LLM Rankers

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Abstract

Large Language Model (LLM) rankers play a crucial role in modern information retrieval by improving the relevance and quality of ranked search results. Unlike traditional ranking methods that rely on keyword matching or statistical models, LLM rankers leverage deep contextual understanding to evaluate document-query relevance more effectively. They enhance retrieval performance in applications such as search engines, recommendation systems, and question-answering frameworks.

1 Introduction

Large Language Models (LLMs) have emerged as powerful tools for document ranking tasks, showcasing their remarkable ability to understand and rank documents without any task-specific training.

Given the user query and candidate documents as input, these methods employ different prompting methodologies to instruct the LLM to output a relevance estimation for each candidate document.

2 Ranking Techniques

Ranking strategies for utilizing LLMs in ranking tasks can be categorized into four main approaches: Pointwise, Pairwise, Listwise, and Setwise Ranking.

Given a query q and a set of candidate items $D = d_1, d_2, \ldots, d_n$, the objective is to determine the ranking of these candidates, represented as $R = r_1, r_2, \ldots, r_n$. Here, $r_i \in 1, 2, \ldots, n$ denotes the rank of the candidate d_i. For example, $r_i = 3$, means that the document d_i is ranked third among the n candidates. A ranking model $f(.)$ assigns scores to the candidates based on their relevance to the query: $s_i = f(q, d_i)$, and the candidates are then ranked according to these relevance scores: $r_i = argsort_i(s_1, s_2, \ldots, s_n)$.

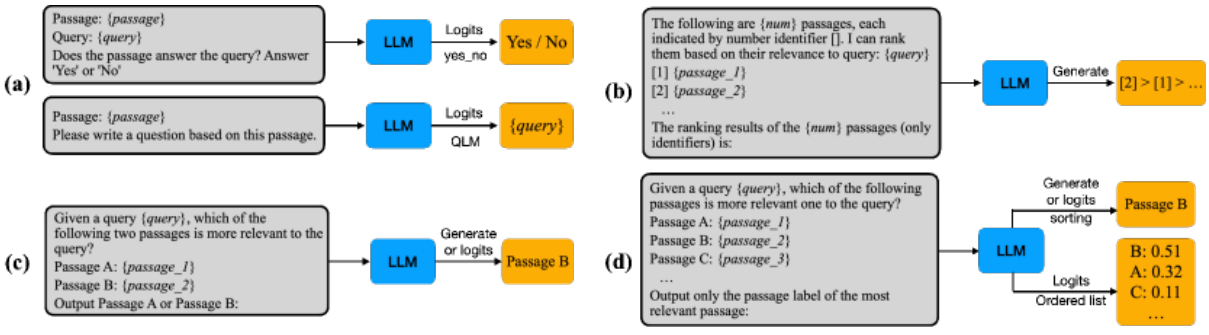

Figure 1: Different prompting strategies. *(a) Pointwise, (b) Listwise, (c) Pairwise and (d) Setwise.*

3 Log Probabilities

Large language models (LLMs) are trained to predict the likelihood of sequences of tokens (e.g., words, characters) based on the given context. Log probabilities, often referred to as logits, are a way to express the likelihood of certain tokens or sequences of tokens occurring in the output of these models. Log

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probabilities of output tokens indicate the likelihood of each token occurring in the sequence given the context.

Consider a model generating the sequence "The quick brown fox". To compute the log probability of this sequence, we would:

1. Retrieve the logits for each token in the sequence.
2. Apply the softmax function to convert logits into probabilities.
3. Calculate the log probabilities of each token.
4. Sum the log probabilities to get the log probability of the entire sequence.

Let's denote the tokens in the sequence as t_1, t_2, t_3, t_4. If the probabilities of these tokens given the previous context are $p(t_1), p(t_2|t_1), p(t_3|t_1, t_2)$, and $p(t_4|t_1, t_2, t_3)$ respectively, then the log probability of the sequence is:

$$\log(p(t_1, t_2, t_3, t_4)) = \log(p(t_1)) + \log(p(t_2|t_1)) + \log(p(t_3|t_1, t_2)) + \log(p(t_4|t_1, t_2, t_3))$$

Difference between Logits and Log Probabilities:

- **Logits** are the raw, unnormalized scores output by a model before they are converted into probabilities. These scores are transformed using the softmax function to produce a probability distribution over the possible next tokens.
- The **log probability** of a token is obtained by taking the natural logarithm of its probability. If p_i is the probability of the i-th token, then its log probability is $\log(p_i)$. Since probabilities range from 0 to 1, log probabilities range from $-\infty$ to 0.

Advantages of using Log Probabilities:

- **Numerical Stability**: Working with log probabilities enhances numerical stability, especially when dealing with very small probabilities. This is crucial for avoiding underflow issues in computations.
- **Additivity:** One of the key advantages of using log probabilities is that they are additive. The log probability of a sequence of tokens is simply the sum of the log probabilities of the individual tokens:

  $$\log(p(\text{sequence})) = \sum_{i=1}^{n} \log(p_i)$$

  This property simplifies the computation of the joint probability of a sequence.
- **Comparative Ranking:** Log probabilities allow for easy comparison between different sequences. Higher log probabilities (closer to 0) indicate higher likelihoods. This enables the ranking of sequences based on their likelihood.

Log probabilities play a crucial role in various natural language processing (NLP) tasks involving Large Language Models (LLMs). Here are some key applications and use cases of log probabilities:

- **Scoring Outputs:** To rank different outputs generated by an LLM, we calculate the log probability of each output sequence. The sequence with the highest log probability is considered the most likely and thus ranked highest.

  Given a sequence of tokens $t_1, t_2, \ldots, t_n$, the log probability of the sequence is:

  $$\log(p(\text{sequence})) = \sum_{i=1}^{n} \log(p(t_i \mid t_1, t_2, \ldots, t_{i-1}))$$

  This summation leverages the chain rule of probability, where each token's probability is conditioned on all previous tokens.

- **Average Per-Token Log Probability:** To normalize the log probability by the length of the sequence, we calculate the average log probability per token. This is particularly useful for comparing sequences of different lengths.

$$\text{Average log probability} = \frac{1}{n}\sum_{i=1}^{n}\log(p(t_i \mid t_1, t_2, \ldots, t_{i-1}))$$

  This metric ensures that longer sequences are not unfairly penalized and provides a normalized measure of likelihood.

- **Confidence Measurement:** Log probabilities offer a quantitative measure of the model's confidence in its predictions. By examining the log probabilities of the top candidate tokens at each position, we can gauge the model's certainty about its choices.

  For a given token position j, the model generates a set of candidate tokens $\{t_{j1}, t_{j2}, \ldots, t_{jk}\}$ with corresponding log probabilities $\{\log(p(t_{j1})), \log(p(t_{j2})), \ldots, \log(p(t_{jk}))\}$. The difference in log probabilities among these candidates indicates the model's confidence.

- **Classification Tasks**: In classification tasks, log probabilities help set confidence thresholds. By associating log probabilities with each class prediction, users can determine the required confidence level for making a classification decision.

  Given a set of classes $C = \{c_1, c_2, \ldots, c_m\}$ with associated log probabilities $\{\log(p(c_1)), \log(p(c_2)), \ldots, \log(p(c_m))\}$, the class with the highest log probability is chosen:

$$\hat{c} = \arg\max_{c_i \in C} \log(p(c_i))$$

  A threshold τ can be applied to $\log(p(\hat{c}))$ to decide if the confidence in $\hat{c}$ is sufficient for classification.

- **Retrieval and Q&A Evaluation:** In retrieval-based applications, log probabilities assist in self-evaluation. For instance, in a question-answering system, the model can use log probabilities to assess if the retrieved content sufficiently answers the query.

  If the model retrieves a set of passages $\{P_1, P_2, \ldots, P_k\}$ and generates answers $\{A_1, A_2, \ldots, A_k\}$ with corresponding log probabilities, the evaluation metric can be:

$$\log(p(\text{answer is correct})) = \log(p(A_j \mid P_j))$$

- **Autocomplete and Token Highlighting:** In autocomplete applications, log probabilities inform the likelihood of each possible next token, aiding in suggestion generation. Token highlighting leverages log probabilities to emphasize tokens with higher likelihoods.

  For a partially typed sequence $t_1, t_2, \ldots, t_i$, the model predicts the next token t_{i+1} with log probabilities for top candidates $\{t_{i+1,1}, t_{i+1,2}, \ldots, t_{i+1,k}\}$:

$$\{\log(p(t_{i+1,1} \mid t_1, t_2, \ldots, t_i)), \log(p(t_{i+1,2} \mid t_1, t_2, \ldots, t_i)), \ldots\}$$

  Highlighting can be based on these log probabilities to visually represent the model's predictions.

- **Calculating Perplexity**: Perplexity is a measure of how well a probability distribution or model predicts a sample. It is commonly used to evaluate language models. The perplexity PP of a sequence $t_1, t_2, \ldots, t_n$ is given by:

$$PP = \exp\left(-\frac{1}{n}\sum_{i=1}^{n}\log(p(t_i \mid t_1, t_2, \ldots, t_{i-1}))\right)$$

Log probabilities are a versatile tool in NLP, enabling precise probability calculations, enhancing numerical stability, and facilitating various applications, from output ranking to confidence measurement and classification. By understanding and leveraging log probabilities, we can significantly improve the performance and reliability of LLM-based applications.

3.1 Pointwise Ranking

In the pointwise ranking method, the reranker takes both the query and a candidate document to directly generate a relevance score. These independent scores assigned to each document d_i are then used to reorder the candidate set D.

This method can be further classified into two popular approaches based on how the ranking score is calculated. The relevance score is typically calculated based on how likely the document is relevant to the query or how likely the query can be generated from the document.

It is worth noting that both pointwise methods require access to the output logits of the model to be able to compute the likelihood scores. Thus, it is not possible to use closed-sourced LLMs to implement these approaches if the corresponding APIs do not expose the logits values.

3.1.1 Instructional Relevance Generation

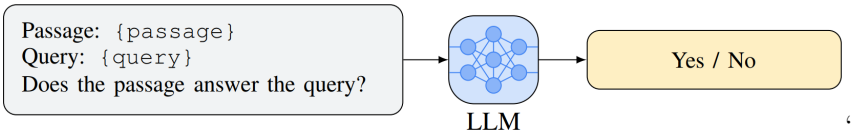

Figure 2: The pointwise relevance generation approach.

In instructional relevance generation approaches (Liang et al. 2022), the LLMs are prompted to output either "Yes" or "No" to determine the relevance of the candidates to a given query.

The generation probability is then converted to the relevance score:

$$s_i = \begin{cases} 1 + f(\text{Yes}|I_{\text{RG}}(q, d_i)), & \text{if output Yes} \\ 1 - f(\text{No}|I_{\text{RG}}(q, d_i)), & \text{if output No} \end{cases}$$

Here $f(.)$ represents the large language model, and I_{RG} denotes the relevance generation instruction that converts the input q and d_i into the text-based prompt.

3.1.2 Instructional Query Generation

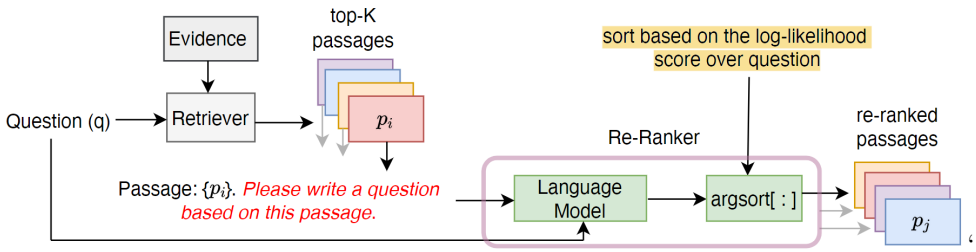

Figure 3: The LLM scores are used for passage reordering in the Instructional Query Generation approach

Query generation approaches (Sachan, Lewis, Yogatama, et al. 2023), use LLMs to generate a query based on the document and measure the probability of generating the actual query. This is done by employing a zero-shot ranking approach using a LLM. A natural language instruction "Please write a question based on this passage" is appended to the document.

The likelihood of tokens generated to be the query is calculated given the document:

$$\log p(q|d_i) = \frac{1}{|q|} \sum_t \log p(d_t|q_{<t}, d_i; \Theta)$$

where Θ denotes the LLM parameters, and $|q|$ denotes the number of query tokens. The candidate set of documents is then sorted based on $\log p(q|z)$.

3.2 Pairwise Ranking

In Pairwise Ranking Prompting (PRP)(Qin et al. 2023), a pair of candidate items (d_i, d_j) along with the user query (q) serve as prompts to guide the LLMs to determine which document is the most relevant to the given query.

$$c_{i,j} = \begin{cases} 1, & \text{if } f(I_{\text{PRP}}(q, d_i, d_j)) = i \\ 0, & \text{if } f(I_{\text{PRP}}(q, d_i, d_j)) = j \\ 0.5, & \text{else} \end{cases}$$

Here, $c_{i,j}$ denotes the choice of LLM $f(.)$, and I_{PRP} is a specific pairwise comparison instruction employed to instruct the LLM. This approach usually consults the LLM twice (with $I_{PRP}(q, d_i, d_j)$ and $I_{PRP}(q, d_j, d_i)$) for every pair d_i and d_j because LLMs exhibit sensitivity to the order of the text in the prompt.

Subsequently, to compute the relevance score of the i-th candidate d_i, this method compares d_i against all other candidates in the set D to aggregate the final relevance score as: $s_i = \sum_{j \neq i} c_{i,j} + (1 - c_{j,i})$. For ties in the aggregated scores, the Pairwise ranking method has been proven to be 0 more effective than pointwise and listwise methods, but it is also inefficient and hence unsuitable for inference in large-scale industrial systems. Pairwise ranking naturally supports both generation and scoring LLM APIs.

Handling inconsistent ranking outcomes: If both $I_{PRP}(q, d_i, d_j)$ and $I_{PRP}(q, d_j, d_i)$ promptings make consistent decisions, we have local ordering $r_i > r_j$ or $r_i < r_j$, else we assume $r_i = r_j$ (each document gets half a point).

3.3 Different methods for Pairwise Ranking:

Pairs are independently then fed into the LLM, and the preferred document for each pair is determined. Subsequently, an aggregation function is employed to assign a score to each document based on the inferred pairwise preferences, and the final ranking is established based on the total score assigned to each document.

3.3.1 All Pairs Comparison

- This method involves enumerating all possible pairs of documents and performing a global aggregation to generate a score for each document.
- LLMs are prompted with a query alongside a pair of documents and are asked to generate a label indicating which document is more relevant to the query.
- Scoring is performed as follows:
  - If the LLM consistently prefers one document over another, the preferred document gets one point.
  - When the LLM is uncertain, producing conflicting or irrelevant results (for the generation API), each document in the pair gets half a point.
- The final ranking is based on the aggregated scores. In case of ties, the method falls back to the initial ranking.
- Advantages of this method include:
  - Simple implementation: all LLM API calls can be executed in parallel.
  - High insensitivity to input ordering.
- However, this approach has significant drawbacks:
  - High query latency: LLM inference on all document pairs can be computationally expensive.
  - Costly complexity: It requires $O(n^2)$ calls to LLM APIs, where n is the number of documents to be ranked for each query.

3.3.2 Sliding Window:

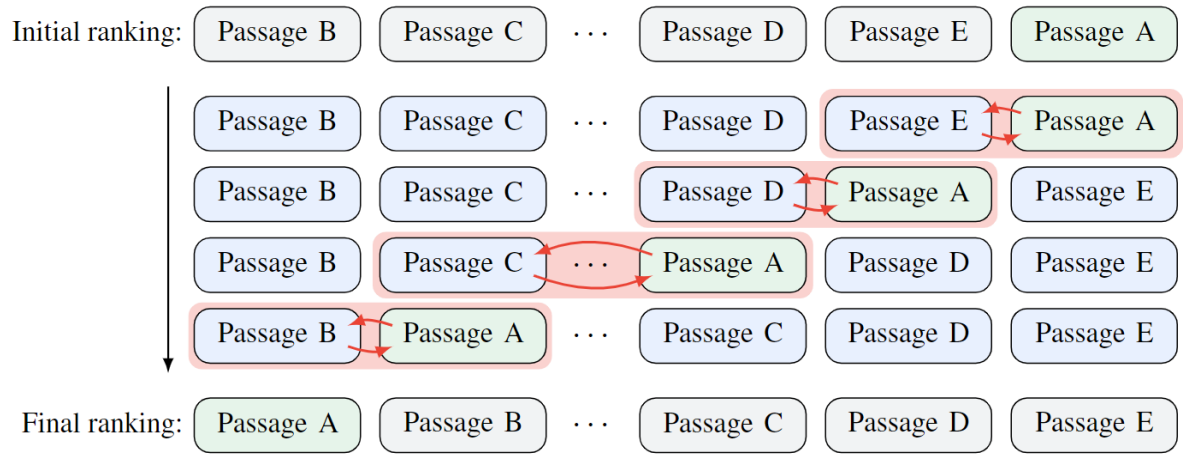

Figure 4: One pass of PRP's sliding window approach. k such passes are performed to get top-k ranking results.

- The Sliding Window approach is similar to one pass in the Bubblesort algorithm. It operates on an initial ranking, starting from the bottom of the list and moving upwards.
- The method compares and swaps document pairs with a stride of 1 on-the-fly based on LLM outputs. This process moves from right to left in the ranking.
- If the LLM output disagrees with the initial ranking for a pair, the documents are swapped. This allows initially lower-ranked documents (like "Passage A") to potentially move up to the top of the ranking.
- One pass of the Sliding Window requires only O(N) time complexity, where N is the number of documents.
- Recognizing that ranking often focuses on Top-K metrics (where K is typically small), the method can be optimized to perform K passes.
- For example, with N=100 documents and K=10, this approach requires only 10% of the LLM API calls compared to the All Pairs Comparison method.
- The Sliding Window method (referred to as PRP-Sliding-K) has a favorable time complexity, making it more efficient than All Pairs Comparison.
- However, this method can be sensitive to input order, especially for small values of K. Despite this potential drawback, experiments have shown surprisingly good results with PRP-Sliding-10, without significant sensitivity to input ordering.

3.4 Listwise Ranking

Listwise Reranker with a Large Language Model (LRL) (Ma, X. Zhang, et al. 2023) takes the query and a list of documents as input and returns a reordered list of the input document identifiers. The key difference is that LRL considers information from multiple documents simultaneously while reranking.

- The LLMs receive a query along with a list of candidate documents and are prompted to generate a ranked list of document labels based on their relevance to the query.
- Each document is identified by a unique identifier like [1], [2], etc. The LLM is then instructed to generate a ranked permutation of these documents, such as [2] > [3] > [1]. By framing its goal as text generation, this approach fuses well with the existing techniques based on generative models.
- In the context of transformers, this means the model can attend to all the candidate documents to determine their relative ranking position.

- **Listwise Ranking prompt:**

```
Passage1 = {passage_1}
...
Passage10 = {passage_10}
Query = {query}
Passages = [Passage1, ..., Passage10]
Sort the Passages by their relevance to the Query.

The LLM Output:
Sorted Passages = [Passage3, ..., Passage7]
```

- The listwise paradigm generalizes the pairwise paradigm. In the listwise ranking strategy, a set of candidate documents is fed to the LLM. This means that the model can attend to all the candidate documents simultaneously while reranking.
- Some work also refer to this approach as the Instructional Permutation Generation approach (Sun, Chen, et al. 2023) as it instructs the LLM to directly output the permutations of a group of passages.
- In contrast to pointwise methods, which utilize the likelihood value of the output tokens for ranking documents, listwise approaches rely on the more efficient process of generation of the ranking list.
- LLMs that are used as rerankers in a multi-stage pipeline, with prompt engineering being the primary means to accomplish the listwise reranking tasks, have also been referred to as the "prompt decoders".
- Listwise approaches can be inefficient because of the substantial number of required tokens in the output as each additional token generated by LLM requires an extra inference step.

3.4.1 Sliding Window Listwise Ranking:

- Due to the limited input length allowed by LLMs, including all candidate documents in the prompt is not feasible. To address this, current listwise approaches use a sliding window method.
- This involves re-ranking a window of candidate documents, starting from the bottom of the original ranking list and progressing upwards.
- This process can be repeated multiple times to achieve an improved final ranking and allows for early stopping mechanisms to target only the top-k ranking, thereby conserving computational resources.

3.5 Setwise Ranking

Setwise prompting technique (S. Zhuang et al. 2023) improves the efficiency of Pairwise prompting (PRP) by comparing multiple documents at each step, as opposed to just a pair.

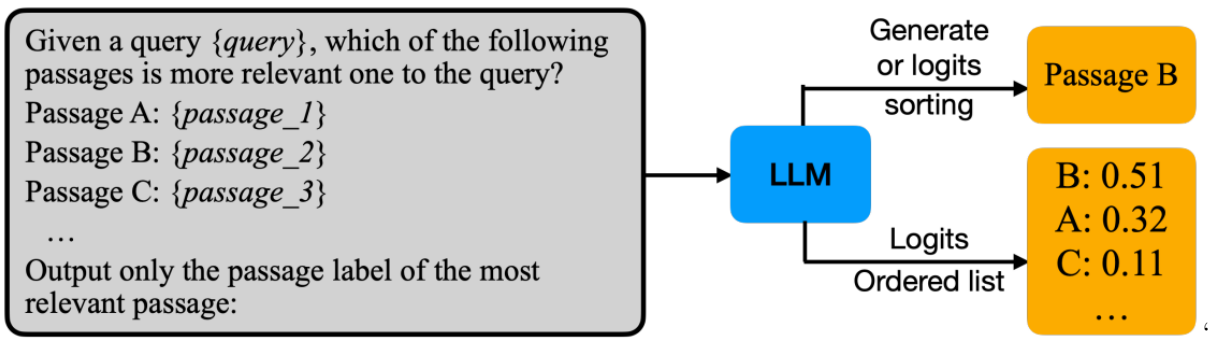

Figure 5: Setwise Ranking

- Their experiments show that incorporating the setwise prompting significantly improves the efficiency of both pairwise and listwise approaches, while also enhancing the robustness to initial document ordering.
- The prompt instructs the LLM to select the most relevant document for the given query from a set of documents, hence the term Setwise prompting.
- The collection of documents is treated as an unordered set and is observed that Setwise prompting is quite robust to document ordering.
- With the prompt, sorting-based Pairwise approaches can be considerably accelerated. This is because the original heap sort and bubble sort algorithm used in the Pairwise approach only compares a pair of documents at each step in the sorting process.
- Setwise prompting is designed to instruct LLMs to compare the relevance of multiple documents at a time, making it well-suited for this purpose.
- Setwise prompting allows the utilization of model output logits to estimate the likelihood of ranks of document labels, a capability not feasible in existing Listwise approaches, which solely rely on document label ranking generation a process that is slow and less effective.

3.6 Comparison of Ranking Approaches

- The Pairwise approach emerges as the most effective but falls short in terms of efficiency even with the assistance of sorting algorithms aimed at improving this.
- The Pointwise approach stands out as the most efficient but lags behind other methods in terms of ranking effectiveness.
- The Listwise approach, which relies solely on the generation of document labels in order, can strike a middle ground between efficiency and effectiveness but this varies considerably based on configuration, implementation and evaluation dataset (highlighting the importance of thoroughly evaluating these model under multiple settings).
- Setwise prompting approach instructs LLMs to select the most relevant document to the query from a set of candidate documents. This straightforward adjustment allows the sorting algorithms to infer relevance preferences for more than two candidate documents at each step, thus significantly reducing the total number of comparisons required; this leads to substantial savings in computational resources.
- Beyond the adjustment to Pairwise approaches, Setwise prompting allows the utilization of model output logits to estimate the likelihood of ranks of document labels, a capability not feasible in existing Listwise approaches, which solely rely on document label ranking generation —— a process that is slow and less effective.
- The incorporation of Setwise prompting substantially improves the efficiency of both Pairwise and Listwise approaches. In addition, Setwise sorting enhances Pairwise and Listwise robustness to variations in the internal ordering quality of the initial rankings: no matter what the initial ordering of the top-k documents to rank is, our method provides consistent and effective results. This is unlike other methods that are highly susceptible to such initial ordering.

4 Datasets

4.1 FIQA

The FIQA (Financial Opinion Mining and Question Answering) dataset has a corpus, queries and qrels (relevance judgments file). The FiQA dataset has roughly 6,000 questions and 57,000 answers. They are in the following format:

- Corpus file: a .jsonl file (jsonlines) that contains a list of dictionaries, each with three fields _id with unique document identifier, title with document title (optional) and text with document paragraph or passage. For example: "_id": "doc1", "title": "Albert Einstein", "text": "Albert Einstein was a German born....".

- Queries file: a .jsonl file (jsonlines) that contains a list of dictionaries, each with two fields _id with unique query identifier and text with query text. For example: "_id": "q1", "text": "Who developed the mass-energy equivalence formula?".
- Qrels file: a .tsv file (tab-seperated) that contains three columns, i.e. the query-id, corpus-id and score in this order.

4.2 NFCorpus

NFCorpus is a full-text English retrieval data set for Medical Information Retrieval. It contains a total of 3,244 natural language queries (written in non-technical English, harvested from the NutritionFacts.org site) with 169,756 automatically extracted relevance judgments for 9,964 medical documents (written in a complex terminology-heavy language), mostly from PubMed.

Each of the training, development and testing subsets comes in three files:

- NutritionFacts.org queries data (.queries files, 5 different types) – natural, non-technical language
- medical documents data (.docs files) – medical, very technical language
- relevance judgments (.qrel files)

4.3 SciFact

SciFact, a dataset of 1.4K expert-written scientific claims paired with evidence-containing abstracts, and annotated with labels and rationales. The dataset consists of:

- claims.jsonl: Claims in SciFact-Open, annotated with evidence.
- claims_metadata.jsonl: Metadata associated with each claim.
- corpus.jsonl: The full SciFact-Open corpus of 500K research abstracts from S2ORC.
- corpus_candidates.jsonl: Subset of documents from corpus.jsonl that were retrieved for at least one claim.

4.4 TREC

The MS MARCO (Microsoft MAchine Reading COmprehension) dataset is a large-scale collection designed to aid in the development and evaluation of machine reading comprehension and information retrieval models. It comprises real anonymized user queries paired with relevant passages or documents, facilitating advancements in natural language understanding and search technologies.

The Text REtrieval Conference (TREC) has incorporated the MS MARCO dataset into its Deep Learning Tracks, notably in TREC 2019, 2020, and 2022. These tracks focus on evaluating and advancing deep learning models for information retrieval tasks.

In TREC 2019 and 2020, they introduced both document and passage ranking tasks using the MS MARCO dataset. Participants developed models to rank documents and passages in response to queries, fostering improvements in retrieval effectiveness.

5 Metrics

5.1 Normalized Discounted Cumulative Gain (NDCG)

- NDCG is a measure of the effectiveness of a ranking system, taking into account the position of relevant items in the ranked list.
- It is based on the idea that items that are higher in the ranking should be given more credit than items that are lower in the ranking.
- NDCG is calculated by dividing the discounted cumulative gain (DCG) of the ranked list by the DCG of the ideal ranked list, which is the list with the relevant items ranked in the most optimal order. NDCG ranges from 0 to 1, with higher values indicating better performance.
- NDCG provides the ability to fine-tune which ranks are more valuable than others, and account for a scale of relevancy scores (graded relevance).

6 Experiments

- Retrieval pipelines with different sorting methods like Heapsort and Bubblesort with the Pairwise and Setwise ranker were created.
- The dense retrieval pipelines were created with the Pairwise, Setwise, Pointwise and Listwise rankers on the FIQA, NFcorpus, SciFact, TREC-19 and TREC 20 datasets.
- Each dense retrieval pipeline was created for the Mistral, Phi-3 and LLama-3 models and evaluated on the NDCG metric.

7 Results

- The RankLlama and RankZephyr rankers performed best on the FIQA, TREC-19, SciFact and NFCorpus datasets.
- The specific rankers like Pairwise, Setwise and Listwise gave the best performance on the heapsort method.
- The setwise ranker with the heapsort method using the LLama-3 model gave the best performance for the FIQA, TREC-19, SciFact, and NFcorpus datasets.
- The RankLlama and RankZephyr models with the pointwise and listwise ranking gave the best output.

7.1 FIQA

Model	**Ranking Method**	**Sorting Method**	**NDCG@3**	**NDCG@5**	**NDCG@7**	**NDCG@10**
Instructor-XL Retrieval	-	-	0.4250	0.4360	0.4450	0.4650
Mistral	Pairwise	Heapsort	0.4250	0.4360	0.4460	0.4660
Mistral	Pairwise	Bubblesort	0.4250	0.4360	0.4460	0.4660
Mistral	Setwise	Bubblesort	0.4260	0.4370	0.4470	0.4680
Mistral	Setwise	Heapsort	0.4260	0.4370	0.4490	0.4680
Phi-3	Setwise	Bubblesort	0.4260	0.4380	0.4530	0.4690
Phi-3	Setwise	Bubblesort	0.4280	0.4380	0.4530	0.4700
Phi-3	Pairwise	Heapsort	0.4270	0.4380	0.4540	0.4710
Phi-3	Setwise	Heapsort	0.4280	0.4380	0.4540	0.4710
LLama-3	Pairwise	Bubblesort	0.4300	0.4390	0.4560	0.4730
LLama-3	Pairwise	Heapsort	0.4310	0.4390	0.4550	0.4740
LLama-3	Setwise	Bubblesort	0.4330	0.4420	0.4580	0.4740
LLama-3	Setwise	Heapsort	0.4340	0.4430	0.4560	0.4760
RankLllama (7B)	Pointwise	-	0.4771	0.4778	0.4789	0.4796
RankZephyr	Listwise	-	**0.4827**	**0.4854**	**0.4861**	**0.4892**

Table 1: Results on the FiQA dataset.

7.2 SciFact

Model	Ranking Method	Sorting Method	NDCG@3	NDCG@5	NDCG@7	NDCG@10
Instructor-XL Retrieval	-	-	0.6630	0.6670	0.6790	0.6920
Mistral	Pairwise	Bubblesort	0.6690	0.6730	0.6810	0.6940
Mistral	Pairwise	Heapsort	0.6710	0.6750	0.6820	0.6940
Mistral	Setwise	Bubblesort	0.6690	0.6720	0.6810	0.6950
Mistral	Setwise	Heapsort	0.6710	0.6760	0.6830	0.6960
Phi-3	Setwise	Bubblesort	0.6740	0.6790	0.6920	0.7060
Phi-3	Setwise	Bubblesort	0.6740	0.6780	0.6930	0.7080
Phi-3	Pairwise	Heapsort	0.6760	0.6810	0.6940	0.7110
Phi-3	Setwise	Heapsort	0.6750	0.6820	0.6920	0.7120
LLama-3	Pairwise	Bubblesort	0.7420	0.7520	0.7520	0.7630
LLama-3	Pairwise	Heapsort	0.7430	0.7510	0.7540	0.7670
LLama-3	Setwise	Bubblesort	0.7470	0.7530	0.7600	0.7720
LLama-3	Setwise	Heapsort	0.7490	0.7540	0.7620	0.7760
RankLllama (7B)	Pointwise	-	0.7785	0.7793	0.7806	0.7812
RankZephyr	Listwise	-	**0.7849**	**0.7854**	**0.7888**	**0.7891**

Table 2: Results on the SciFact dataset.

7.3 NFCorpus

Model	Ranking Method	Sorting Method	NDCG@3	NDCG@5	NDCG@7	NDCG@10
Instructor-XL Retrieval	-	-	0.3960	0.3980	0.4060	0.4180
Mistral	Pairwise	Bubblesort	0.4120	0.4160	0.4210	0.4270
Mistral	Pairwise	Heapsort	0.4110	0.4160	0.4220	0.4280
Mistral	Setwise	Bubblesort	0.4110	0.4180	0.4240	0.4300
Mistral	Setwise	Heapsort	0.4120	0.4180	0.4260	0.4310
Phi-3	Setwise	Bubblesort	0.4160	0.4210	0.4310	0.4350
Phi-3	Setwise	Bubblesort	0.4180	0.4200	0.4300	0.4360
Phi-3	Pairwise	Heapsort	0.4170	0.4210	0.4320	0.4380
Phi-3	Setwise	Heapsort	0.4190	0.4220	0.4310	0.4390
LLama-3	Pairwise	Bubblesort	0.4210	0.4270	0.4360	0.4400
LLama-3	Pairwise	Heapsort	0.4200	0.4240	0.4340	0.4410
LLama-3	Setwise	Bubblesort	0.4200	0.4250	0.4340	0.4420
LLama-3	Setwise	Heapsort	0.4220	0.4280	0.4360	0.4430
RankLllama (7B)	Pointwise	-	0.4481	0.4492	0.4507	0.4518
RankZephyr	Listwise	-	**0.4528**	**0.4546**	**0.4567**	**0.4578**

Table 3: Results on the NFCorpus dataset.

7.4 TREC-19

Model	Ranking Method	Sorting Method	NDCG@10
Instructor-XL Retrieval	-	-	0.5230
Mistral	Pairwise	Bubblesort	0.7080
Mistral	Pairwise	Heapsort	0.7090
Mistral	Setwise	Bubblesort	0.7110
Mistral	Setwise	Heapsort	0.7140
Phi-3	Setwise	Bubblesort	0.7190
Phi-3	Setwise	Bubblesort	0.7190
Phi-3	Pairwise	Heapsort	0.7210
Phi-3	Setwise	Heapsort	0.7220
LLama-3	Pairwise	Bubblesort	0.7390
LLama-3	Pairwise	Heapsort	0.7410
LLama-3	Setwise	Bubblesort	0.7440
LLama-3	Setwise	Heapsort	0.7460
RankLllama (7B)	Pointwise	-	0.7511
RankZephyr	Listwise	-	**0.7693**

Table 4: Results on the TREC-19 dataset.

7.5 TREC-20

Model	Ranking Method	Sorting Method	NDCG@10
Instructor-XL Retrieval	-	-	0.5040
Mistral	Pairwise	Bubblesort	0.6890
Mistral	Setwise	Bubblesort	0.6920
Mistral	Pairwise	Heapsort	0.6940
Mistral	Setwise	Heapsort	0.6950
Phi-3	Setwise	Bubblesort	0.7010
Phi-3	Setwise	Bubblesort	0.7010
Phi-3	Pairwise	Heapsort	0.7020
Phi-3	Setwise	Heapsort	0.7030
LLama-3	Pairwise	Heapsort	0.7220
LLama-3	Pairwise	Bubblesort	0.7230
LLama-3	Setwise	Bubblesort	0.7250
LLama-3	Setwise	Heapsort	0.7270
RankLlama (7B)	Pointwise	-	0.7642
RankZephyr	Listwise	-	**0.7743**

Table 5

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