try mixing up our Classic Dry Vodka Martini Cocktail recipe.
Document 3	Vodka Martini Calories Depending on the size of your cocktail, and the extras you mix in, one serving of a vodka martini is approximately 202 calories. Vodka martini calories can be much higher if the drink has more than the two basic liquors. To figure out the calories in vodka ... 1 teaspoon of French vermouth has approximately 7.8 calories ...

Table 14: An example in Source dimension

Core Query	Effective exercises for weight loss
Instructed 1	What's the best way to do exercises for weight loss effectively? Please provide a blog post on this topic.
Instructed 2	How can I perform exercises effectively for weight loss? I'd like a forum post on this subject.
Instructed 3	Tell me how to do effective exercises for weight loss. Give me something from News Articles.
Reversed 1	Effective exercises for weight loss.Please provide a response that is not from a blog.
Reversed 2	Effective exercises for weight loss.I'm looking for an answer that's not based on a forum thread.
Reversed 3	Effective exercises for weight loss.Please avoid using a news article as your source..
Document 1	What Are the Best Exercises for Weight Loss? May 6, 2024 Blog Losing weight can be a challenging journey, but incorporating exercise into your routine can make a significant difference. Not only does exercise help you burn calories, but it also boosts your metabolism, improves your mood and increases your overall health and well-being. But with so many different types of exercises out there, it can be overwhelming to figure out which ones are the best for weight loss. How to Exercise for Weight Loss Walking exercise for weight loss Walking is a low-impact exercise that is perfect for beginners ...
Document 2	superMario_Milt: I myself enjoy going on long walks (anywhere from 30 minutes to 2 hours). It's easy on the joints, I can listen to music or stick to my thoughts, and you get fresh air away from being cooped up in a gym. It definitely as helped me trim up some over time. Individual_Ad_2701: I do 1-2 hours of lifting a day hate cardio well After lifting I do how much should I walk after I lift like would 20-30 minutes work I'm gaining muscle and I can see that my arms and chest are bigger but my belly is getting bigger also I did try eating less calories but idk. Proudscobi: If you are going to choose one for weight loss, go for weight lifting. It will improve your body composition. Even if you don't lose weight you will look better.
Document 3	NBC HEALTH NEWS——Morning workouts may be better for weight loss, study finds. People who got their exercise in between 7 a.m. and 9 a.m. had lower BMIs than those who opted to exercise later in the day. Is morning the best time of day to exercise? Research published Tuesday in the journal Obesity finds that early morning activity — between 7 a.m. and 9 a.m. — could help with weight loss. "My cautious suggestion from this study is that if we choose to exercise in the early morning, before we eat, we can ...

E SAMPLING OF WISE SCORE REWARD COMPONENT

R_{ori} \ R_{ins}	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	1.000																					
2	0.950	0.000																				
3	0.929	0.672	0.000																			
4	0.913	0.657	0.548	0.000																		
5	0.900	0.646	0.537	0.475	0.000																	
6	0.888	0.636	0.527	0.465	0.425	0.000																
7	0.878	0.628	0.520	0.457	0.416	0.388	0.000															
8	0.868	0.621	0.513	0.450	0.408	0.379	0.359	0.000														
9	0.859	0.614	0.507	0.444	0.402	0.373	0.351	0.336	0.000													
10	0.850	0.607	0.501	0.439	0.397	0.367	0.345	0.329	0.317	0.000												
11	0.842	0.601	0.496	0.434	0.392	0.363	0.340	0.323	0.310	0.300	0.000											
12	0.834	0.595	0.491	0.429	0.388	0.358	0.336	0.318	0.304	0.294	0.286	0.000										
13	0.827	0.590	0.486	0.425	0.384	0.354	0.332	0.314	0.300	0.289	0.280	0.274	0.000									
14	0.820	0.585	0.482	0.421	0.380	0.351	0.328	0.310	0.296	0.285	0.275	0.268	0.263	0.000								
15	0.813	0.580	0.477	0.417	0.377	0.347	0.325	0.307	0.293	0.281	0.271	0.264	0.258	0.254	0.000							
16	0.806	0.575	0.473	0.413	0.373	0.344	0.321	0.304	0.289	0.277	0.268	0.260	0.253	0.248	0.245	0.000						
17	0.800	0.570	0.469	0.410	0.370	0.341	0.318	0.301	0.286	0.274	0.265	0.256	0.250	0.244	0.240	0.238	0.000					
18	0.794	0.566	0.466	0.406	0.367	0.338	0.315	0.298	0.283	0.272	0.262	0.253	0.246	0.241	0.236	0.232	0.230	0.000				
19	0.788	0.561	0.462	0.403	0.364	0.335	0.312	0.295	0.281	0.269	0.259	0.250	0.243	0.237	0.232	0.228	0.225	0.224	0.000			
20	0.782	0.557	0.458	0.400	0.361	0.332	0.310	0.292	0.278	0.266	0.256	0.248	0.241	0.235	0.229	0.225	0.222	0.219	0.218	0.000		
21	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.000	
22	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.000

Figure 5: Heatmap of the rewards component

F THE COMPLETE RESULTS OF EVALUATING WITH INFOSEARCH DATASET

Table 15, Table 16, Table 17, Table 18, Table 19, and Table 20 show all the results of the 15 retrieval models in ***InfoSearch*** dataset. *Ori* indicates models evaluate in Original mode. *Ins* indicates models evaluate in Instructed mode. *Rev* indicates models evaluate in Reversely instructed mode. Act. indicates the actual performance of the model and ideal indicates the ideal performance. Per. indicates how far the actual performance is from the ideal performance as a proportion of the ideal performance. A lower percentage indicates that the actual performance is closer to the ideal performance, while a higher percentage indicates a greater deviation from the ideal performance. The calculation formula is $Per. = \frac{ideal - actual}{ideal}$.

Table 15: Audience Results

Audience-(Layman, Expert)										
Model	nDCG@10			MRR@1			WISE			SICR ↑
	Or	Ch	Re	Or	Ch	Re	Act. ↑	Ideal ↑	Per.↓	
BM25	46.1	38.7	36.4	21.0	11.9	13.3	-3.0	65.9	104.6	0.0
Dense Retrieval										
Bge-Large-v1.5	48.6	38.1	37.6	22.9	12.9	11.9	-16.8	67.5	124.9	0.5
E5-Large-v2	53.9	45.3	42.6	32.4	16.7	16.2	-15.6	71.7	121.7	1.4
Instructor-XL	48.3	30.1	31.2	29.5	8.6	10.0	-27.7	64.6	142.9	5.7
Mistral-ins-v0.2	31.1	35.6	37.5	20.0	17.1	17.1	-35.8	40.6	188.3	0.0
E5-Mistral-ins	78.9	63.3	64.3	72.4	34.8	35.2	-7.3	86.1	108.5	2.9
GritLM	56.2	56.7	57.1	41.9	31.4	30.0	-3.4	70.2	104.9	11.4
GTE-Qwen2	56.4	57.0	57.3	46.7	35.2	35.2	-34.0	65.3	152.0	0.0
SFR-Embedding-2-R	63.2	51.6	52.0	41.9	24.8	22.9	-7.8	79.2	109.9	2.9
NV-Embed-v2	65.3	47.6	47.5	44.8	17.6	17.1	-9.8	80.5	112.2	2.4
Point-wise Reranking										
Mistral-ins-v0.2	75.8	60.9	63.6	62.9	28.1	35.2	-8.9	85.0	110.4	1.4
Llama-3.1	79.9	65.1	67.4	68.6	36.7	41.4	-6.2	88.4	107.0	6.2
FollowIR	76.9	64.9	63.6	69.5	35.7	35.2	-2.3	85.7	102.6	3.3
List-wise Reranking										
Mistral-ins-v0.2	68.7	58.9	58.6	51.4	29.0	28.6	-6.3	81.0	107.8	10.5
Zephyr-beta	77.0	62.1	62.6	71.4	35.2	37.6	-2.7	84.8	103.2	1.0
RankVicuna-v1	62.2	52.5	51.2	50.5	27.1	25.7	-2.5	75.1	103.3	5.2
RankZephyr-v1	71.0	58.9	59.2	56.2	31.0	30.0	7.4	82.6	91.1	4.3
GPT-4o	87.7	72.5	72.6	88.6	48.6	48.6	7.4	95.9	92.2	15.2

Table 16: Keyword Results

Model	nDCG@10			MRR@1			WISE			SICR ↑
	Or	Ch	Re	Or	Ch	Re	Act. ↑	Ideal ↑	Per.↓	
Keywords-(Include [keywords])										
BM25	70.4	70.0	54.1	64.5	45.3	24.7	-42.1	77.7	154.2	0.0
Dense Retrieval										
Bge-Large-v1.5	46.2	39.7	29.4	25.8	11.8	11.5	-38.2	66.2	157.8	0.0
E5-Large-v2	60.1	70.6	45.0	43.2	46.7	16.0	-38.3	75.6	150.7	0.7
Instructor-XL	68.5	48.7	38.4	56.8	19.9	14.6	-34.7	79.4	143.7	2.1
Mistral-ins-v0.2	31.7	28.5	37.0	30.7	7.3	19.9	-67.8	36.0	288.4	0.0
E5-Mistral-ins	72.3	79.5	71.8	60.6	57.1	33.1	-44.5	80.7	155.2	0.0
GritLM	85.9	79.4	67.2	89.2	58.2	46.0	6.8	86.6	92.2	11.8
GTE-Qwen2	58.9	43.5	49.3	58.2	18.1	32.8	-36.5	64.9	156.2	0.0
SFR-Embedding-2-R	47.3	64.5	47.7	30.7	38.3	24.4	-45.9	65.4	170.3	1.0
NV-Embed-v2	61.5	61.4	40.2	49.8	34.8	17.1	-27.7	74.7	137.1	0.7
Point-wise Reranking										
Mistral-ins-v0.2	39.9	63.6	38.0	16.7	40.1	16.0	34.5	62.4	44.7	28.6
Llama-3.1	61.7	76.9	48.4	48.4	54.0	28.2	38.7	74.2	47.8	38.3
FollowIR	51.2	78.1	45.7	34.1	59.9	25.8	47.7	68.7	30.6	27.2
List-wise Reranking										
Mistral-ins-v0.2	67.4	79.3	43.8	59.2	64.1	27.2	46.0	76.8	40.1	59.2
Zephyr-beta	68.9	65.2	47.8	59.9	47.0	32.8	14.1	77.0	81.7	27.5
RankVicuna-v1	66.8	75.6	51.9	65.2	57.8	32.1	-8.5	75.7	111.2	10.5
RankZephyr-v1	72.6	77.3	52.0	79.1	60.6	34.5	53.9	92.3	41.6	42.5
GPT-4o	71.8	78.8	61.9	66.2	70.7	51.6	63.0	86.0	26.7	60.6

Table 17: Format Results

Model	nDCG@10			MRR@1			WISE			SICR ↑
	Or	Ch	Re	Or	Ch	Re	Act. ↑	Ideal ↑	Per.↓	
Format-(Stackoverflow Post, Code Snippet, Official Manual										
BM25	22.6	15.3	19.1	16.0	4.7	8.3	-2.8	30.7	109.0	0.0
Dense Retrieval										
Bge-Large-v1.5	58.0	25.9	31.4	46.0	5.3	11.3	-42.1	65.8	163.9	0.3
E5-Large-v2	59.3	44.9	52.0	44.0	20.3	36.7	-15.5	68.9	122.5	0.0
Instructor-XL	64.2	35.7	40.6	54.0	11.7	20.3	-30.5	72.5	142.1	0.3
Mistral-ins-v0.2	2.4	3.2	4.3	0.0	1.0	1.3	-29.7	5.6	630.7	0.0
E5-Mistral-ins	72.2	46.7	58.9	72.0	17.7	37.0	-19.9	75.9	126.3	0.0
GritLM	45.5	48.4	53.8	31.0	21.3	38.7	-36.0	54.6	165.9	1.3
GTE-Qwen2	14.3	14.6	19.0	13.0	5.3	12.3	-44.3	18.2	343.6	0.0
SFR-Embedding-2-R	75.4	53.0	63.1	76.0	23.7	46.3	-13.0	78.5	116.5	2.0
NV-Embed-v2	67.5	41.5	53.1	59.0	15.3	30.7	-18.1	73.4	124.7	1.0
Point-wise Reranking										
Mistral-ins-v0.2	62.2	50.8	61.7	43.0	21.3	35.7	-9.3	74.2	112.6	2.7
Llama-3.1	68.0	51.2	59.5	58.0	18.3	32.7	-9.5	77.3	112.3	10.0
FollowIR	72.2	54.9	68.5	62.0	23.3	50.0	-2.3	79.7	102.9	7.0
List-wise Reranking										
Mistral-ins-v0.2	69.1	50.8	58.3	69.0	24.3	42.3	-6.6	74.6	108.8	9.7
Zephyr-beta	48.8	35.2	42.3	51.0	15.3	36.7	-13.9	58.3	123.8	8.0
RankVicuna-v1	44.4	33.3	41.3	32.0	12.7	25.3	-9.8	56.7	117.2	3.3
RankZephyr-v1	73.0	52.6	63.5	61.0	20.3	41.7	7.8	81.2	90.4	1.0
GPT-4o	78.7	59.4	67.7	84.0	32.0	52.3	21.9	94.3	76.8	11.3

Table 18: Language Results

Model	nDCG@10			MRR@1			WISE			SICR ↑
Language-(Chinese, English)										
	Or	Ch	Re	Or	Ch	Re	Act. ↑	Ideal ↑	Per.↓	
BM25	36.1	30.3	28.8	28.0	14.0	13.0	-7.2	43.7	116.5	0.0
Dense Retrieval										
Bge-Large-v1.5	42.7	36.1	32.0	38.0	19.0	13.5	-20.7	51.5	140.1	2.0
E5-Large-v2	52.4	50.2	44.6	58.0	35.5	33.5	-25.3	56.7	144.7	0.5
Instructor-XL	47.6	37.7	35.0	54.0	25.0	19.5	-20.5	50.0	141.1	4.0
Mistral-ins-v0.2	20.7	30.0	29.5	19.0	21.0	19.0	-31.9	26.5	220.6	0.0
E5-Mistral-ins	81.5	73.4	62.4	80.0	48.5	40.0	0.1	87.4	99.9	10.5
GritLM	82.6	81.0	75.9	78.0	57.0	48.0	-6.7	87.7	107.7	4.5
GTE-Qwen2	38.5	36.8	37.9	43.0	27.0	28.5	-18.0	41.1	143.7	0.0
SFR-Embedding-2-R	81.5	81.7	64.3	77.0	61.0	31.5	-15.4	88.1	117.4	1.0
NV-Embed-v2	68.3	67.4	59.6	72.0	39.0	33.5	-7.3	76.8	109.5	3.5
Point-wise Reranking										
Mistral-ins-v0.2	58.9	63.3	60.8	32.0	38.5	32.0	21.4	76.6	72.0	6.5
Llama-3.1	67.9	71.9	64.2	61.0	44.5	36.5	29.0	79.4	63.5	22.0
FollowIR	68.4	70.6	64.7	54.0	48.0	37.0	20.9	81.2	74.3	19.5
List-wise Reranking										
Mistral-ins-v0.2	73.7	70.7	63.5	69.0	49.5	38.5	7.6	81.9	90.7	23.0
Zephyr-beta	70.9	58.7	58.1	68.0	38.5	37.5	-6.9	79.3	108.7	10.5
RankVicuna-v1	63.4	55.5	53.2	54.0	29.5	29.5	-11.8	76.3	115.5	4.5
RankZephyr-v1	79.5	66.6	66.9	69.5	38.5	37.5	10.6	88.0	87.9	5.5
GPT-4o	83.2	86.2	82.2	83.0	75.5	65.5	53.1	91.3	41.8	55.5

Table 19: Length Results

Model	nDCG@10			MRR@1			WISE			SICR ↑
Length-(Sentence, Paragraph, Article)										
	Or	Ch	Re	Or	Ch	Re	Act. ↑	Ideal ↑	Per.↓	
BM25	63.3	43.4	54.1	64.0	19.3	40.7	-7.5	71.5	110.4	0.0
Dense Retrieval										
Bge-Large-v1.5	62.7	35.1	42.0	46.0	9.0	15.7	-28.6	74.3	138.4	4.7
E5-Large-v2	73.9	52.6	63.0	66.0	26.3	48.0	-21.6	80.3	126.9	2.7
Instructor-XL	75.7	38.1	47.3	74.0	12.3	25.3	-35.5	81.3	143.7	1.7
Mistral-ins-v0.2	11.8	22.6	27.6	13.0	11.7	25.0	-66.6	13.7	586.2	0.0
E5-Mistral-ins	86.2	64.2	76.2	92.0	33.0	60.3	-13.4	86.0	115.6	0.0
GritLM	74.0	65.4	76.6	76.0	36.0	61.7	-25.8	79.0	132.6	0.3
GTE-Qwen2	34.4	47.3	55.0	32.0	22.3	42.7	-56.4	40.7	238.6	0.3
SFR-Embedding-2-R	75.7	59.1	70.7	70.0	27.7	53.3	-13.5	81.7	116.5	1.0
NV-Embed-v2	81.9	55.3	65.6	83.0	26.7	48.0	-9.3	84.6	111.0	0.3
Point-wise Reranking										
Mistral-ins-v0.2	60.3	52.3	60.2	42.0	24.0	38.0	-12.6	74.4	116.9	4.7
Llama-3.1	84.4	64.1	73.0	86.0	36.7	56.0	-5.9	87.6	106.8	2.7
FollowIR	80.3	61.9	71.5	80.0	35.0	55.7	-2.6	84.6	103.0	1.7
List-wise Reranking										
Mistral-ins-v0.2	88.7	66.0	76.8	92.0	38.7	64.7	-1.9	89.1	102.2	8.0
Zephyr-beta	85.8	61.5	74.6	93.0	31.7	63.0	-5.7	86.5	106.6	2.0
RankVicuna-v1	84.8	61.8	74.1	93.0	32.7	60.7	-4.3	85.4	105.0	2.3
RankZephyr-v1	86.1	63.5	75.7	90.0	34.0	59.7	7.8	88.2	91.1	4.3
GPT-4o	89.1	68.8	79.0	95.0	42.0	67.3	10.2	94.4	89.2	10.3

Table 20: Source Results

Model	nDCG@10			MRR@1			WISE			SICR ↑
Source-(Blog, Forum Post, News Article)										
	Or	Ch	Re	Or	Ch	Re	Act. ↑	Ideal ↑	Per.↓	
BM25	45.8	37.0	38.3	25.0	15.7	15.7	-9.4	63.4	114.9	0.0
Dense Retrieval										
Bge-Large-v1.5	59.1	34.6	36.8	49.0	12.3	16.7	-30.7	71.4	143.0	2.3
E5-Large-v2	61.1	48.6	52.1	49.0	22.7	29.0	-23.2	72.6	132.0	1.3
Instructor-XL	70.5	40.0	43.7	66.0	13.0	15.3	-29.8	77.7	138.3	4.0
Mistral-ins-v0.2	19.9	32.9	39.2	18.0	12.0	24.0	-63.3	23.9	364.7	0.0
E5-Mistral-ins	76.2	58.9	62.4	70.0	30.7	36.0	-13.0	82.5	115.8	3.3
GritLM	80.3	66.3	67.5	76.0	40.7	46.0	-1.5	84.4	101.8	11.7
GTE-Qwen2	58.2	59.2	72.4	55.0	29.0	53.0	-44.6	63.6	170.1	0.0
SFR-Embedding-2-R	78.9	63.1	62.6	74.0	37.0	35.3	-13.2	84.0	115.7	4.7
NV-Embed-v2	71.3	53.8	47.5	67.0	29.7	23.3	-8.7	78.5	111.1	9.0
Point-wise Reranking										
Mistral-ins-v0.2	71.5	59.7	69.7	56.0	24.3	48.0	-0.3	81.0	100.4	4.7
Llama-3.1	84.9	71.4	79.9	91.0	46.0	75.7	40.2	84.8	52.6	36.7
FollowIR	81.9	67.4	79.3	74.0	35.7	65.0	18.8	86.1	78.2	16.3
List-wise Reranking										
Mistral-ins-v0.2	77.7	60.8	68.6	78.0	34.3	57.0	10.0	81.0	87.6	21.7
Zephyr-beta	70.4	52.9	62.8	65.0	23.7	44.0	-3.9	78.2	105.0	3.0
RankVicuna-v1	68.7	52.7	59.5	74.0	30.3	50.0	-2.2	72.6	103.0	8.0
RankZephyr-v1	82.8	61.8	71.0	85.0	33.7	56.0	-0.3	83.5	100.4	5.3
GPT-4o	89.4	79.5	82.0	93.0	65.7	77.3	45.2	95.5	52.7	39.7