ListT5: Listwise Reranking with Fusion-in-Decoder Improves Zero-shot Retrieval

Anonymous ACL submission

Abstract

We propose ListT5, a novel reranking approach based on Fusion-in-Decoder (FiD) that handles multiple candidate passages at both train and inference time. We also introduce an efficient inference framework for listwise ranking based on m-ary tournament sort with output caching. We evaluate and compare our model on the BeIR benchmark for zero-shot retrieval task, demonstrating that ListT5 (1) outperforms the state-of-the-art RankT5 baseline with a notable +1.3 gain in the average NDCG@10 score, (2) has an efficiency comparable to pointwise ranking models and surpasses the efficiency of previous listwise ranking models, and (3) overcomes the lost-in-the-middle problem of previous listwise rerankers. Our code, model checkpoints, and the evaluation framework will be fully open-sourced.

1 Introduction

Recent advancements on neural retrievers have made significant progress in their semantic search capabilities. However, they still struggle in zero-shot or out-domain tasks where statistical retrievers such as BM25 (Robertson and Zaragoza, 2009) often outperform, a crucial challenge since the setting is closely related to diverse real-world scenarios.

Until now, the field of zero-shot reranking has been generally driven by models such as MonoT5 (Nogueira et al., 2020) or RankT5 (Zhuang et al., 2022), which rely on pointwise reranking at inference time. This approach separately scores the relevancy of each query-passage pair, lacking the ability to compare between passages relatively. This could lead to a suboptimal solution in the task of reranking, where discrimination and ordering between passages are crucial.

Recently, listwise reranking (Ma et al., 2023; Sun et al., 2023b,a), which evaluates multiple passages together, is gaining attention for its effectiveness in zero-shot retrieval. Listwise rerankers can condition on and compare multiple passages to calibrate the relevance scores better, and can reduce the inaccuracy of predictions arising from domain shift, as theoretically supported by Xian et al. (2023), and empirically supported by a line of works such as Ma et al. (2023); Sun et al. (2023a).

However, existing approaches that attempt listwise reranking have limitations. DuoT5 (Pradeep et al., 2021) implements pairwise reranking, a form

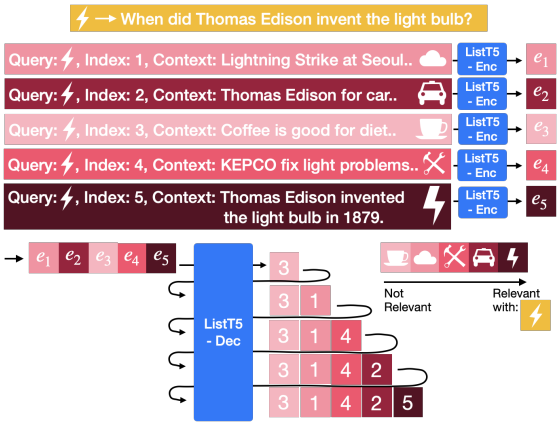

Figure 1: Illustration of ListT5. ListT5 jointly considers $m = 5$ candidate passages at once using FiD architecture, each concatenated with the query and an identifier. The output is an ordered list of the identifiers (numbers) where the most relevant passage comes at the *last*.

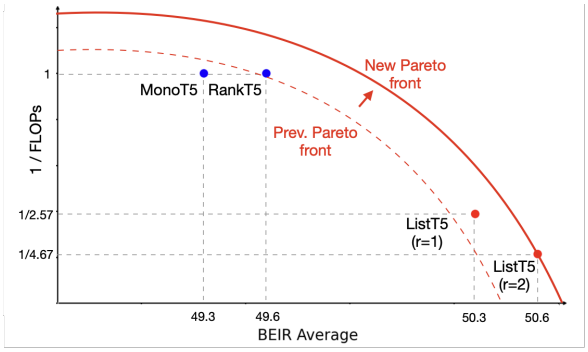

Figure 2: We aim to improve the Pareto front of the performance (avg. in BeIR) and efficiency (FLOPs) in zero-shot retrieval.

of listwise reranking as pair, which incurs quadratic time complexity to the number of candidate passages. On the other hand, Large Language Models (LLMs) that use listwise reranking (Pradeep et al., 2023; Sun et al., 2023b,a; Ma et al., 2023) sacrifice efficiency in another aspect due to large parametric model size, and also face the "Lost in the middle" problem (Liu et al., 2023; Tang et al., 2023).

In this work, we present ListT5, a novel Fusion-in-Decoder (FiD) (Izacard and Grave, 2021) approach with T5 (Raffel et al., 2020) for zero-shot reranking, illustrated in Fig. 1. ListT5 jointly considers the relevancy of multiple (m, which we fix to 5) candidate passages at both training and inference time. ListT5 outputs a sorted list of them in the *increasing* order of relevance and employs a m-ary tournament tree structure at inference time for efficient sorting. Our contributions are threefold:

(1) Computational Effectiveness. In order to obtain top-k relevant passages from an arbitrary number of candidate passages n, the application of our m-ary tournament tree enables ListT5 to achieve the asymptotic complexity of $\mathcal{O}(n + k \log n)$. This is far more efficient than pairwise models of $\mathcal{O}(n^2)$ and competitive with pointwise models of $\mathcal{O}(n)$, described in Fig. 4.

(2) Robustness to Positional Bias. Importantly, ListT5 utilizes FiD that overcomes the "lost in the middle" problem commonly encountered in listwise ranking models, showing robustness to the position, or index of relevant passages, with experiments in Tab. 4.

(3) Zero-shot Performance. Notably, ListT5 demonstrates superior performance in zero-shot retrieval, resulting in an average of +1.3 gain in NDCG@10 compared to established models like RankT5 (Zhuang et al., 2022) or MonoT5 (Nogueira et al., 2020) on BeIR (Thakur et al., 2021), a widely used benchmark for zero-shot retrieval, with results in Tab. 2 and 3.

With these contributions, we aim to push the Pareto front of rerankers between performance and efficiency, as shown in Fig. 2.

2 Related Work

2.1 Generative Models for Reranking

In the reranking scenario, rather than dual encoder models (Karpukhin et al., 2020), which separately encode query and passage information, models that see query and passage information jointly at inference time (Reimers and Gurevych, 2019; Nogueira et al., 2020) are shown to be effective for zero-shot retrieval (Rosa et al., 2022). Among those, formulating reranking as sequence generation, such as conducting listwise sorting (Ma et al., 2023; Sun et al., 2023b; Pradeep et al., 2023) or generating rationales (Ferraretto et al., 2023), shows an advantage in application to zero-shot retrieval by leveraging the language model's auto-regressive generation capabilities.

2.2 Listwise Reranking for T5

As mentioned in Sec. 2.1, a series of studies that use the encoder-decoder architecture of T5 for reranking scenarios, such as MonoT5 (Nogueira et al., 2020), RankT5 (Zhuang et al., 2022), and DuoT5 (Pradeep et al., 2021), are shown to be powerful. RankT5 (Zhuang et al., 2022) uses listwise training objectives but only performs pointwise reranking at inference. DuoT5 (Pradeep et al., 2021) only sees two passages at each prediction, and is inefficient and impractical as it has to run prediction on every pair of candidate passages (thus requiring $n^2 - n$ predictions to rerank n passages).

2.3 Listwise Reranking with LLMs

Compared to previous listwise ranking models that build upon T5, we can consider a more direct way for listwise reranking by providing multiple passages at once as input. Motivated by Sun et al. (2023b); Pradeep et al. (2023); Ma et al. (2023), this line of work usually follows the format of taking 20 passages per input, with a sliding window of stride 10. However, this format presents a challenge due to the monolithic and lengthy input size. The model must process all tokens at once, limiting its applicability to LLMs trained with large context lengths. The lengthy input size also leads to the "lost in the middle" problem (Liu et al., 2023) for LLMs, as they exhibit strong positional bias to the information in the first and last parts of a long input, and often fail to comprehend relevant information in the middle. This positional bias problem is also prevalent in listwise reranking (Tang et al., 2023). Furthermore, this approach comes at the cost of sacrificing computational efficiency in the already computation-intensive reranking scenarios.

2.4 FiD in a Similar Setup

Hofstätter et al. (2022) assigned index numbers to each query and passage pair, directing an FiD model to generate relevant passage indexes—an idea initially proposed by Lakhotia et al. (2020).

Figure 3: Two variants of LISTT5, (r=1) and (r=2). The underlying model is identical and only the inference method varies. (r=1) keeps only the top 1 relevant index from the output, and (r=2) keeps top 2 relevant indices.

While their approach is similar to ours, it diverges in that they only generate a single positive index, not the sorted list of all indices.

3 Methods

In this section, we first introduce the basic operating unit of LISTT5 that takes m passages as input and ranks the top-r passages as output (Sec. 3.1). Then, we explain how we take inspirations from the classic tournament tree sort algorithm to extend this basic unit to rank top-k passages from a full set of n passages (Sec. 3.2).

3.1 LISTT5: Basic Operating Unit ($m \rightarrow r$)

Fig. 3 illustrates the basic inference unit. LISTT5 processes inputs using the FiD (Izacard and Grave, 2021) architecture. Given a query $\mathbf{q}$ and a set of m candidate passages $[\mathbf{p}_1, ..., \mathbf{p}_m]$, LISTT5 ranks top-$r$ candidates from m. To do this, for each passage, LISTT5 concatenates $\mathbf{q}$, i, and $\mathbf{p}_i$ in the following format and then separately feeds to the Encoder, which outputs the following:

$$\mathbf{e}_i = \text{Enc}(\text{"Question: } \mathbf{q}\text{, Index: } i\text{, Context: } \mathbf{p}_i\text{"}) \quad (1)$$

Then, the resulting output representation $\mathbf{e}_i$ are concatenated to form one long sequence to be fed to the decoder, which outputs an ordered sequence of indices i in the increasing order of relevance:

$$[i'_1, ..., i'_m] = \text{Dec}(\text{concat}(\mathbf{e}_1, ..., \mathbf{e}_m)), \\ \text{where } \text{rel}(\mathbf{q}, \mathbf{p}_{i'_1}) < ... < \text{rel}(\mathbf{q}, \mathbf{p}_{i'_m}) \quad (2)$$

Lastly, we decide how many relevant passages we will keep; **LISTT5 (r = 1)** keeps one, so only $\mathbf{p}_{i'_m}$ is selected as the output of the inference unit. **LISTT5 (r = 2)** keeps two, selecting $\mathbf{p}_{i'_m}$ and $\mathbf{p}_{i'_{m-1}}$ as the output of the inference unit.

In our experiments, we set m to 5. Ablations on varying m is at App. A.

3.2 Extension using Tournament Sort ($n \rightarrow k$)

Tournament Sort. In most cases, the total number of candidate passages n often exceeds the number of contexts m ($= 5$) the model can see at once. In order to design an efficient algorithm that can sort top-k passages from an arbitrary number n, we adopt the concept of tournament sort (McLuckie and Barber, 1986) (App.B.1). Tournament sort leverages the tournament tree structure for efficient sorting by utilizing the information explored from the previous selection (we call this "Output Caching"). This minimizes the number of comparisons for the next iteration from $\mathcal{O}(n)$ to $\mathcal{O}(\log n)$ as we only need to redo computation for a *single* path that traverses from a leaf to the root, and all others can be inferred from the previous computation.

Modifications on Tournament Sort. Fig. 4 illustrates our inference process to rank top-k passages from an arbitrary number of n passages. We use a modified version of tournament sort to iteratively select the top-1 passage k times, where each iteration performs a bottom-up comparison. To fit our needs, (1) we extend the original 2-ary tree structure to take m inputs at once, and (2) modify the structure to also accept LISTT5 (r = 2) (App. Fig. 8) along with LISTT5 (r = 1). Also, since we need to ensure the model always views exactly m passages for every comparison, we (3) replace the top-1 passage with a random passage after each iteration and (4) add a random dummy passage for inputs with a smaller number of candidate passages than m. Note that the random passage comes from the not-yet selected passage pool, and we ensure the model does not see duplicate passages at once after random replacement, unless the total number of leftover passages is smaller than m. Details are at App. B.

Computational Complexity. At first iteration, we need a total of $n/m*(1+1/m+1/m^2+...) = n/m*(1/(1-1/m))$ forward passes to LISTT5, which is about $\mathcal{O}(n)$. After the initial iteration, we only compute one path from leaf to root, resulting in the computational complexity of $\mathcal{O}(\log_m n)$ for each iteration out of $k-1$. Thus, our method achieves $\mathcal{O}(n + k \log_m n)$ asymptotic complexity to the number n of given passages. If we compare this asymptotic time complexity with others at Tab. 1, we can see that our method is much more efficient than pairwise ranking models (Pradeep

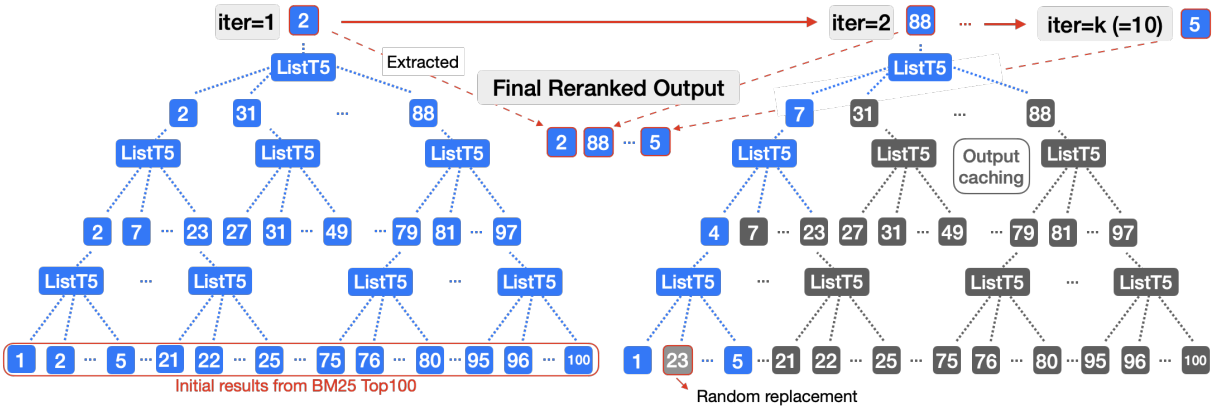

Figure 4: Illustration of our inference framework using m-ary tournament sort, with LISTT5 (r = 1) as the basic unit. Given n candidates, we can order top-k most relevant passages in $O(n + k \log n)$ asymptotic complexity. We can use either (r = 1) or (r = 2) for the basic unit, but the uppermost unit always outputs 1 (r = 1). We fix m to 5 in our experiments. Full illustration at Appendix Fig.8.

Method Name	Reranking Method	Complexity
MonoT5 (Nogueira et al., 2020), RankT5 (Zhuang et al., 2022)	Pointwise	$\mathcal{O}(n)$
DuoT5 (Pradeep et al., 2021)	Pairwise	$\mathcal{O}(n^2)$
ListT5 (Ours)	Listwise	$\mathcal{O}(n + k \log n)$

Table 1: Comparison of the computational complexity of different ranking methods on obtaining top-k passages from n candidate passages. The base of the log function is m. While being able to see multiple passages, LISTT5 has lower time complexity than pairwise models and is competitive with pointwise models.

et al., 2021), and comparable to pointwise ranking models (Nogueira et al., 2020; Zhuang et al., 2022).

4 Experimental Setup

4.1 Training Dataset

To train LISTT5, we use the official train subset of the MS MARCO (Bajaj et al., 2018) passage ranking dataset[1]. The dataset consists of 532,761 distinct queries and 8.8M passages. For each query, relevant passages are labeled with 1 and 0 otherwise. Although we have the query and relevant passage information, there is no labeled list of negative (irrelevant) passages and the orderings between them. Therefore, to construct the training data, we sampled $m - 1$ (= 4) distinct negative passages per one relevant passage from the full corpus. For ordering and selecting $m - 1$ negative passages from the full corpus, we use the COCO-DR large (Yu et al., 2022) dual-encoder model, which has been shown to perform well on MS MARCO. By using COCO-DR, we retrieve top 1000 passages on each query of the train subset of MS MARCO, randomly sample $m - 1$ (= 4) distinct passages from the subset that are not labeled as relevant, and make 20 different versions of negatives per each query-relevant passage pair. We set the target output to be a sequence of indices, where the index of the relevant passage comes at the *last*, and the ordering of other (negative) passages follows the dot product similarity scores computed by COCO-DR in *increasing* order. We randomly assign identifiers $1, \ldots, m$ to input passages so that the indexes of positive passages are evenly distributed in $\{1, \ldots, m\}$.

[1] https://microsoft.github.io/msmarco/Datasets

4.2 Training Details

We train two model versions: T5-base and T5-3B. We train the T5-base model for 20k steps with a learning rate of 1e-4 and T5-3B for 3k steps with a learning rate of 1e-5. Linear learning rate scheduler with 10% warmup and an effective batch size of 256 in bfloat16 precision is used. We set the maximum input length to 230 and 128, and the maximum output length to 8 and 7 for T5-base and T5-3B, respectively. With DeepSpeed stage 2, training T5-base took approximately 8 hours on 4×NVIDIA RTX A6000 GPUs with 48GB, while T5-3B training took 3 hours on 8×NVIDIA A100 GPUs with 40GB.

4.3 Baseline Models

All baseline models are downloaded from the official released HuggingFace checkpoint, including

MonoT5[2], **RankT5**, and **DuoT5**[3]. For RankT5, we download the released T5X checkpoint from the official repository[4] and convert to a PyTorch checkpoint using the conversion script from HuggingFace.[5] We evaluate DuoT5 on the same setup to the paper's final experiments - we rerank 100 passages using MonoT5, select top 50 passages to be run on DuoT5, and then aggregate relevancy scores of individual documents by the SYM-SUM method. Due to resource constraints, our replication uses BM25 top 100 (not top 1000) as the first-stage retrieval output.

4.4 Evaluation Dataset

We evaluate our method and baseline models with the official dev set of MS MARCO, TREC-DL19, and TREC-DL20 (Craswell et al., 2021) for in-domain performance, and the BeIR benchmark (Thakur et al., 2021) for zero-shot out-domain performance. TREC-DL19 and TREC-DL20 consist of 43 and 54 queries, respectively. BeIR contains 18 diverse sets of domains and tasks. We download the dumped index of the top 100 retrieved passages by BM25 from the official Pyserini repository. We also conduct reranking using the top 100 results of COCO-DR-large. For this experiment, we could only utilize the evaluation subset that is uploaded (fully open) in the BeIR repository. Details with links used for dataset download are at App. D.

4.5 Evaluation Metric

We use the evaluation metric of the Normalized Discounted Cumulative Gain@10 (NDCG@10) (Järvelin and Kekäläinen, 2002), the official evaluation metric for BeIR (Thakur et al., 2021). All reported scores are rounded to the first floating point. We also report the Mean Reciprocal Rank@10 (MRR@10) scores at App. Tab. 7.

5 Experimental Results

We present three main results in the following order: (1) General performance and efficiency comparison of our models with respect to pointwise and listwise ranking models at Sec. 5.1, (2) Analyzing the lost-in-the-middle problem by measuring the robustness to positional bias between ListT5 and listwise ranking models at Sec. 5.2, and (3) Ablation experiments on the design choice at Sec. 5.3. All results are based on the T5-base model except explicitly mentioning 3B.

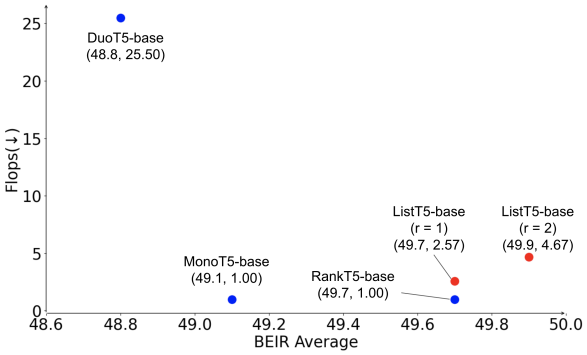

Figure 5: Real-time FLOPs comparison of the models, including DuoT5. Due to its high inference time of DuoT5, The reported BeIR performance is averaged from a subset of BeIR, same of those evaluated at Tab. 3.

5.1 Performance and Efficiency

Performance. We measure and compare the performance of ListT5 against pointwise ranking models in Tab. 2, and against pairwise and listwise ranking models in Tab. 3. ListT5 (r = 2) achieves an average of +1.3 point gain on NDCG@10 than the previous best checkpoint, RankT5, for reranking on BM25 Top100, and an average of +1.5 point gain for reranking on COCO-DR Top100, showing its effectiveness on both lexical-based and neural-based first-stage retrieval modules. Additionally, ListT5 excels on 3B model variants, showing its scalability to model size. Additional qualitative analysis is at App. F.

Efficiency in FLOPs. In addition to comparing the computational complexity in Sec. 3.2, we also conduct real-time measurements of floating point operations (FLOPs) using the FlopsProfiler of the DeepSpeed library[6]. We rerank Top-10 passages from BM25-Top100 candidate passages for TREC-DL19 (43 queries, maximum input length of 256), fix the model size as T5-base, run the profiler, and report the relative FLOPs when we set the FLOPs of MonoT5 (pointwise model) as 1[7]. The results in Fig. 5 shows that ListT5 (r=1) and (r=2) are comparable with MonoT5 and RankT5 and much more efficient than DuoT5. We also measure the FLOPs

[2] castorini/monot5-base-msmarco-10k, monot5-3b-msmarco-10k

[3] castorini/duot5-base-msmarco

[4] https://github.com/google-research/google-research/tree/master/rankt5

[5] convert_t5x_checkpoint_to_pytorch.py

[6] https://deepspeed.readthedocs.io/en/latest/flops-profiler.html

[7] The exact value of FLOPs for MonoT5 in this setup was 229,732,539,806,400.

Dataset	BM25 Top100				BM25 Top100 + 3B models			COCO-DR (Large) Top100			
	Initial	MonoT5	RankT5	**ListT5 (r = 2)**	MonoT5-3B	RankT5-3B	**ListT5-3B (r = 2)**	Initial	MonoT5	RankT5	**ListT5 (r = 2)**
MS MARCO (Top1000)	22.8	43.6	44.7	**44.9**	-	-	-	41.9	43.1	46.2	**46.3**
TREC-COVID	59.5	**78.3**	77.7	**78.3**	79.8	81.7	**84.7**	80.8	**83.5**	**83.5**	**83.5**
NFCorpus	32.2	**35.7**	35.1	35.6	37.3	**37.4**	37.0	35.5	35.6	35.5	**36.2**
BioASQ	52.2	55.3	**58.2**	56.4	57.5	**58.3**	**58.3**	-	-	-	-
NQ	30.5	52.1	**53.2**	53.1	56.4	**57.8**	56.2	54.3	57.9	59.6	**60.0**
HotpotQA	63.3	71.2	**72.8**	72.6	74.3	74.8	**75.6**	63.3	68.7	**71.1**	70.9
FiQA-2018	23.6	39.2	39.2	**39.6**	**46.0**	45.2	45.1	32.3	41.2	41.3	**41.7**
Signal-1M (RT)	33.0	32.0	30.8	**33.5**	32.2	31.9	**33.8**	-	-	-	-
TREC-NEWS	39.5	48.0	45.4	**48.5**	48.3	49.5	**53.2**	-	-	-	-
Robust04	40.7	53.4	**54.3**	52.1	**58.5**	58.3	57.8	-	-	-	-
Arguana	40.8	34.4	35.5	**48.9**	46.8	37.4	**50.6**	46.9	33.0	34.8	**49.3**
Touche-2020	**44.2**	29.6	37.1	33.4	32.5	**38.8**	33.6	21.6	25.7	**35.7**	29.6
CQADupStack	30.0	38.6	37.0	**38.8**	41.3	40.3	**42.1**	37.3	40.5	38.7	**40.9**
Quora	78.9	84.6	83.3	**86.4**	84.0	83.6	**86.9**	**87.3**	84.0	83.0	86.3
DBPedia	31.8	42.8	**43.7**	**43.7**	44.8	45.0	**46.2**	40.7	44.4	**46.1**	45.4
SCIDOCS	14.9	16.7	16.8	**17.6**	19.0	18.9	**19.5**	17.3	17.5	17.5	**18.3**
FEVER	65.2	78.4	77.6	**79.8**	80.0	79.8	**82.0**	74.9	78.9	79.7	**81.4**
Climate-FEVER	16.5	23.1	21.2	**24.0**	**26.2**	24.5	24.8	23.1	24.2	22.9	**24.9**
SciFact	67.9	73.1	73.5	**74.1**	76.3	**77.1**	77.0	71.9	73.5	73.6	**74.3**
Avg (BeIR)	42.5	49.3	49.6	**50.9**	52.3	52.2	**53.6**	49.1	50.6	51.6	**53.1**

Table 2: NDCG@10 values for MS MARCO dev set and BeIR. All results are run in the same setup using the released checkpoint. MS MARCO-Top1000 results for 3B models are omitted due to their long inference time. LISTT5-base excels in both performance and model size (than MonoT5-3B or RankT5-3B) for datasets in red.

	DuoT5	RankGPT	ListT5 (r=1)	ListT5 (r=2)
TREC-DL19	71.4	65.8	71.2	**71.8**
TREC-DL20	67.4	62.9	67.3	**68.1**
TREC-COVID	**80.1**	76.7	76.7	78.3
NFCorpus	35.0	**35.6**	35.5	**35.6**
Signal-1M (RT)	31.4	32.1	33.3	**33.5**
TREC-NEWS	**49.1**	48.9	47.9	48.5
Robust04	49.6	50.6	52.0	**52.1**
Touche-2020	31.8	**36.2**	34.2	33.4
DBPedia	43.9	**44.5**	43.9	43.7
SciFact	69.6	70.4	**74.1**	**74.1**
Avg (DL19, DL20)	69.4	64.4	69.3	**70.0**
Avg (BeIR)	48.8	49.4	49.7	**49.9**

Table 3: Comparison of LISTT5 against listwise (RankGPT) and pairwise (DuoT5) ranking models. The scores of RankGPT are from the paper, and the base model of RankGPT is GPT-3.5-turbo-0301. The best average is in bold. DuoT5 is applied on top 50 passages reranked by MonoT5. LISTT5 excels in both in-domain (DL19, DL20) and on the selected subset of BeIR.

of listwise ranking models - RankVicuna (Pradeep et al., 2023), a 7 billion listwise reranking model with a 4096 context size and a sliding window of 20. The FLOPs of RankVicuna was *107* times MonoT5-base, which is 42 times more of LISTT5 (r=1) and 23 times more of LISTT5 (r=2). By using the FiD architecture, encoder self-attention is efficiently computed only within each pair of query and passage. In contrast, in RankVicuna, it is computed over the entire list of query and passage pairs. By using the tournament tree structure with output caching, LISTT5 is much more efficient over previous listwise ranking models and comparable with pointwise ranking models, not only by the computational algorithmic complexity (Tab. 1), but also by the real-time FLOPs calculation. Even better, the LISTT5 model is *flexible* - according to their needs, users can have the choice to select between the trade-off of inference speed (r=1) and performance (r=2), an option not available for other models.

5.2 Robustness to Positional Bias

Background. One of the biggest problems of lengthy input of zero-shot listwise rerankers is the lost in the middle problem (Liu et al., 2023). Recent studies show that LLMs exhibit strong positional bias to the information in the first and last parts of the input, and often fail to comprehend relevant information in the middle of a long input. A recent work also pointed out that this positional bias problem is also prevalent in applying LLMs to listwise reranking (Tang et al., 2023), and proposed an approach called permutation self-consistency.

	GPT-3.5 -turbo-0301	ListT5 (r=1)
(1) Accuracy (%) when the gold passage is at index #:		
1	90.9	85.3
2	80.4	85.6
3	78.5	82.2
4	63.8	83.3
5	64.3	82.6
standard deviation	10.3	**1.4**
(2) Agreement ratio (%) within index change of positive		
points to same passage	60.5	**90.4**
other	39.5	9.6

Table 4: Positional robustness on varying the index of positive passages on the FiQA-2018 test set. We can see that using FiD can effectively mitigate the problem of the positional bias of positive passages (lower standard deviation) with a higher agreement ratio.

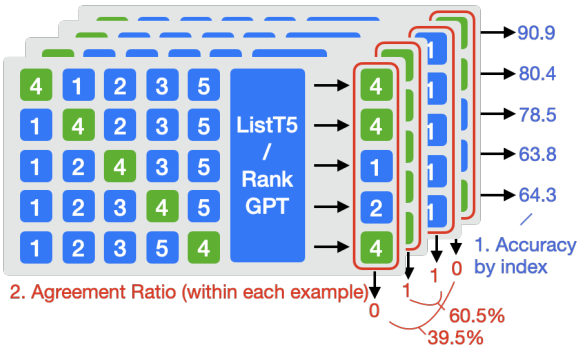

Figure 6: Measuring the robustness to positional bias by shuffling the index of the relevant passage. 4 is the gold (ground truth) relevant passage in the figure.

The main problem arises from the different assignment of positional encoding. We believe using the FiD architecture effectively addresses this issue, as each passage is processed by the encoder with identical positional encoding. Consequently, the decoder *cannot* exploit positional bias. To validate our statement, we conduct a comparative study to answer the following questions:

(1) How sensitive is the accuracy of each model to the position (location) of the positive passage?

(2) How often does each model *consistently* point to the same passage under position changes? How strong is the agreement within variants?

Baseline Models. We experiment with GPT3.5-turbo-0301 model from OpenAI (OpenAI, 2022), as it is the base model used for RankGPT (Sun et al., 2023b), one of the representative works for listwise reranking. To enforce a scenario where

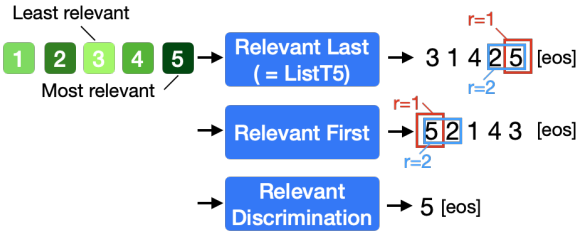

Figure 7: Variants of the output format of listwise ranking models while fixing the input.

the model takes lengthy inputs at once, we apply the instruction format of permutation generation (text), and use the same prompt described in the RankVicuna (Pradeep et al., 2023) paper. Detailed prompts and examples are in Appendix E.

Experiment and Data Setup. We use the BM25 top 100 retrieved results from the FiQA-2018 test subset as candidate passages for our experiment. Referencing the metric from Tang et al. (2023), we setup a permutation inconsistent scenario, illustrated at Fig. 6. We randomly sample 4 negative passages from the BM25 top 100 retrieved passages for each query-passage pair to make one instance of input with 1 relevant and 4 negative passages. We run 5 different variations for each instance (gray in the figure) and measure the (1) Accuracy (blue) by measuring across instances and (2) Agreement ratio (red) by measuring consistency within each instance. The results in Tab. 4 show that (1) our model suffers less from the positive index change and (2) our model has a higher agreement ratio. We can conclude that since each passage is distinguished by identifiers instead of positions, LISTT5 effectively overcomes the positional bias for long inputs by separately encoding each query-passage pair at the encoder and aggregating the output at the decoder, compared to other listwise reranking models. Still, the decoder can utilize and integrate the encoded information of all passages and, therefore, effectively perform listwise reranking, achieving a better zero-shot reranking performance than LLMs (Tab. 3) or non-listwise counterparts (Tab. 2).

5.3 Ablation Study

To break down and see what features play a crucial role in our method, we experiment and report performance with different variants of our model. Illustrations of the variants are in Fig. 7, and the results are in Tab. 5. Additional ablation experiments, including varying the number of passages the model sees at once, are in App. A.

Dataset	Relevant Discrimination	Relevant First		Relevant Last (ListT5)	
		(r = 1)	(r = 2)	(r = 1)	(r = 2)
In-domain					
MS MARCO	40.3	40.8	**40.9**	40.7	40.7
TREC-DL19	**72.5**	69.6	70.8	71.2	71.8
TREC-DL20	67.3	67.0	66.8	67.3	**68.1**
Avg (in-domain)	60.0	59.1	59.5	59.7	**60.2**
Out-domain (BeIR)					
TREC-COVID	74.0	74.9	75.9	76.7	**78.3**
NFCorpus	34.8	35.5	35.6	35.5	**35.6**
BioASQ	55.8	56.6	56.6	**57.2**	56.4
NQ	51.1	52.7	52.9	52.0	**53.1**
HotpotQA	70.9	72.5	72.6	72.1	**72.6**
FiQA-2018	38.1	39.3	39.0	39.5	**39.6**
Signal-1M (RT)	32.9	31.8	31.7	33.3	**33.5**
TREC-NEWS	43.9	46.6	47.3	47.9	**48.5**
Robust04	49.8	**52.3**	**52.3**	52.0	52.1
Arguana	26.1	32.8	34.6	**49.7**	48.9
Touche-2020	**34.2**	31.5	31.3	**34.2**	33.4
CQADupStack	**38.8**	38.3	38.4	38.4	**38.8**
Quora	81.9	84.4	84.8	86.1	**86.4**
DBPedia	42.4	43.4	43.6	**43.9**	43.7
SCIDOCS	16.3	17.3	17.3	17.2	**17.6**
FEVER	77.6	77.4	77.7	77.8	**79.8**
Climate-FEVER	20.7	22.8	23.0	22.8	**24.0**
SciFact	73.0	74.1	**74.2**	74.1	74.1
Avg (BeIR)	47.9	49.1	49.4	50.6	**50.9**

Table 5: NDCG@10 results at in-domain and BeIR on varying the output format and generation order of passages. Generating from the least relevant passages shows better average performance on BeIR.

r = 1 vs r = 2. Conducting inference by (r = 2) improves the average BeIR performance by 0.3, compared with that of (r = 1). We believe that the performance gain is significant, since it is equivalent to the improvement from MonoT5 (49.1) to RankT5 (49.4). Since this gain is also applicable to the Relevant First variants, which is the model trained to generate relevant index first, we hypothesize that r = 2 serves as giving a second chance for the model to view passages with different candidates to make a decision with different viewpoints, where there are confusing passages (hard negatives), resulting in better ability to rank. We have also tried increasing the number of preserved passages to 3 or 4, but found no significant gain in performance compared with the additional burden of increased inference time.

Discrimination vs Sequential Sorting. Given the same setup with the same dataset, we also train the model to output only relevant index, annotated as *Relevant Discrimination*, similar to Hofstätter et al. (2022). However, the Relevant Discrimination model shows the lowest performance amongst all our model variants, with an average NDCG@10 of 47.9. We hypothesize that training the model to distinguish and order between negatives provides additional information for the model. While tasks that only generate positive indexes only learn the decision boundary between positive and negative contexts, learning to order negatives provides more informative signals and more accurate ranking results, since the model additionally learns to calibrate between any kind of passages.

Relevant First vs Relevant Last (ListT5). We also compare models by changing the ordering of the output. Compared to ListT5, Relevant first shows a performance drop of 1 to 2 points in average on BeIR. We conclude that generating in reversed order is important, hypothetically because it effectively eliminates false negatives and acts as a reasoning chain for the model. The setup is similar to when one solves a confusing multiple-choice question; crossing out the options that are definitely not the answer until the last remaining option serves as a good strategy. In the case of ListT5, after the model generates some index i and autoregressively generates the next token, the index i gets outside of the consideration pool. We conjecture that the elimination of non-answers effectively reduces the window size the model has to see at once, thus effectively lessens the burden of decoder computation as every step goes by, leading to more accurate comparison at the last.

6 Conclusion

In this work, we propose ListT5, a FiD-based listwise reranking model that jointly considers multiple passages as input and outputs an ordered list of passages, in increasing order of relevance. While ListT5 excels in the zero-shot benchmark (BeIR) with a notable +1.3 gain of average NDCG@10 performance, ListT5 is also competitive in efficiency compared to previous pairwise ranking models or listwise ranking LLMs, in terms of asymptotic complexity and real-time FLOPs. Finally, we demonstrate that ListT5 overcomes the lost-in-the-middle problem in LLMs. In summary, ListT5 effectively extends the current Pareto front of zero-shot ranking models, in terms of performance and efficiency.

7 Limitations

- We believe that the efficiency of our models can be greatly optimized using simple ideas. For example, if we can implement early stopping at sequential decoding (assuming that the model outputs permutation of 5), we can reduce the decoding step by 80% for ListT5 (r=1) and 60% For ListT5 (r=2). There could also be other options, such as designing a more efficient way that uses the tournament sort with fewer number of forward passes.

- We believe there are still space for optimization of ListT5, for example trying out m other than 5 or 10, exploring with different learning rate or batch size on training, and so on. However, we were only able to experiment a few due to resource and time limitations.

- Our results are mainly reported with BM25 Top-100 and COCO-DR Top-100 as first-stage retrieval modules, since evaluating reranking with Top-1000 takes more resource and time. Also, our main results are based on the T5-base model and only a few were experimented with 3B models, due to the resource constraints. We hope to evaluate on these setups for future work.

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	Sort5, negfirst		Sort10, negfirst	
	1/5 (ListT5, r=1)	2/5 (ListT5, r=2)	1/10 (r = 1)	4/10 (r = 4)
MS MARCO	**40.7**	**40.7**	40.5	**40.7**
+ top1000	44.7	44.9	44.6	**45.0**
TREC-DL19	71.2	**71.8**	70.1	70.5
TREC-DL20	67.3	**68.1**	66.9	67.2
TREC-COVID	76.7	**78.3**	76.2	77.9
NFCorpus	35.5	35.6	36.2	**36.6**
BioASQ	**57.2**	56.4	55.4	56.4
NQ	52.0	**53.1**	51.5	52.5
HotpotQA	72.1	**72.6**	71.4	71.9
FiQA-2018	39.5	**39.6**	39.0	38.9
Signal-1M (RT)	33.3	**33.5**	31.7	32.0
TREC-NEWS	47.9	**48.5**	47.1	47.8
Robust04	52.0	52.1	52.2	**53.1**
Arguana	**49.7**	48.9	38.6	46.6
Touche-2020	**34.2**	33.4	32.4	32.7
CQADupStack	38.4	**38.8**	38.2	28.8
Quora	86.1	86.4	85.5	**86.8**
DBPedia	43.9	**43.7**	42.7	43.6
SCIDOCS	17.2	17.6	17.2	**18.0**
FEVER	77.8	**79.8**	76.7	79.1
Climate-FEVER	22.8	**24.0**	22.7	23.9
SciFact	74.1	74.1	73.4	**74.2**
Avg(In-domain)	56.0	**56.4**	55.5	55.9
Avg(BeIR)	50.6	**50.9**	49.3	50.0

Table 6: NDCG@10 performance results for in-domain & BeIR with ListT5-base trained on seeing 5 / 10 passages at once.

A Ablation—Design Choice of ListT5

This aligns with Sec. 5.3 from the main paper. In addition to varying the output format, we try to increase the number of passages m the model sees at once, with variants on r as well. (See Sec. 3.1 for basic notation) The results show that setting m as 10 is not as effective as setting m as 5. We conjecture that there is a trade-off between the (1) benefits from seeing more negatives at once, and (2) the complexity of the ordering task itself. If we increase m, the model can get more information, but at the same time, the task becomes very hard, and the boundary of negative order becomes very weak (and not very informative). Therefore, in the case of T5-base models, we find that 5 performed better than 10 passages, but we believe the optimal nu can be improved for larger (T5-large, T5-3b) models.

B Details about Our Inference Framework

This aligns with Sec. 3.2 from the main paper.

B.1 Background: Tournament Sort

Tournament sort is a variation of heap sort, inspired by the concept from sports tournaments, where

its objective is to identify not just the best player, but also the k-best, with the minimum number of games. While naive selection sort takes $\mathcal{O}(n)$ operations to iteratively select the best element, *tournament sort* leverage its tournament tree structure for efficient sorting, resulting in needing only $\mathcal{O}(\log n)$ operations after the initial building of the tree in $\mathcal{O}(n)$

B.2 Modification to Accept LISTT5 (r = 2)

Fig. 8 illustrates and compare the inference scenario for LISTT5 (r = 1) and LISTT5 (r = 2). Since the (r=2) variant outputs *2* different passage indices, the total number of candidate passages we need to compute is multipled by 2 for the next level of a tree. For example, if we use LISTT5 (r = 1) with m = 5 at the initial iteration, after computation of the bottom-level, we would get a total of 20 (100 / 5) filtered candidates which will go to the next round for comparison. In contrast, if we use LISTT5 (r = 2) with m = 5, we would get a total of 40 (100/5 $*$ 2) candidates to compute at the next round. However, it is important to note that we only use the inference method of (r = 1) for the root computation, since we always outputs the top-1 candidates for every iteration.

B.3 Details on Random Replacement

As explained as the 3rd and 4th modification at the main paper Sec. 3.2, we explain in detail the random assignment process here. Unlike the original tournament sort where they mark the final selected values to infinity, it is not an option for us since we cannot define a passage that has infinity scores of relevance. Therefore, we choose to randomly fill out the place, by the following rules;

Random assignment of top-1 selected passage After one iteration, one index is selected as most relevant out of n candidate passages. Then, we add that index into the global exclude pool and remove the index from the consideration pool. After that, using the initial ordering of the passage by the first-stage retrieval, we add $+21$ to the original selected index. (For example, if the selected index was 8, we replace that passage with 29. We just set it to a larger value than m=5 to avoid meeting duplicates, but it can be anything) If the index is already in the global exclude pool *or* have duplicates inside the input window m, we consider the next passage by adding 1 until the conditions are met.

Random assignment of dummy values to fill m The basic unit of LISTT5 always accepts exactly m passages as the input. However, there are cases when the leftover passages are not a multiple of m. For example, as we proceed to the upper level on the tournament tree, there will be a total of 100 $\mapsto$ 20 $\mapsto$ 4 passages left if we rank 100 passages using LISTT5 (r=1) with m=5. In this case, we would need one more dummy passage to make 4 candidate passages to 5. For reproducibility, we select a dummy passage in a deterministic way by considering the first passage from the inital candidate passage pool. If that passage is already selected as top-k indices during the previous round *or* we have duplicates inside the input window m, we proceed to the next index until the conditions are met.

Edge Cases. There are some cases, especially for the case of NFCorpus, that the initial retrieval module doesn't give exactly n passages as initial candidate passages. Sometimes, they give n that is smaller than m (e.g., 1,2,3,4). For this case, we exceptionally allow duplicates within the input window m, run one basic unit of LISTT5 with (r=n) (We remove duplicate passage indexes so that the output ordering reduces to n). That is, we only run the inference once, and use the output ordering as it is. Also, if k is bigger than n-m, we inevitably meet the case where the leftover (unselected) passage number becomes smaller than m. (For example, ranking the 96th candidate passage for n=100 with m=5). Similar to the previous case, we also allow duplicates for this case and run the basic unit once to order the leftover indices.

B.4 Example Scenario using Output Caching

For example, if we consider reranking top 10 passages from 100 candidate passages (n = 100, k = 10), without output caching results in 250 forward passes in total; since we would need ((100/5) + (20/5) + 1) = 25 forward passes for each iteration, the total will be 25 * 10 = 250. With output caching, after the initial iteration, we only need to do one computation for each level of a tree, resulting in (1+1+1) = 3 forward passes. Summing up results in 25 + 3*9 = 54 forward passes, almost reducing **80%** of the total number of inferences.

C MRR scores

Table 7 reports the corresponding MRR scores for BeIR evaluation on the main table.

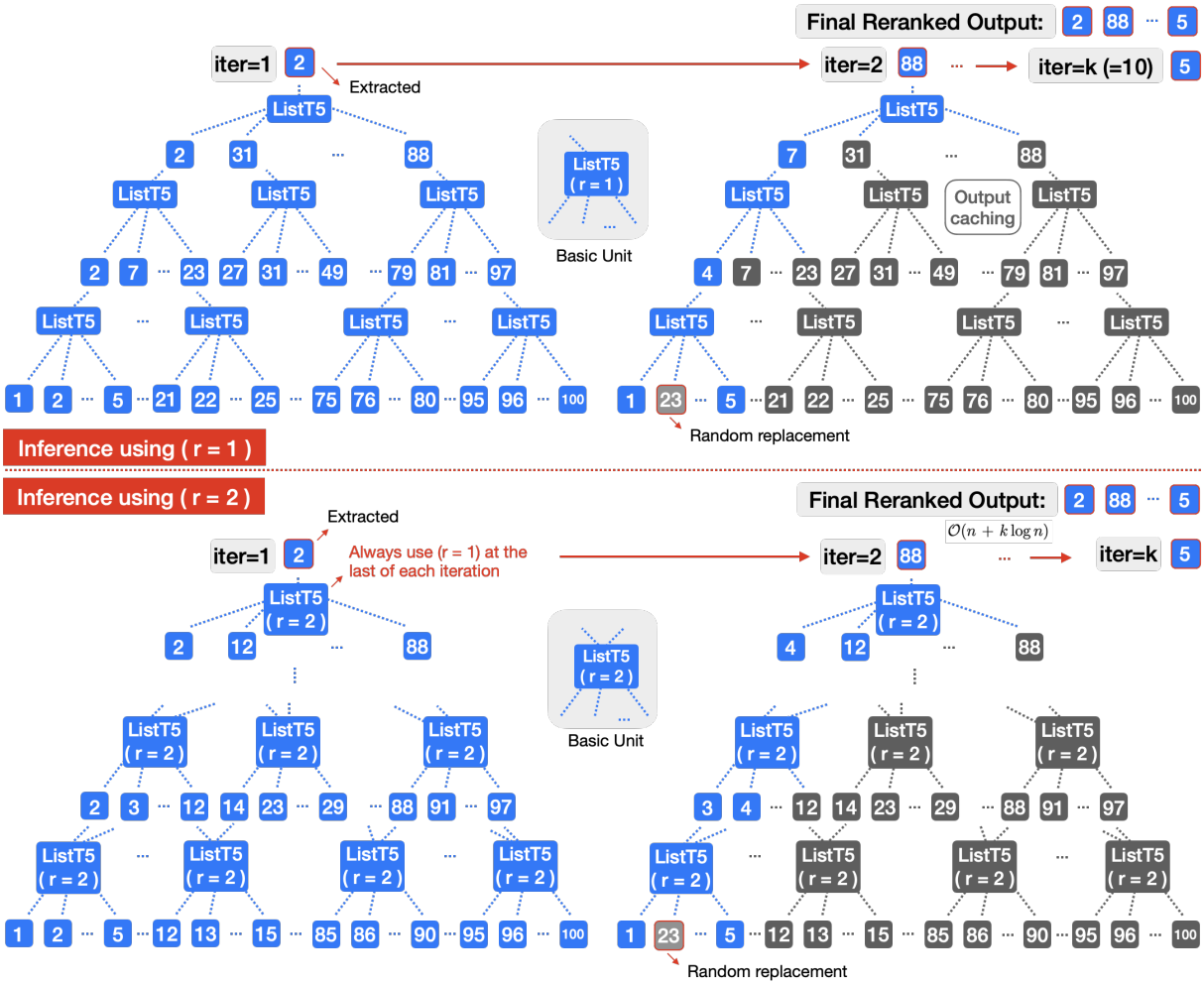

Figure 8: Illustration of our inference scenario. We show and compare the process with (r=1) and (r=2).

D Details on Evaluation Dataset

D.1 Links, Maximum Input Length

Since the average length of query and passage differs greatly for each BeIR subset, we assign the appropriate sequence length for each BeIR dataset and evaluate all models in the same setup. We download the dumped index of the top 100 retrieved passages by BM25 from the official Pyserini repository[8], and download the inital query, corpus, and qrels from the BeIR repository.[9]

We referenced the average query + passage length from the official beir paper. We selected the smallest maximum length from [256, 512, and 1024], but is still bigger than the (sum of average query + passage length) multiplied by two(for better coverage). One exception is the trec-news, which added up to be bigger than 1024, but we just capped it to be 1024. The *exact* alias with the maximum input length is listed below;

'msmarco': 256, 'dl19': 256, 'dl20': 256, 'trec-covid': 512, 'nfcorpus': 512, 'bioasq': 512, 'nq': 256, 'hotpotqa': 256, 'fiqa': 512, 'signal': 256, 'news': 1024, 'robust04': 1024, 'arguana': 1024, 'touche': 1024, 'cqadupstack': 512, 'quora': 256, 'dbpedia-entity': 256, 'scidocs': 512, 'fever': 256, 'climate-fever': 256, 'msmarco_top1000': 256, 'scifact': 512

D.2 Other Replication Details

We run the same evaluation setup with the BeIR library to do evaluation. For example, we append title with a space along with the text(passage) part and treat as full passage. For evaluating reranked results for both BM25 Top100 and COCO-DR Top100 candidate passages, we remove duplicates before evaluation[10] For CQADupStack, we follow

[8] https://github.com/castorini/pyserini

[9] https://public.ukp.informatik.tu-darmstadt.de/thakur/BEIR/datasets/

[10] For example, quora had 1 (out of 10000) duplicates, so the NDCG@10 for BM25 may differ from the BeIR paper.

First-stage retrieval by:		BM25 Top100					COCO-DR Large Top100				
		Baselines			Ours		Baselines			Ours	
Task (Domain)	Dataset	BM25 (Initial)	MonoT5	RankT5	ListT5 (r = 1)	ListT5 (r = 2)	COCO-DR (Initial)	MonoT5	RankT5	ListT5 (r = 1)	ListT5 (r = 2)
Passage Retrieval	MS MARCO	18.0	34.9	**35.8**	35.6	35.8	36.0	38.2	**40.5**	40.3	40.2
	+ top1000	18.0	37.3	38.6	38.5	**38.8**	36.0	37.2	**40.3**	40.1	40.2
	TREC-DL19	82.3	98.3	100.0	98.5	98.8					
	TREC-DL20	82.4	93.8	95.4	**95.8**	95.6					
In-domain average		61.0	66.1	**67.4**	67.1	67.2	36.0	37.7	**40.4**	40.2	40.2
Bio-Medical Information Retrieval	TREC-COVID	85.3	**95.4**	93.0	93.8	95.0	96.7	96.7	93.8	**97.0**	95.5
	NFCorpus	52.4	58.0	56.3	57.5	**58.5**	56.0	55.9	57.1	58.1	**58.4**
	BioASQ	59.4	64.9	**67.8**	67.6	67.2					
Question Answering (QA)	NQ	26.3	48.2	**49.8**	48.2	49.5	49.2	52.6	54.7	54.6	**55.1**
	HotpotQA	80.3	85.9	88.3	88.2	**88.7**	81.9	84.7	87.9	87.6	**88.5**
	FiQA-2018	29.6	47.7	48.5	**48.7**	48.5	39.1	49.2	**49.8**	49.6	**49.8**
Tweet Retrieval	Signal-1M (RT)	**57.4**	52.6	55.0	55.6	55.4					
News Retrieval	TREC-NEWS	73.9	74.8	75.8	77.9	**79.2**					
	Robust04	67.3	81.5	**82.0**	79.6	80.0					
Argument Retrieval	Arguana	32.8	27.1	27.7	**40.7**	39.6	39.2	26.8	28.6	40.5	**40.8**
	Touche-2020	**74.4**	51.3	62.9	58.5	54.9	45.4	47.0	**61.9**	51.1	51.2
Duplicate Q. Retrieval	CQADupStack	29.6	38.5	36.8	38.3	**38.7**	36.9	40.2	38.4	40.7	**40.8**
	Quora	77.9	83.1	81.2	85.1	**85.2**	**86.4**	82.0	80.5	84.9	84.7
Entity Retrieval	DBPedia	58.2	73.4	74.4	75.7	**76.3**	74.2	73.4	77.2	76.8	**77.8**
Citation Pred.	SCIDOCS	26.0	29.5	29.9	30.9	**31.2**	30.9	30.2	30.6	31.1	**32.0**
Fact Checking	FEVER	62.4	78.4	77.6	77.6	**80.2**	74.2	79.0	80.1	80.3	**82.1**
	Climate-FEVER	22.0	31.9	29.1	31.3	**33.7**	32.9	33.0	31.3	33.0	**34.8**
	SciFact	64.6	70.3	70.6	71.8	**71.9**	68.4	70.9	70.4	71.8	**71.8**
BeIR average		54.4	60.7	61.5	62.6	**63.0**	58.0	58.7	60.2	61.2	**61.7**

Table 7: Reporting Mean Reciprocal Rank (MRR)@10 scores for the main table.

the same procedure and aggregated all sub-domains ranging from android to wordpress to make 13,145 test queries, and report the average performance.

E Details about the Experiment Measuring Positional Bias.

We briefly explain here about the evaluation process. 1. We break down the original FiQA dataset into pairs of one query and one positive passage associated with the query. For each query-positive pair, we randomly sample 4 negative passages from the BM25 top100 results and additionally pair them to make one sample. Preprocessing them makes 818 distinct samples. 2. For every sample, we make 5 variants of the input text, so that the first one assigns index 1 to the positive passage, and the last one assigns index 5 to the positive passage. Note that only the index of the positive passage is changed, and we keep the order of other passages (negatives) as the same. Third, we forward the inputs to each model, and collect the output that corresponds to the most relevant index. To answer (1), we measure the accuracy with respect to the index of positive passage. To answer (2), we analyze the ratio of samples where the model points to the same passage regardless of positive index change.

We discard queries that doesn't have positive indexes in the bm25 top100 dataset, or those that don't have 4 distinct negative contexts.

For reproducibility, all randomly sampled experiments are conducted with fixed seed. (seed=0) The prompts we use to give inputs to GPT-3.5-turbo-0301 are the following:

```
I will provide you with 5 passages,
each indicated by numerical identifier [].
Rank the passages based on their
relevance to the search query: {query}.

[1] {passage_1}
[2] {passage_2}
[3] {passage_3}
[4] {passage_4}
[5] {passage_5}

Search Query: {query}

Rank the 5 passages above based on their
relevance to the search query.
All the passages should be included and
listed using identifiers, in descending
order of relevance. The output format
should be [] > [], e.g., [4] > [2].
Only respond with the ranking
results, do not say any word or explain.
```

Given the above input, we collect the output of gpt3.5. Following the setup from Sun et al. (2023b), we use the ChatCompletion api by the openai li-

brary. Using the openai api, running the whole process cost about $35. After the run, we found that 3 out of 818 outputs had malformed outputs, in a format such as: "[No relevant passage found] > ... [1]", rather than in a correct format such as: "[3] > [1] > [5] > [2] > [4]". We discard those 3 malformatted instances with incorrect output formats into consideration and compared only with the rest. (That is, we also discard those instances for the fid-t5 variant) To give an exactly same scenario to both models, we truncate each passages up to 512 tokens (based on the t5 tokenizer), since that is exactly what our fid model sees. After truncation, we also validated that all of the input sizes are below the range of 4096 (as the maximum input window size of gpt-3.5-turbo-0301 is 4096)

F Qualitative Analysis

Tab. 8 reports a sample output selected from the Arguana Dataset, which seeks the counter-argument most opposed to the query argument .[11] Considering the NDCG@10 reranking performance for MonoT5-base, RankT5-base, and ListT5-base is 34.4, 35.5, and 48.9, respectively, ListT5 excels on Arguana than other pointwise baseline models with a large margin. From inspection, we conclude that the listwise reranking nature of ListT5 helps to discern and select which features are important in determining relevancy in this dataset, with respect to other passages.

We hypothesize that listwise comparison makes the model to favor counterarguments - (Different point of view, but the discussion topic is the same) over similar topics. For example at Tab. 8, RankT5 places passages that talks about accountability and criminal law in a moral aspect as the most relevant passage, which is quite similar to the original query (since it includes words such as 'Prosecuting') but not exactly the same about prosecuting offenders. Also, the passage that is scored highest from MonoT5 talks about ICC's prosecution policy, but the original query is not related to ICC. In contrast, since perhaps ListT5 is able to see different passages, it correctly determines the GT passage as top-1, giving more weight on talking about the same topic (even though the aspect can be different).

[11] The query is always included in the corpus, so for qualitative analysis, we excluded the passage that is exactly the same with the original query.

	GT Rank / GT Score	1st Rank / 1st Score	Passage
LISTT5	1	1	Most often, prosecutions that occur are not just with only the **losing side** being prosecuted for their crimes. The Nuremburg trials prosecuted Nazi's for offences they committed, but none of the Allied forces were ever brought for trial(...)
MonoT5	78/ -0.32	1 / -0.13	As the ICC intentionally limits its prosecutions to group leaders, many of those who actually commit atrocities need have no fear of prosecution By prosecuting only those leaders deemed 'most responsible' for the crimes in question, the ICC is effectively allowing lower-ranked perpetrators to commit crimes with impunity. (...)
RankT5	25/ -5.86	1 / -4.58	Accountability It is a fundamental principle of morality that individuals should be held responsible for their crimes – that is the reason why we, as societies, have criminal law. Prosecuting people – holding them responsible for their crimes – is a moral imperative. We all wish to live in a society where everyone is equally accountable when they commit crime as one in which not everyone is held to account is fundamentally unjust (...)
Query			(...) Prosecuting offenders is the **only way to get a just outcome** when there have been horrific crimes committed. At a most principled level, those who commit a crime ought to be held accountable for their actions even if they are powerful or it damages the chances of peace because the powerful must be shown not to be above the law (...)
Relevant Passage			Most often, prosecutions that occur are not just with only the **losing side** being prosecuted for their crimes. The Nuremburg trials prosecuted Nazi's for offences they committed, but none of the Allied forces were ever brought for trial(...)

Table 8: Example of ListT5, MonoT5, RankT5 retrieval result on Arguana dataset. Relevant topics are highlighted with red, non-relevant topics in blue, and opinions are **bolded**.