

IRanker: Towards Ranking Foundation Model

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Abstract

Ranking tasks are ubiquitous, encompassing applications such as recommendation systems, LLM routing, and item re-ranking. We propose to unify these tasks using a single ranking foundation model (FM), as it eliminates the need for designing different models for each specific ranking task. However, unlike general supervision tasks in LLMs, ranking tasks do not have clear labels for supervision, posing great challenges to developing a ranking FM. To overcome these challenges, we propose IRanker, a ranking FM framework with reinforcement learning (RL) and iterative decoding. Our insight is to decompose the complex ranking task into an iterative decoding process that eliminates the worst candidate from the candidate pool step by step, which significantly reduces the output combinatorial space and better utilizes the limited context length during RL training. We meticulously train and comprehensively evaluate an IRanker-3B model on nine datasets across three scenarios: recommendation, routing, and passage ranking. The results show that a single IRanker-3B achieves state-of-the-art results on several datasets compared to models of similar size, and even surpasses the performance of larger models on certain datasets. We further demonstrate the effectiveness of our RL design and the robustness of the iterative mechanism across different LLM sizes. Moreover, we conducted both in-domain and out-of-domain zero-shot generalization experiments, which showed that IRanker-3B achieved good generalization on in-domain ranking tasks compared to the base LLM by at least 5% improvement. Surprisingly, on out-of-domain generic LLM tasks, IRanker-3B outperformed the base model by at least 9% on GSM8K, IFEval, and MathQA. In addition, the thoughts generated by IRanker-3B during training could further enhance zero-shot LLM performance. Our code for IRanker is released at <https://github.com/ulab-uiuc/IRanker>.

1 Introduction

Ranking tasks are ubiquitous across various domains, playing a crucial role in applications such as recommendation sys-

tems [Cremonesi *et al.*, 2010; He *et al.*, 2017], large language model (LLM) routing [Li *et al.*, 2023; Zhang *et al.*, 2023a], and passage re-ranking in retrieval-based systems [Nogueira and Cho, 2019; Khattab and Zaharia, 2020]. The goal of a ranking task [Liu, 2009; Guo *et al.*, 2020] is to generate an ordered list of candidates that best satisfy a user’s query. Unifying all ranking tasks using a single Ranking Foundation Model (FM) is crucial, as it eliminates the need to design separate methods for each specific ranking task and generalizes better for unseen ranking tasks. However, due to the semantic differences among various ranking tasks [Lewis *et al.*, 2020; Thakur *et al.*, 2021] and the diversity of supervision signals [Gao *et al.*, 2021; Luan *et al.*, 2021], traditional embedding-based approaches struggle to effectively address this challenge [Khattab and Zaharia, 2020; Xiong *et al.*, 2021]. LLMs have emerged as one of the most promising approaches for unifying multiple tasks and building foundation models, as they can represent diverse tasks using textual descriptions to align them within a shared semantic space [Sanh *et al.*, 2022; Chung *et al.*, 2022]. Therefore, our paper aims to raise attention to this pressing research question: *How can we build a ranking FM to unify multiple ranking tasks with LLMs?*

Existing studies primarily leverage LLMs to address ranking tasks in two main aspects: LLM-as-embedding methods and LLM-as-ranker methods. The insight of LLM-as-embedding approaches is that instruction-tuned LLMs can generate semantically rich and generalizable representations that enhance performance in various ranking tasks [Liu *et al.*, 2024; Li and Zhang, 2024; Zhang *et al.*, 2023b; Neelakantan *et al.*, 2022], *e.g.*, LLMEmb uses contrastively fine-tuned LLMs to generate item embeddings for sequential recommendation [Liu *et al.*, 2024]. However, as embedding-based methods, they still struggle to unify task-specific ranking semantics, thus limiting their ability to generalize across diverse real-world ranking tasks [Nogueira and Cho, 2019; Khattab and Zaharia, 2020; Lewis *et al.*, 2020]. LLM-as-ranker approaches [Sun *et al.*, 2023; Yoon *et al.*, 2024; Hou *et al.*, 2024a] leverage the reasoning and instruction-following capabilities of large language models to directly generate candidate rankings in a unified text-based format, *e.g.*, RankGPT [Sun *et al.*, 2023] explores the use of generative LLMs for relevance ranking in information retrieval tasks, and LLM4Ranking [Liu *et al.*, 2025] provides a framework that enables users to adopt various ranking methods using open-source or API-based LLMs for

document reranking tasks. Despite their promising results, LLMs-as-ranker methods often suffer from limited ability to incorporate downstream feedback for iterative improvement and the lack of explicit supervision signals [Liu *et al.*, 2023; Shi *et al.*, 2023]. These challenges significantly hinder the development of a unified and ranking FM with LLMs.

To overcome these challenges, we propose IRanker, a ranking FM framework with reinforcement learning (RL) and iterative decoding. Two major insights contribute to the success of IRanker – RL and iterative decoding. We propose to train a ranking FM with RL, treating the performance feedback of ranking tasks as rewards and incorporating the long-thought ability of LLMs to enhance RL optimization. Here, we considered a simpler approach that directly asks the LLM to generate the candidate rankings and optimizes the rankings according to the rewards with RL, named DRanker. However, since the DRanker needs to compare and rank multiple candidates, it faces challenges such as an excessively large output space and limited context length for thinking. Instead, our proposed IRanker decomposes the complex ranking task into an iterative decoding process that eliminates the worst candidate from the candidate pool step by step, which significantly reduces the output combinatorial space and better utilizes the limited context length of LLMs during LLM training, leading to a more efficient and effective ranking procedure. To optimize IRanker, we further design a step-wise reward to guide IRanker to first exclude lower-ranked candidates; candidates excluded later receive higher ranks, and the final ranking is constructed by reversing the exclusion order.

We meticulously train and evaluate a unified 3B ranking foundation model, IRanker-3B, on nine representative datasets spanning three scenarios: recommendation, routing, and passage ranking. Our results show that a single IRanker-3B matches or surpasses the domain-specific methods for each task, achieves state-of-the-art (SOTA) performance compared to general ranker baselines, and even surpasses larger 7B LLM models on some tasks and achieves a 15.7% relative improvement on average. We also perform extensive ablation studies, confirming the effectiveness of our RL design and the robustness of the iterative mechanism across different LLM sizes. Additionally, both in-domain and out-of-domain zero-shot generalization experiments demonstrate strong performance: IRanker-3B improves over the base model by at least 5% on in-domain ranking tasks, and by over 9% on out-of-domain tasks such as GSM8K, IFEval, and MathQA. Notably, we show that the intermediate thoughts generated during training further enhance the zero-shot ranking capabilities of other LLMs. For example, based on the 3B backbone model, intermediate thoughts can lead to a 22.87% relative improvement in zero-shot performance for the base model.

2 Preliminaries

Ranking tasks. Given a query q , a ranking task [Liu, 2009; Li, 2011; Cao *et al.*, 2007] is to learn a ranker f that ranks a set of candidates $D = \{c_1, c_2, \dots, c_n\}$ with n elements. The candidate set is typically divided into a positive candidate set D_p and a negative candidate set D_n . The positive candidate set refers to the items actually selected by the user, for example, the items a user really purchased in

a recommendation system. To evaluate how well the ranker recovers these positive candidates, the performance of the ranking task is measured by an evaluator E , which is usually a ranking metric such as Normalized Discounted Cumulative Gain (nDCG) [Järvelin and Kekäläinen, 2002] or Mean Reciprocal Rank (MRR) [Voorhees and others, 1999; Cremonesi *et al.*, 2010]. The goal of the ranker π is to learn a function that maps a query q and its candidate set D to a ranking order $O = \{c_1^{r_1}, c_2^{r_2}, \dots, c_n^{r_n}\} \in \mathbb{S}_n$ with r_i as the rank of candidate c_i , such that the evaluation metric E is maximized:

$$\pi : (q, D) \rightarrow O, \quad O \in \mathbb{S}_n, \quad (1)$$

where \mathbb{S}_n denotes the set of all possible permutations over $n = |D|$ elements.

Formally, the optimal ranker π^* is learned by solving:

$$\pi^* = \arg \max_{f \in \mathcal{F}} \mathbb{E}_{(q,D) \sim \mathcal{Z}} [E(\pi(q, D))], \quad (2)$$

where \mathcal{F} is the function class and \mathcal{Z} is the data distribution over queries and candidate sets.

Examples. As shown in Figure 1, we have listed some representative instantiations that can be unified into a ranking foundation model from three aspects. **(a) Recommendation**, shown in Figure 1(a), the goal of the recommendation [Ricci *et al.*, 2010; Adomavicius and Tuzhilin, 2005; Covington *et al.*, 2016] is to capture user preferences by analyzing their histories, rank the current set of candidate items, and predict those that the user is most likely to favor. Here, the user history is modeled as query q , each element of the candidates is an item, and positive candidate set D_p contains the real items that the user would choose. **(b) Routing**, routing task [Ong *et al.*, 2024; Feng *et al.*, 2024; Huang *et al.*, 2025; Hu *et al.*, 2024] aims to recommend appropriate LLMs for handling diverse user queries by ranking them based on both effectiveness and response cost, shown in Figure 1(b). The final LLM recommendation list is generated through a ranking process that balances performance with efficiency. Specifically, a user query is regarded as query q , each element of the candidates is a LLM name or LLM description [Feng *et al.*, 2024], and the positive candidate set D_p means the ground truth LLMs for the query. **(c) Passage ranking**, passage ranking [Guu *et al.*, 2020; Karpukhin *et al.*, 2020; Lewis *et al.*, 2020] aims to identify and reorder the most relevant passages from a set of candidates given a user query, often arises in retrieval-augmented generation, shown in Figure 1(c). This is achieved by modeling the relevance between the query and each passage to produce a final ranking list. For this task, the user query is regarded as query q , each element of the candidates is a passage, and the positive candidate set D_p contains the ground truth passages.

3 DRanker: A Basic Ranking FM with Reinforcement Learning

3.1 Unify ranking tasks with LLM

Due to the significant semantic differences among various ranking tasks and the varying supervised signals, traditional embedding-based methods struggle to unify all ranking tasks [Lewis *et al.*, 2020; Nogueira and Cho, 2019; Khattab and Zaharia, 2020]. To address this issue, we

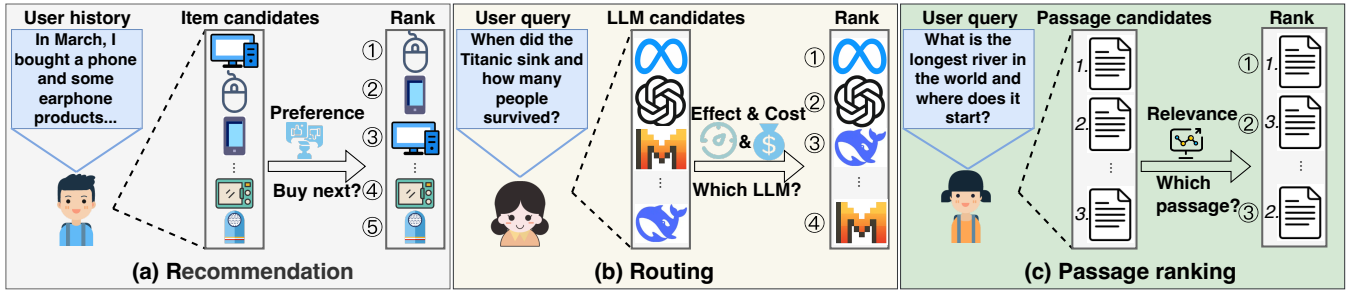


Figure 1: Example ranking tasks that a proposed ranking FM can solve. (a) The recommendation task aims to model the user’s preferences based on their historical behaviors. It will rank the current item candidates and predict which items the user is most likely to prefer. (b) The routing task is to recommend suitable LLMs to respond to different user queries. The recommendation process takes into account the effectiveness and cost of each LLM’s response, and performs ranking to generate the final recommendation list. (c) Passage ranking involves retrieving a set of passages from candidate passages based on a given user query for retrieval-augmented generation. It ranks the passages by modeling the relevance between the query and the passages to produce the final list of passages.

propose DRanker as shown in the upper part of Figure 2, which maps diverse ranking tasks into a unified text space. DRanker leverages LLMs to prompt both the task query and its candidates, and directly outputs the ranking of the candidates. Specifically, we use a prompt P to convert the task query q and its candidates D into a textual description $P(q, D)$. Motivated by the strong reasoning capabilities of LLMs in enhancing generation quality [Wei *et al.*, 2022; Kojima *et al.*, 2022; Chung *et al.*, 2022; Guo *et al.*, 2025], we follow [Guo *et al.*, 2025] and augment $P(q, D)$ with a system prompt P_t to encourage reasoning. The final prompt is then fed into the DRanker π_θ to produce the ranked output: $O_d = \pi_\theta(P_t(q, D))$. The detailed prompts for different ranking tasks can be seen in Appendix A.

3.2 Training and inference via RL

Since ranking tasks do not have explicit ground truth, it is difficult to perform supervised learning directly. However, as we explained in Section 2, the performance of the ranking task is measured by an evaluator E . Considering that the evaluator E serves as a non-differentiable feedback signal for the DRanker π_θ , we introduce reinforcement learning to address this problem.

Ranking reward. We first model the evaluator E as a ranking reward $r_a = E(O_d)$, with the objective of maximizing E . Specifically, since the number of candidates varies across different ranking tasks, we choose MRR as the evaluator E . However, due to the limited instruction-following ability of LLMs, the output candidate rankings often miss or add candidates, which violates the standard requirements of a valid ranking. To regularize the output of the DRanker, we introduce a format reward as a penalty term $r_g = \Omega(O_d, D) - 1$, where Ω calculates the F1 score measuring the overlap between O_d and D . Thus, the final reward is defined as $r_d = r_a + r_g$.

Training and inference via PPO. To optimize the DRanker π_θ for maximizing the final reward r_d , we adopt the Proximal Policy Optimization (PPO) algorithm [Schulman *et al.*, 2017], a widely used actor-critic RL method for LLMs. PPO trains

the policy by maximizing the following objective:

$$\mathcal{J}_{\text{PPO}}(\theta) = \mathbb{E}_{(q,D) \sim \mathcal{Q}, y \sim \pi_\theta^{\text{old}}(\cdot | P_t(q,D))} \left[\sum_{t=1}^{|y|} \min \left(\frac{\pi_\theta(y_t | P_t(q,D), y_{<t})}{\pi_\theta^{\text{old}}(y_t | P_t(q,D), y_{<t})} A_t, \text{clip} \left(\frac{\pi_\theta(y_t | P_t(q,D), y_{<t})}{\pi_\theta^{\text{old}}(y_t | P_t(q,D), y_{<t})}, 1 - \epsilon, 1 + \epsilon \right) A_t \right) \right] \quad (3)$$

where π_θ and π_θ^{old} denote the current and previous policies, respectively. The pair $(q, D) \sim \mathcal{Q}$ is sampled from the training distribution, where q denotes the input query and D the associated candidate set. $y = \{y_1, y_2, \dots, y_{|y|}\}$ is the token-level sequence generated by the policy model. This sequence is parsed into a ranking candidate list $O_d = \text{Parse}(y, D)$ using a matching function based on string similarity or identifier alignment with D . The advantage estimate A_t is computed using Generalized Advantage Estimation (GAE) [Schulman *et al.*, 2015], based on future rewards $\{r_{\geq t}\}$ and a learned value function V_ϕ . The clipping parameter ϵ is used to ensure stable policy updates. After obtaining the optimal π_θ^* , we can obtain the final ranking candidate list $O_d = \text{Parse}(\pi_\theta^*(P_t(q, D)), D)$.

4 IRanker: Advanced Ranking FM with RL and Iterative Decoding

4.1 Decompose candidates ranking into single candidate selections

Although DRanker can rank candidates in a simple and direct manner, it is limited by the large action space and the constrained context length for reasoning. To address this problem, we propose IRanker, as shown in the lower part of Figure 2. The insight of IRanker is to decompose the complex ranking task into an iterative process that excludes a candidate from the candidate pool step by step, making the ranking procedure more efficient and effective. Similar to the method introduced in section 3.1, we design a prompt P_d (details in Appendix A) that encodes the query q and the current candidate set $D^{(k)}$, and instructs the IRanker π_ω to exclude one candidate $c_k \in D^{(k)}$ at each iteration k . The process is defined as:

$$c_k = \pi_\omega(P_d(q, D^{(k)})), D^{(k-1)} = D^{(k)} \setminus \{c_k\}, r_k = |D| - k + 1 \quad (4)$$

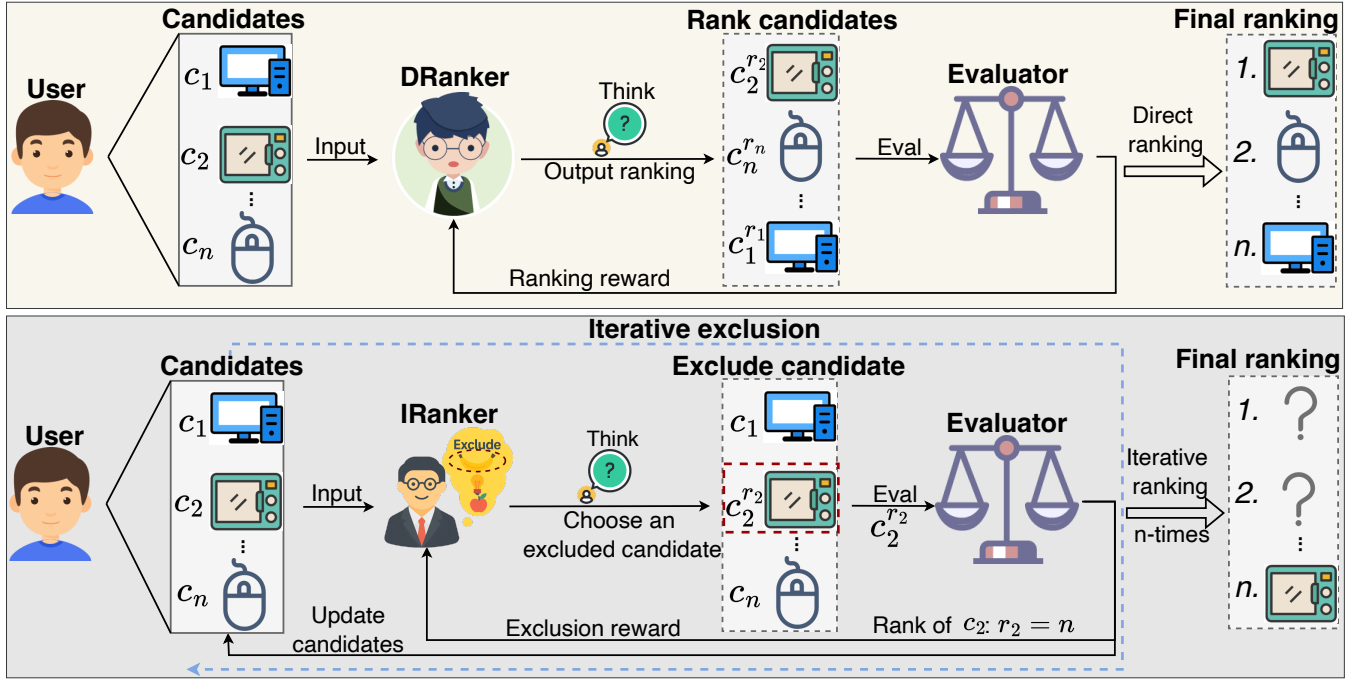


Figure 2: **Framework of our proposed ranking FMs.** Both DRanker and IRanker are RL-enhanced LLM frameworks. They take as input the candidate information in text form, along with user information (such as user history or a query), and utilize the LLM’s reasoning capabilities to produce a final candidate ranking. This ranking is then evaluated by an evaluator to generate a corresponding reward function, which is used to optimize the decision-making of both rankers. The key distinctions are: 1) DRanker generates the full ranking in a single step, whereas IRanker iteratively excludes the least likely item from the candidates to arrive at the final ranking. 2) The reward in DRanker is a ranking reward based on the final candidate ranking, while the reward in IRanker is an exclusion reward given for each individual exclusion decision. 3) DRanker always receives the full set of candidates as input with a fixed size, whereas IRanker’s input candidates are dynamically updated based on the excluded items.

After $|D|$ iterations, we obtain the complete ranking list:

$$O_d = [c_1^{r_1}, c_2^{r_2}, \dots, c_{|D|}^{r_{|D|}}] \quad (5)$$

Here, candidates excluded later receive higher ranks, and the final ranking O_d is constructed by reversing the exclusion order.

4.2 Training and inference with via iterative RL

Exclusion reward. To train this iterative process, we first define the exclusion reward r_e^k for each exclusion step k :

$$r_e^k = \begin{cases} 1, & \text{if } c_k \in D_n \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

where D_n is the negative candidate set illustrated in section 2. The exclusion reward is designed to guide the IRanker π_ω to prioritize excluding negative candidates, thereby encouraging positive candidates to be ranked as early as possible.

Training and inference via iterative PPO. Similar to section 3.2, we utilize PPO to optimize the IRanker π_ω by maximizing the following objective:

$$\mathcal{J}_{\text{PPO}}(\omega) = \mathbb{E}_{(q, D^{(k)}) \sim \mathcal{B}, y \sim \pi_{\omega}^{\text{old}}(\cdot | P_d(q, D^{(k)}))} \left[\sum_{t=1}^{|y|} \min \left(\frac{\pi_{\omega}(y_t | P_d(q, D^{(k)}), y_{<t})}{\pi_{\omega}^{\text{old}}(y_t | P_d(q, D^{(k)}), y_{<t})} A_t, \right. \right. \\ \left. \left. \text{clip} \left(\frac{\pi_{\omega}(y_t | P_d(q, D^{(k)}), y_{<t})}{\pi_{\omega}^{\text{old}}(y_t | P_d(q, D^{(k)}), y_{<t})}, 1 - \epsilon, 1 + \epsilon \right) A_t \right) \right] \quad (7)$$

where $(q, D^{(k)}) \sim \mathcal{B}$ is sampled from the training distribution; $P_d(q, D^{(k)})$ is the prompt encoding the query q and

current candidate pool $D^{(k)}$; π_ω and π_ω^{old} denote the current and previous policies, respectively; A_t is the estimated advantage at decoding step t ; ϵ is the PPO clipping threshold; $y = (y_1, y_2, \dots, y_T)$ is the response sequence generated by the policy; $c_k = \text{Parse}(y, D^{(k)})$ is the excluded candidate parsed from y . Once the optimal π_ω^* is obtained, we can get the final ranking candidate list O_d with equation (5) by repeating the equation (4) with π_ω^* .

5 Experiments

We conduct comprehensive training and evaluation of the proposed ranking FMs, DRanker and IRanker. Notably, **the same ranking FM is being evaluated across diverse 9 interdisciplinary tasks**, which is compared against general ranking methods and domain-specific methods. First, we introduce the tasks within the ranking FM framework.

Task description. The details of the tasks are summarized across three aspects in Table 1. **(1) Recommendation (Rec):** For the recommendation ranking task, we utilize three widely-used sequential recommendation datasets: MovieLens ml-1m [Hou *et al.*, 2024b], Amazon’s CD and Vinyl dataset [McAuley *et al.*, 2015; Ni *et al.*, 2019], and Amazon’s Video Game dataset [McAuley *et al.*, 2015; Ni *et al.*, 2019]. For each user across all datasets, following the settings of [Hou *et al.*, 2024b], we extracted 20 consecutive interactions as the historical sequence and designated the 21st interaction as the ground

Table 1: **Detailed summarization of tasks used in our ranking tasks.** We summarize the task names, scenarios, candidate sizes, training/test case counts, and positive/negative ratios.

Dataset	Scenario	Candidate Size	# Train Cases	# Test Cases	Positive/Negative Ratio
Movie	Recommendation	20	9975	2508	1:19
Music	Recommendation	20	9975	2508	1:19
Game	Recommendation	20	9424	2337	1:19
Performance	Routing	10	1467	153	1:9
Cost	Routing	10	1467	153	1:9
Balance	Routing	10	1467	153	1:9
5 Passage	Passage ranking	5	10000	1448	1:4
7 Passage	Passage ranking	7	9996	3894	1:6
9 Passage	Passage ranking	9	10000	1792	1:8

Table 2: **Model performance comparison with general baselines across nine ranking tasks of three scenarios on MRR.** **Bold** and underline denote the best and second-best results. We can observe the following: 1) Compared to the baselines, IRanker-3B achieves state-of-the-art performance in almost all tasks. 2) The comparison between methods with and without RL validates the enhancement effect of RL on ranking tasks. 3) The comparison between iterative-based ranking and direct ranking demonstrates the suitability of the iterative design for models of different sizes.

Model	Recommendation			Routing			Passage Ranking		
	Movie	Music	Game	Performance	Cost	Balance	5 Passages	7 Passages	9 Passages
<i>Retrieval-based Models</i>									
BM25	17.56	18.09	14.96	18.41	13.52	13.39	53.63	44.95	39.69
Contriever	18.29	17.04	23.98	20.75	16.29	16.74	41.91	36.41	33.10
<i>Direct-Rank LLMs without RL</i>									
Qwen2.5-3B-Instruct-direct	16.92	16.68	13.17	10.00	10.00	10.00	38.08	22.47	15.94
Qwen2.5-7B-Instruct-direct	16.59	17.29	18.63	13.38	13.51	18.41	44.57	23.69	17.79
<i>Iterative LLMs without RL</i>									
Qwen2.5-3B-Instruct-iter	22.01	21.97	29.49	20.87	20.22	12.42	57.74	43.47	39.40
Qwen2.5-7B-Instruct-iter	<u>22.11</u>	<u>23.36</u>	<u>33.14</u>	19.13	<u>21.06</u>	26.09	62.01	<u>50.94</u>	<u>48.74</u>
<i>Direct-Rank LLMs with RL</i>									
DRanker-3B	18.71	15.70	15.77	20.63	9.06	13.38	43.85	22.86	16.11
<i>Iterative LLMs with RL</i>									
IRanker-3B	34.69	29.18	42.49	23.62	30.39	<u>24.44</u>	<u>60.98</u>	53.22	49.96

truth item. To create a balanced candidate set, we randomly sampled 19 items from the complete item catalog (excluding items in the user’s history and the ground truth item) and combined them with the ground truth item to form a candidate list of 20 items. This approach creates a realistic recommendation scenario with a 5% chance of randomly selecting the relevant item, while maintaining a manageable evaluation space. (2) **Routing (Router)**: For the LLM routing task, following the setting of [Feng *et al.*, 2024], we selected four datasets from [Feng *et al.*, 2024] and ten large language models (LLMs). Based on different weights of LLM response effectiveness and cost, we followed three settings in [Feng *et al.*, 2024]: Performance First (Performance), Balance, and Cost First (Cost), corresponding to scenarios where users prioritize high performance, value both high performance and low cost equally, or prioritize low cost, respectively. For each query, we computed the reward based on the weighted sum of effectiveness and cost, and selected the LLM with the highest reward as the

ground-truth LLM. The remaining nine LLMs were treated as negative LLMs. (3) **Passage Ranking (Passage)**: For the passage ranking task, we employ the MS MARCO passage dataset [Nguyen *et al.*, 2016], a large-scale information retrieval benchmark derived from Bing search logs. To evaluate models under different retrieval complexity scenarios, we created three distinct settings with varying candidate passage sizes: 5, 7, and 9 passages per query. For each query, these candidate sets include one relevant passage (as judged by human annotators in the dataset) and 4, 6, or 8 irrelevant passages respectively. This configuration allows us to assess how model performance scales with increasing candidate pool sizes and how effectively models can identify the single relevant passage among varying numbers of distractors.

Baselines and metrics. We evaluate a variety of baseline methods across three scenarios. The baselines are categorized into two groups: (a) *General baselines* that apply across tasks, and (b) *Task-specific baselines* tailored to each sce-

nario. For all methods, we primarily use Mean Reciprocal Rank (MRR) [Voorhees and others, 1999; Cremonesi *et al.*, 2010] to evaluate ranking performance in the main text. A full evaluation with additional metrics and generation cases are provided in Appendix E and B for details. The implementation details and computational analysis can be seen in Appendix F and D. (a) **General baselines**: We implemented two types of general baselines: retrieval-based methods and LLM-based methods. For the retrieval-based methods, the user queries or user history are regarded as query and candidates are modelled as corpus. We introduced a probabilistic retrieval model and a dense retrieval model: 1) **BM25** [Robertson *et al.*, 2009]: A classical probabilistic retrieval function based on term frequency, inverse document frequency, and document length normalization. BM25 is utilized for keyword matching and retrieval between the query and the candidates. 2) **Contriever** [Izacard *et al.*, 2021]: A state-of-the-art dense retrieval model that learns representations through contrastive learning with hard negatives. We adapted Contriever to handle all three ranking tasks by encoding queries/user histories and candidate items/LLM descriptions/passages into the same embedding space. As for the LLM-based methods, they will prompt the user query/history and candidates using text and output the ranking or the choice of the candidates via zero-shot generation. Specifically, we select Qwen2.5-3B-Instruct and Qwen2.5-7B-Instruct [Yang *et al.*, 2024] as the backbone models for the LLM-based baselines. Furthermore, inspired by the designs of DRanker and IRanker, we explore two variants, **LLM-direct** and **LLM-iter**, based on these backbone models to represent direct ranking and iterative ranking, respectively. (b) **Task-specific baselines**: For the recommendation task, we implemented three sequential recommendation baselines: 1) **SASRec** [Kang and McAuley, 2018]: A self-attention based sequential recommendation model that captures users’ sequential behavioral patterns using a transformer-based architecture. 2) **BPR** [Rendle *et al.*, 2012]: It performs sequential recommendation ranking by optimizing pairwise preferences between items, encouraging the model to rank a user’s previously interacted item higher than unobserved ones based on their interaction order. 3) **R1-Rec** [Lin *et al.*, 2025]: It is a reinforcement learning-based framework that directly optimizes retrieval-augmented LLMs for recommendation tasks using feedback from downstream tasks. As for the routing task, we compared three representative routers: 1) **RouterKNN** [Hu *et al.*, 2024]: It is a simple yet effective routing baseline that assigns queries to the most suitable model by retrieving similar examples from training data and selecting the majority route among their labels. 2) **RouterBERT** [Ong *et al.*, 2024]: A lightweight BERT model fine-tuned for routing decisions using classification over task labels. 3) **GraphRouter** [Feng *et al.*, 2024]: A SOTA graph-based router that can trade off between performance and cost. Finally, for the passage ranking task, we implemented three specialized baselines that were pre-trained on the MS MARCO passage dataset: 1) **RankBERT** [Nogueira and Cho, 2019]: A BERT-based passage reranker that fine-tunes the BERT model on MS MARCO relevance judgments, treating ranking as a binary classification problem. It is pretrained on 503k query-passage pairs. 2) **MonoT5** [Nogueira *et al.*, 2020]: A T5-based reranker that formulates

passage ranking as a sequence-to-sequence task, generating relevant or irrelevant tokens for each query-passage pair. It is pretrained on 503k examples. 3) **RankLLama-8B** [Ma *et al.*, 2024]: A ranking-specialized version of Llama-2-8B that has been fine-tuned specifically for passage ranking tasks using pairwise and listwise ranking objectives. The model is pretrained on 503k ranking examples.

5.1 IRanker achieves SOTA performance compared with general ranking methods

We train a unified IRanker-3B on all tasks and test it across all tasks without further fine-tuning, compared with general ranking methods. We report the comparison results in Table ???. We can observe that: (1) IRanker-3B surpasses all baseline models in the majority of ranking tasks. Notably, it even outperforms the larger Qwen2.5-7B-Instruct-iter model in 7 out of 9 tasks, despite having fewer parameters. On average, IRanker-3B achieves a 15.7% relative improvement in MRR over Qwen2.5-7B-Instruct-iter across the nine evaluated tasks. (2) The performance gap between models with and without reinforcement learning (RL), particularly when comparing IRanker-3B to its counterparts without RL, confirms the positive impact of RL on ranking quality. For example, IRanker-3B significantly improves over Qwen2.5-3B-Instruct-iter in routing tasks (e.g., Cost: 30.39 vs. 20.22) and recommendation tasks (e.g., Game: 42.49 vs. 29.49), highlighting the effectiveness of RL-enhanced optimization. (3) When comparing direct ranking models to their iterative counterparts, iterative designs (e.g., Qwen2.5-7B-Instruct-iter and IRanker-3B) generally outperform direct methods across all task domains. This trend is consistent across both small and large model sizes, suggesting that the iterative inference mechanism better captures task-specific alignment and enables more robust generalization across tasks of varying complexity.

5.2 IRanker matches the performance of domain-specific methods across multiple tasks

We further compared IRanker-3B with domain-specific methods as shown in Figure 3. Specifically, we compared IRanker-3B with three representative SOTA methods (denoted as SOTA-1, SOTA-2, and SOTA-3) and Qwen2.5-3B-Instruct-iter across three domains. In the recommendation scenario, SOTA-1, SOTA-2, and SOTA-3 refer to SASRec, BPR, and R1-Rec, respectively; in routing, they correspond to GraphRouter, RouterBert, and RouterKNN; and in passage ranking, they denote RankLLama-8B, RankBERT, and MonoT5. We can observe that: (1) IRanker-3B matches the performance of domain-specific methods across multiple tasks. (2) In the recommendation scenario, IRanker-3B outperforms all baselines and achieves state-of-the-art results. (3) Even in the passage ranking scenario, IRanker-3B performs on par with models that have significantly larger parameter sizes (e.g., RankLLama-8B) or were trained with much more data samples (e.g., RankBERT and MonoT5) as illustrated in the part of task-specific baselines.

5.3 IRanker boosts zero-shot performance

To further investigate the generalization ability of IRanker as a foundation model, we conduct analyses from the following three aspects.

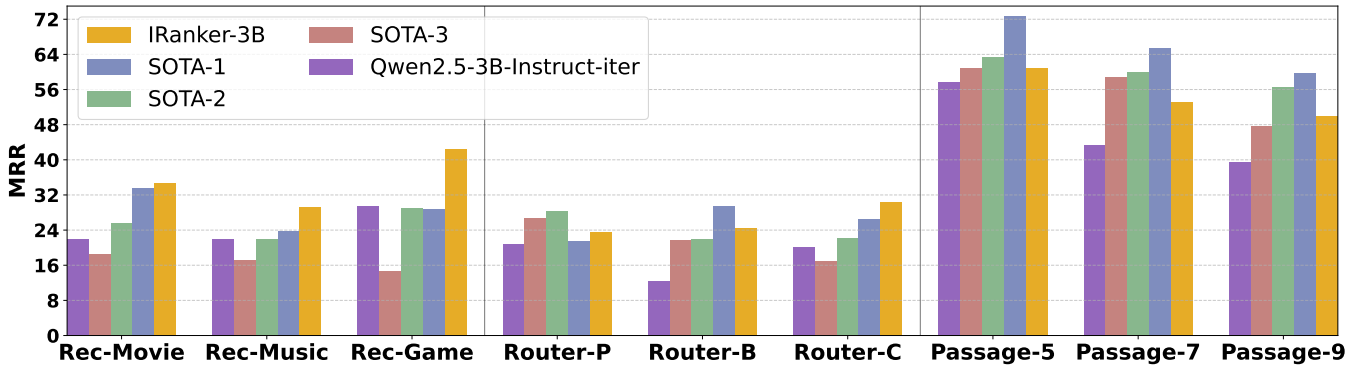


Figure 3: **IRanker-3B matches the performance of domain-specific methods across multiple tasks with fewer training samples and smaller model size.** We compared the performance of IRanker-3B against three representative SOTA methods and Qwen2.5-3B-Instruct-iter across three scenarios. SOTA-1, SOTA-2, and SOTA-3 correspond to SASRec, BPR, and R1-Rec in the recommendation (Rec) scenario; GraphRouter, RouterBert, and RouterKNN in the routing (Router) scenario; RankLLama-8B, RankBERT, and MonoT5 in the passage ranking (Passage) scenario.

Table 3: **Zero-shot performance comparison across different ranking tasks on MRR.** Bold and underline denote the best and second-best results. The results for each ranking scenario were obtained by training on the data from the other two ranking scenarios and then performing zero-shot testing on the target scenario.

Model	Recommendation			Routing			Passage Ranking		
	Movie	Music	Game	Performance	Cost	Balance	5 Passages	7 Passages	9 Passages
Qwen2.5-3B-Instruct-iter	22.01	21.97	29.49	20.87	20.22	12.42	57.74	43.47	39.40
IRanker-3B	34.69	29.18	42.49	23.62	30.39	24.44	60.98	53.22	49.96
IRanker-3B (zero-shot)	<u>25.95</u>	<u>23.21</u>	<u>31.16</u>	20.41	<u>23.10</u>	<u>21.89</u>	56.42	<u>51.19</u>	<u>42.45</u>

IRanker achieved good generalization on in-domain ranking tasks compared to the base model. We first investigate the in-domain generalization capability of IRanker on ranking tasks, by training it on two different ranking tasks and then conducting zero-shot testing on the target ranking task, reported in Table 3. It can be observed that IRanker-3B (zero-shot) outperforms Qwen2.5-3B-Instruct-iter on nearly all tasks and even approaches the performance of IRanker on the Performance and 7 Passages tasks. This demonstrates the strong in-domain generalization ability of IRanker.

Thoughts emerged from IRanker could enhance zero-shot performance of the base model. To investigate whether the emergent thoughts generated during IRanker training can enhance the zero-shot performance of the base model, we propose IRanker-COT-3B. This model adopts an iterative framework that, for each test query, retrieves semantically similar queries along with their corresponding thoughts produced during IRanker training. These retrieved thoughts are used as templates (details in Appendix C) to guide zero-shot inference. We evaluate IRanker-COT-3B on nine benchmark tasks and compare its performance against IRanker-3B and Qwen2.5-3B-Instruct-iter. As shown in Figure 4, IRanker-COT-3B consistently outperforms Qwen2.5-3B-Instruct-iter and even exceeds the performance of IRanker-3B on the Rec-Game task.

IRanker outperformed the base model on five out-of-domain generic LLM tasks. Finally, we investigate the out-of-domain generalization capability of IRanker on non-ranking

tasks. To this end, we evaluate IRanker-3B and Qwen2.5-3B-Instruct on eight widely used LLM benchmarks shown in Table 4. IRanker-3B outperforms Qwen2.5-3B-Instruct on five of the eight tasks, with notable improvements on math and reasoning-intensive datasets such as GSM8K, IFEval, and MathQA. Conversely, Qwen2.5-3B-Instruct shows stronger performance on code generation tasks, including MBPP and HumanEval. On general QA tasks like OpenBookQA and HellaSwag, the two models achieve comparable results. These findings demonstrate that IRanker-3B is particularly effective at structured reasoning, while Qwen2.5-3B-Instruct retains a marginal advantage in programming-related scenarios.

6 Conclusion

In this work, we address the challenge of unifying diverse ranking tasks by introducing IRanker, an iterative ranking FM optimized via reinforcement learning. By decomposing ranking into a step-wise exclusion process and leveraging the reasoning capabilities of large language models, IRanker overcomes limitations of traditional embedding-based and direct-ranking methods. Our proposed IRanker-3B achieves competitive or state-of-the-art performance across nine datasets from recommendation, routing, and passage ranking scenarios. Extensive experiments demonstrate its strong generalization abilities, achieving over 5% improvement in in-domain zero-shot settings and over 9% gains in out-of-domain LLM tasks. These results highlight IRanker’s effectiveness as a unified and scalable ranking FM framework, setting a foundation for

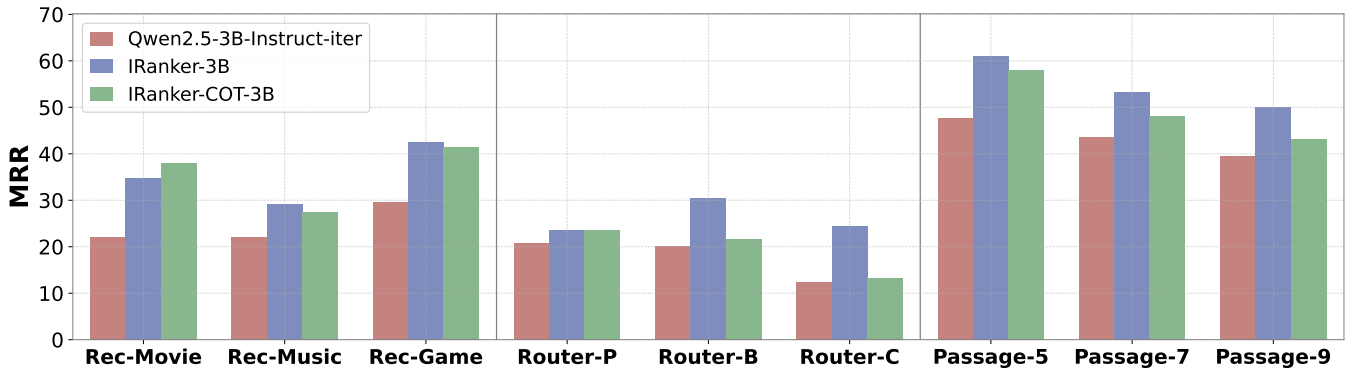


Figure 4: **Thoughts emerged by IRanker during training can enhance zero-shot performance of the base model.** IRanker-COT-3B is an iterative framework that, for each test query, retrieves similar queries and their corresponding thoughts that emerged during the training of IRanker, using them as thought templates to guide zero-shot responses. We evaluate IRanker-COT-3B on nine tasks and compare its performance with IRanker-3B and Qwen2.5-3B-Instruct-iter. The results show that IRanker-COT-3B consistently outperforms Qwen2.5-3B-Instruct-iter and even surpasses IRanker-3B in the Rec-Game task.

Table 4: **IRanker outperformed the base model on three out-of-domain generic LLM tasks.** Bolded values indicate higher performance. This table compares the performance of IRanker-3B and Qwen2.5-3B-Instruct across eight widely-used benchmarks. IRanker-3B leads in five out of eight tasks, especially on math and reasoning-heavy datasets like GSM8K, IFEval, and MathQA. Qwen2.5-3B-Instruct performs better on code generation tasks, including MBPP and HumanEval. The models are nearly tied on general QA tasks like OpenBookQA and HellaSwag. These results highlight IRanker-3B’s strength in structured reasoning, while Qwen2.5-3B-Instruct maintains a slight edge in coding ability.

Model	GSM8K	IFEval	MMLU	MBPP	HumanEval	OpenBookQA	HellaSwag	MathQA
Metric	Exact Match Acc.	Loose Acc.	Acc.	Pass@1	Pass@1	Acc.	Acc.	Acc.
Qwen2.5-3B-Instruct	0.6353	0.6799	0.6537	0.5280	0.4756	0.3280	0.5633	0.3538
IRanker-3B	0.7369	0.7122	0.6510	0.4560	0.4573	0.3300	0.5634	0.3856

future advances in LLM-based ranking systems with wide applications in recommendation, retrieval, and decision making.

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727	[Shi et al., 2023] Weijia Shi, Nora Kassner, Rajarshi Das,	A Prompt usage	769
728	Patrick Lewis, Wen-tau Yih, Daniel Khashabi, and Dan	This section provides a detailed overview of the prompt tem-	770
729	Roth. Promptagator: Few-shot tuning of llms for domain	plates used for each task scenario, corresponding to DRanker	771
		and IRanker. Specifically, P_t denotes the prompt template used	772
		for DRanker , and P_d refers to the template used for IRanker .	773
		Each prompt is carefully designed with explicit formatting	774
		instructions and consistently requires the model to articulate	775
		its reasoning process before producing a final answer, which	776
		is enclosed within <code><answer></code> and <code></answer></code> tags for	777
		ease of parsing. Illustrative examples of the P_t templates are	778
		shown in Tables 5, 6, and 7 , while representative P_d templates	779
		are presented in Tables 8, 9, and 10 .	780
		B Case studies of DRanker and IRanker	781
		This appendix presents a comprehensive set of case studies	782
		illustrating the behavior of DRanker and IRanker across dif-	783
		ferent ranking scenarios. For each model, we provide detailed	784

Table 5: Prompts for DRanker in Passage Task.

```

<|im_start|>
system
You are a helpful assistant that ranks passages by relevance to a given query.
<|im_end|>
<|im_start|>
user
## Here is a query: {query}
{formatted_passages}
Please think step by step according to the content of each passage and how well it supports or
relates to the query. Rank all passages from most relevant to least relevant. Return the passage
IDs in order, one per line (e.g.,
passage 1
passage 3
passage 2). You MUST rank all passages from the candidate list. You can not generate content
that is not in the given candidate list.
Show your work in <think ></think >tags. And return the final answer in <answer ></an-
swer >tags.
<|im_end|>
<|im_start|>
assistant
Let me solve this step by step.
<think >

```

examples from three distinct tasks, each further divided into three subtasks, resulting in **nine case tables per ranker**.

Each case study table includes the following components:

- **Question:** The input query or prompt that initiates the ranking task.
- **Positive Sample:** The ground-truth relevant passage or item that should ideally be highly ranked.
- **Answer:** The model’s output, including its ranked list and any intermediate reasoning (when applicable).

These examples serve to highlight both the strengths and failure modes of each ranker, offering qualitative insights into their decision-making processes. DRanker case studies are provided in Tables 20 to 28, while IRanker case studies are shown in Tables 11 to 19.

C Examples of thought template generated by IRanker

This section presents examples of *thought templates* generated by IRanker and DRanker’s thinking process, each summarizing the model’s step-by-step reasoning for representative queries. These templates are derived from model inference traces and can be used as in-context learning exemplars for models not explicitly trained on the ranking tasks. See Tables 29,30

D Analysis on computational efficiency of DRanker and IRanker

We conduct inference time comparisons between two ranking mechanisms using vLLM version 0.6.3 on a single A6000 GPU, performing batch inference over the entire test set with default vLLM settings. IRanker performs ranking in a single iteration, which results in longer output sequences per

query. Consequently, its average time per query per iteration is slightly higher, especially as the candidate list length increases. In contrast, IRanker employs an iterative refinement strategy, which can introduce additional latency. To mitigate this, we incorporate an early stopping mechanism: if the positive passage is excluded during any intermediate round, the ranking process is terminated prematurely. This optimization avoids unnecessary iterations and ensures that the overall inference time does not scale linearly with the candidate size.

E Additional Results on Extended Metrics

This section presents supplementary results using additional evaluation metrics. The detailed outcomes can be found in Tables 34, 35, and 36. While zero-shot performance can be found in Tables 39, 38, and 37

F Implementation details

We train and evaluate a single ranking FM across all tasks, comparing its performance against both general-purpose ranking baselines and domain-specific methods tailored for each task. For reinforcement learning, we adopt Proximal Policy Optimization (PPO) [Schulman *et al.*, 2017], following the implementation details provided in VeRL [Sheng *et al.*, 2024]. Both the DRanker and IRanker are initialized from Qwen-2.5-3B-Instruct, and optimized using KL-regularized policy gradients. To manage policy divergence, we incorporate a low-variance KL loss with a regularization coefficient of 1e-4. Rollouts are conducted using vLLM with a maximum GPU memory utilization cap of 40%, temperature set to 0.9, and a maximum response length of 1024 tokens. Training is performed over 5 epochs, using a learning rate of 1e-6 for the actor and 2e-6 for the critic. The optimization uses a global mini-batch size of 36 and a micro-batch size of 8. To en-

Table 6: Prompts for DRanker in Recommendation Task.

```

<|im_start|>
system
You are a helpful assistant that ranks products by how likely the user is to buy them, based on
their previous purchase history.
<|im_end|>
<|im_start|>
user
I've purchased the following items in the past, in order:
{historical_interactions}
Now there are 20 candidate items that I might purchase next:
{candidate_items}
Please rank these items by measuring the possibilities that I would like to buy next most,
according to my purchase history. Please think step by step.
Split your output with line break. You MUST rank the given candidate items. You can not
generate items that are not in the given candidate list. Show your work in <think ></think
>tags. And return the final answer in <answer ></answer >tags.
<|im_end|>
<|im_start|>
assistant
Let me solve this step by step.
<think >

```

846 sure memory efficiency, we enable gradient checkpointing and
847 apply Fully Sharded Data Parallelism (FSDP) with both param-
848 eter and gradient offloading. All experiments are conducted
849 on a setup of 4 NVIDIA A6000 GPUs.

850 G Broader Impacts

851 Our work on IRanker, a unified ranking foundation model,
852 has several potential positive societal implications. By creat-
853 ing a single model capable of handling multiple ranking tasks
854 across recommendation systems, LLM routing, and passage
855 retrieval, we significantly increase efficiency and reduce com-
856 putational resources needed across various applications. This
857 could lead to more sustainable AI deployment and democra-
858 tize access to high-quality ranking technologies for smaller
859 organizations with limited resources. The improved zero-shot
860 capabilities demonstrated by IRanker could enhance informa-
861 tion retrieval in low-resource domains or for underrepresented
862 languages where task-specific training data is scarce. This has
863 the potential to bridge information access gaps across differ-
864 ent communities. Furthermore, IRanker’s ability to perform
865 well on out-of-domain tasks suggests that the techniques de-
866 veloped in this work may have beneficial spillover effects to
867 other AI domains beyond ranking. Our iterative decoding ap-
868 proach, which decomposes complex ranking tasks into simpler
869 decisions, represents a more interpretable way of understand-
870 ing how AI systems make ranking decisions. This improved
871 transparency could foster greater trust in recommendation and
872 information retrieval systems. Additionally, the efficient use of
873 context length in our approach enables more effective reason-
874 ing with limited computational resources, potentially reducing
875 the environmental footprint of deploying such systems at scale
876 while maintaining high performance.

Table 7: Prompts for DRanker in Router Task.

```

<|im.start|>
system
You are a helpful assistant that selects the most suitable large language model (LLM) for a
given query, based on performance and token cost.
<|im.end|>
<|im.start|>
user
{llm_descriptions}
## This scenario is analyzing a set of sales data to uncover trends and insights. Please provide
useful insights with reasonable depth, balancing accuracy and efficiency. Here is a query:
{query} and LLM candidates: {llm_candidates}. Please think step by step according to the
description of each query and LLM, and evaluate from the perspectives of performance in
answering the query and token price. Rank all LLMs from most suitable to least suitable for
this query. Return the LLM names in order, one per line. Split your output with line break.
You MUST rank all LLMs from the candidate list. You can not generate content that is not in
the given candidate list.
Show your work in <think ></think >tags. And return the final answer in <answer ></an-
swer >tags.
<|im.end|>
<|im.start|>
assistant
Let me solve this step by step.
<think >

```

Table 8: Prompts for IRanker in Passage Task.

```

<|im.start|>
system
You are a helpful assistant that ranks passages by relevance to a given query.
<|im.end|>
<|im.start|>
user
## Here is a query: {query}
{formatted_passages}
Please think step by step according to the content of each passage and how well it supports or
relates to the query. Select the least likely passage from the candidate list. Only return the
passage ID corresponding to the excluded passage (e.g., "passage 3"). You MUST choose one
passage from the candidate list. You can not generate content that is not in the given candidate
list.
Show your work in <think ></think >tags. And return the final answer in <answer ></an-
swer >tags.
<|im.end|>
<|im.start|>
assistant
Let me solve this step by step.
<think >

```

Table 9: Prompts for IRanker in Recommendation Task.

```

<|im.start|>
system
You are a helpful assistant that ranks products by how likely the user is to buy them, based on
their previous purchase history.
<|im.end|>
<|im.start|>
user
I've purchased the following items in the past, in order:
{historical_interactions}
Now there are 20 candidate items that I might purchase next:
{candidate_items}
Please select the one item that is least likely to be my next purchase, according to my purchase
history. Please think step by step. You MUST choose exactly one item from the given
candidate list. You can NOT generate or reference items that are not in the given candidate
list. Show your work in <think ></think >tags. And return the final answer in <answer
></answer >tags.
<|im.end|>
<|im.start|>
assistant
Let me solve this step by step.
<think >

```

Table 10: Prompts for IRanker in Router Task.

```

<|im.start|>
system
You are a helpful assistant that selects the most suitable large language model (LLM) for a
given query, based on performance and token cost.
<|im.end|>
<|im.start|>
user
{llm_descriptions}
## This scenario is analyzing a set of sales data to uncover trends and insights. Please provide
useful insights with reasonable depth, balancing accuracy and efficiency. Here is a query:
{query} and LLM candidates: {llm_candidates}. Please think step by step according to the
description of each query and LLM, and evaluate from the perspectives of performance in
answering the query and token price, and select the least likely LLM from the LLM candidates.
Only return the LLM name corresponding to the LLM. You MUST choose one LLM name
from LLM candidates. You can not generate content that are not in the given LLM candidates.
Show your work in <think ></think >tags. And return the final answer in <answer ></an-
swer >tags.
<|im.end|>
<|im.start|>
assistant
Let me solve this step by step.
<think >

```

Table 11: Router-cost IRanker Case Study

<p>Query: # The LLM names and their descriptions are: # LLaMA-3 (8b): Each token price is 0.2. Handles simple Hybrid QA, basic reasoning, short reading comprehension, and concise summaries. # Mixtral-8x7B: Each token price is 0.6. Excels at instruction-based tasks, step-by-step reasoning, solid reading comprehension, and structured summaries. # NousResearch (34b): Each token price is 0.9. Ideal for complex research queries, multi-step reasoning, deep reading comprehension, and thorough summaries. # LLaMA-2 (7b): Each token price is 0.2. Lightweight chat model for straightforward Hybrid QA, moderate reasoning, short reading comprehension, and concise summaries. # Mistral-7b: Each token price is 0.2. Fast for moderate Hybrid QA, quick reasoning, short reading comprehension, and brief summaries. # LLaMA-3 (70b): Each token price is 0.9. High-capacity model for advanced Hybrid QA, deep reasoning, detailed reading comprehension, and extensive summaries. # LLaMA-3-Turbo (8b): Each token price is 0.2. Balanced performance for moderate Hybrid QA, reasonable reasoning, clear reading comprehension, and concise summaries. # LLaMA-3-Turbo (70b): Each token price is 0.9. Powerful model for advanced Hybrid QA, strong reasoning, in-depth reading comprehension, and high-quality summaries. # Llama-3.1-Turbo (70b): Each token price is 0.9. Instruction-focused, providing thorough reasoning, structured reading comprehension, and well-organized summaries. # Qwen-1.5 (72b): Each token price is 0.9. Versatile for challenging Hybrid QA, nuanced reasoning, extended reading comprehension, and comprehensive summaries. ## This scenario is analyzing a set of sales data to uncover trends and insights. Please give a quick, high-level summary of the trends with minimal computation, even if the insights are less detailed. Here is a query: What city did Super Bowl 50 take place in? LLM candidates: ['LLaMA-3-Turbo (70b)', 'LLaMA-3-Turbo (8b)', 'Mistral-7b', 'LLaMA-3 (8b)', 'Llama-3.1-Turbo (70b)', 'Qwen-1.5 (72b)', 'NousResearch (34b)', 'Mixtral-8x7B', 'LLaMA-3 (70b)']. Please think step by step according to the description of each query and LLM, and evaluate from the perspectives of performance in answering the query and token price, and select the least likely LLM from the LLM candidates</p>	
<p>Ground Truth: LLaMA-3 (8b)</p>	
<p><think > First, I'll evaluate each LLM based on the description of the query: "What city did Super Bowl 50 take place in?" Super Bowl 50 was held in 2016. LLaMA-3.1-Turbo (70b), LLaMA-3-Turbo (70b), and Mixtral-8x7B have instructions focused on reasoning and detailed/structured reading comprehension. These models are likely to have strong knowledge of historical events and locations. LLaMA-3 (8b) and LLaMA-3-Turbo (8b) have pricing as low as \$0.2, making them more affordable and potentially suitable for cost-sensitive tasks. NousResearch (34b) is ideal for complex research queries, suggesting it might handle detailed factual information well. Mistral-7b, LLaMA-3 (8b), and LLaMA-3 (70b) offer lower token prices but are described as having simple or basic reasoning capabilities, which might limit performance on historical recall questions. Qwen-1.5 (72b) is noted for producing nuanced and comprehensive summaries, but its high token price (\$0.9) makes it less cost-effective for straightforward factual queries. LLaMA-3.1-Turbo (70b) also has a higher token price (\$0.9) but is instruction-focused, which may enhance its understanding of direct factual prompts. Considering these factors: - The LLM with the highest likelihood of answering the query well given its token price is LLaMA-3-Turbo (8B or 70B). - The LLM with the lowest token price while still being likely to answer correctly is LLaMA-3-Turbo (70B). - LLaMA-3 is slightly cheaper, but its basic reasoning may reduce its confidence or accuracy. Finally, the model least likely to provide a confident and correct answer is Qwen-1.5 (72B), due to its high token price and its strengths being more aligned with nuanced reasoning tasks than simple location recall.</p>	
<p></think > <answer > Qwen-1.5 (72b) </answer ></p>	

Table 12: 7 Passage IRanker Case Study

Question: What type of profession does Chris Jericho and Gary Barlow have in common?
Ground Truth: passage 6
<p><think > First, let's analyze each passage in terms of how well it relates to the query "when does winter end in australia".</p> <ul style="list-style-type: none"> - Passage 1: It states the dates for each season but does not clearly mention when winter ends. - Passage 2: It provides a relationship between US and Australian seasons but does not specify when winter ends in Australia. - Passage 3: It describes when it becomes winter in Southern Hemisphere (Midwinter) but does not mention when it ends. - Passage 4: It lists the dates for seasons in Australia, including winter, but does not specify when winter ends. - Passage 5: It talks about different times in the year for various activities but does not mention when winter ends. <p>Passage 6, although it mentions daylight saving time ending, is not directly about when winter ends, so it can be a candidate. </think ></p> <p><answer > passage 6 </answer ></p>

Table 13: case study 3: Music IRanker

<p>Question: ['0. Wildewoman', '1. True North', '2. Platinum & Gold Collection', '3. The Very Best of Ben E. King', '4. All My Life', '5. Opera Goes to the Movies', '6. Charo and Guitar', '7. Greatest Hits', '8. Carole King Tapestry', '9. Cheers to the Fall', '10. Ravel: Ma Mere L'oye / Bolero / la Valse / Pavane', '11. Rimski Korsakov, Borodin: Sheherazade Op.35', '12. Without You: The Best of Harry Nilsson', '13. Blue Film', '14. The Very Best Of Aaron Neville', '15. American Bach: Cello Suite No. 1 in G Major, BWV 1007; Cello Suite No. 3 in C Major, BWV 1009 / Miles: Suite for the Americas', '16. Martha Argerich: The Collection 1 - The Solo Recordings', '17. Eagles: The Very Best Of', '18. Didn't He Ramble', '19. Greatest Hits']</p>
Ground Truth: Pli selon pli
<p><think > First, let's consider the patterns in your purchase history. We see that you have mostly purchased music albums by various artists like Ben E. King, Carole King, Aaron Neville, and the Eagles. Additionally, you own a few classical music albums by composers like Ravel and Rimsky-Korsakov.</p> <p>Now, looking at the list of candidate items you might purchase next:</p> <ul style="list-style-type: none"> - 0. Pli selon pli — This is a track from an electronic duo, so we don't have a past history of purchasing this type of music. - 1. In Through the Out Door 2015 — This is also an artist-based product, but the name of the album is quite specific and not aligned with your past purchase history. - 2. Love Deluxe — It's another artist-based product, likely by Coldplay, and similar to your past albums. - 3. Exposed Valerie Simpson — This is an artist-based product that matches the pattern of your past purchases with traditional artists. - 4. State of Emergency — This is another artist-based product, possibly by a punk rock band, though it somewhat resembles the classical/classical fusion albums you've bought. <p>We need to determine which item feels the least likely based on patterns in your past purchases. Observing your history, we see a strong trend toward:</p> <ol style="list-style-type: none"> 1. Popular artists' albums 2. Various classical music albums 3. Professional or well-known albums <p>Pli selon pli stands out the most as it's an electronic piece, distinctly different from what you've traditionally bought. While Exposed Valerie Simpson follows the same pattern as <i>The Very Best of Ben E. King</i>, the electronic nature of Pli selon pli makes it the least consistent with your preferences.</p> <p>Conclusion: Since Pli selon pli is completely different (electronic music) from everything else in your purchase history, it appears to be the <i>least likely</i> selection, despite being a music album. </think ></p> <p><answer > Pli selon pli </answer ></p>

Table 14: Movie IRanker Case Study

<p>Question: ['0. Cop Land', '1. Great White Hype, The', '2. Toys', '3. Mummy, The', '4. Frighteners, The', '5. Blair Witch Project, The', '6. Pleasantville', '7. Midsummer Night's Dream, A', '8. Haunting, The', '9. Home Alone 2: Lost in New York', '10. Addams Family Values', '11. Fatal Attraction', '12. Brady Bunch Movie, The', '13. White Men Can't Jump', '14. I Still Know What You Did Last Summer', '15. Mighty Ducks, The', '16. Jingle All the Way', '17. Jack', '18. Dunston Checks In', '19. Santa Clause, The']</p>
<p>Ground Truth: Stuart Saves His Family</p>
<p><think > First, let's consider the genre and style of the movies I've watched. My previous 17 movies cover a range of genres and styles:</p> <ul style="list-style-type: none"> - Action: <i>Cop Land, Toys, Frighteners, White Men Can't Jump, Dick Tracy, Edge, Shallow Grave</i> - Comedy: <i>Toys, Frighteners, Pleasantville, I Still Know What You Did Last Summer, Jingle All the Way, S Curve, Dunston Checks In</i> - Drama: <i>The Mummy, Midsummer Night's Dream, Sense and Sensibility, From the Journals of Jean Seberg, Stuart Saves His Family, Bonfire of the Vanities</i> - Horror: <i>The Blair Witch Project, Frighteners, Halloween, Addams Family & Addams Families, Addams Family Values</i> - Fantasy: <i>Alice in Wonderland, Santo vs. Frankenstein, Santo vs. Werewolf</i> - Family: <i>Home Alone, The Mummy, The Christmas Rush, Under the Cherry Tree, The Santa Clause, The Vampire Bros.</i> - Romance: <i>Pleasantville, Fatal Attraction, Shallow Grave, Six Ways to Sunday</i> - Psychological Thriller: <i>Fatal Attraction, Frighteners, The Mummy</i> - Crime: <i>Budgerigar, Doll Face, Star, Searchers</i> - Sports: <i>The Mighty Ducks</i> <p>Now, let's examine my candidate list for each genre and style:</p> <ol style="list-style-type: none"> 1. Action: No movies. 2. Comedy: No movies. 3. Drama: No movies. 4. Horror: <i>Sense and Sensibility</i> is the only drama. 5. Fantasy: <i>Desiree</i> is the only fantasy. 6. Family: <i>Unzipped, Welcome to Woop-Woop, Fred Claus</i> are the only family movies. 7. Romance: <i>Desperate</i> is the only romance. 8. Psychological Thriller: There are no movies that fit 'psychological thriller' perfectly, but <i>Jane Eyre</i> is a psychological drama. 9. Crime: <i>Unzipped</i>. 10. Sports: Without adding new sports movies. <p>Looking at this, <i>Unzipped</i> (Drama/Horror) is the most common genre among my previous movies. In contrast, among the list we're given, only <i>Dick Tracy</i> and <i>Stuart Saves His Family</i> fit the Drama and Action genres, respectively. <i>From the Journals of Jean Seberg</i> and <i>Sense and Sensibility</i> fall more in the drama range, but not in my usual combined movie tastes.</p> <p>Considering the genres, <i>Dick Tracy</i> stands out as it's a good comic book buddy cop movie, but it doesn't feature the action elements in my watching history. However, since it's a new addition and not part of my past genre preferences, it's still slightly out of place. Between the two, <i>Stuart Saves His Family</i> might be slightly more out of place as it's a bit dated in terms of its style and is closer to my usual genre than <i>Dick Tracy</i>.</p> <p>So, <i>Stuart Saves His Family</i> is the one that does not seem to align with my usual pattern in my watching history. </think ></p> <p><answer > Stuart Saves His Family </answer ></p>

Table 15: Game IRanker Case Study

<p>Question: ['0. HDE ® Dual Charging Station Dock for 2 Sony Playstation PS3 Controllers', '1. Far Cry 4 - PS3 [Digital Code]', '2. Turtle Beach Call of Duty Advanced Warfare Ear Force Sentinel Task Force Gaming Headset for PlayStation 4', '3. Nyko Modular Charge Station (New Version) Dual Port Controller Charging Station with Patented Charging Dongles for All PS4 , PS4 Slim and PS4 Pro', '4. Wipeout 2 - Xbox 360', '5. Kinect Star Wars - Xbox 360', '6. Far Cry Primal - PlayStation 4 Standard Edition', '7. Uncharted 4: A Thief's End - PlayStation 4', '8. Battlezone - PlayStation VR', '9. Eve: Valkyrie - PlayStation VR', '10. Robinson: The Journey - PlayStation VR', '11. Dead Rising 4 - Xbox One', '12. LEGO Jurassic World - Xbox One Standard Edition', '13. Halo 5: Guardians 9 Gold REQ Packs - Xbox One [Digital Code]', '14. Sniper Elite 4 - PlayStation 4', '15. Resident Evil 7: Biohazard - PlayStation 4', '16. Corsair VOID Wireless RGB Gaming Headset, White', '17. DOOM VFR - PlayStation 4', '18. Star Wars Battlefront II - Xbox One', '19. Far Cry 5 Gold Edition - Xbox One [Digital Code]']</p> <p>Ground Truth: Dark Tales Edgar Allan Poe THE MASQUE OF RED DEATH Hidden Object PC Game +</p> <p><think > First, I'll compare the purchased items to the candidate list. The purchased items are all console games, wireless headsets, and a flying motorcycle simulator. None of the candidate items include a flying motorcycle simulator, so that's out.</p> <p>Next, I'll check the types of console games:</p> <ol style="list-style-type: none"> 1. PS3 - I own dozens of PS3 games 2. PS4/PS4 Slim/PS4 Pro - I bought several PS4 games 3. Xbox 360/DX - I own Xbox 360 games 4. PS VR - I own PSVR games 5. Other - I don't have games for these platforms, and want to keep watching/playing the Xbox 360 games until they're no longer on sale / Xbox 360 is apt to vanish <p>The PSVR and Xbox 360 game categories are more diverse, with more than one of these categories in my initial purchase history. Except for the PSVR, it seems that I was more interested in PS4 and Xbox consoles. Now, among the candidate list:</p> <ol style="list-style-type: none"> 1. PC Hidden Object game - This is a genre I haven't tried before. It's far more different from console games I've purchased. 2. Nintendo Switch Game - A different hardware platform. I prefer game diversity over another system. <p>Both candidate games are different enough types that I haven't had the chance to play them yet.</p> <p>Considering diversity and my interest, PC Hidden Object appears to be the less likely purchase since it's kind of a different category from the other games. I would rather pick a new game to add to my PlayStation or Xbox, rather than start on a new gaming experience. Nintendo Switch would likely be fun, but I've seen that people who owned it tend to go back to their preferred gaming platform. Therefore, I would avoid the Nintendo Switch game.</p> <p>Thus, <i>Dark Tales: Edgar Allan Poe – The Masque of Red Death Hidden Object PC Game + Bonus</i> appears unlikely to be my next purchase. </think ></p> <p><answer > Dark Tales Edgar Allan Poe THE MASQUE OF RED DEATH Hidden Object PC Game +</p> <p></answer ></p>

Table 16: 9 Passage IRanker Case Study

<p>Question: how long do car battery usually last</p> <p>Ground Truth: passage 4</p> <p><think > First, I'll compare the most relevant information in each passage that relates to the question "how long do car batteries usually last." Then, I'll assess the consistency and comprehensiveness of the information provided in each passage.</p> <p>Passage 1: Discussed general factors affecting battery life but didn't provide an average lifespan.</p> <p>Passage 2: Suggested four years on average but was somewhat vague about factors affecting life.</p> <p>Passage 3: Explicitly stated an average of three to five years with driving habits affecting brevity.</p> <p>Passage 4: Difficult to check, didn't mention battery lifespan directly.</p> <p>Passage 0: Between three to four years with average care – aligns with Passage 3.</p> <p>Passage 7: Generalized to about 60 to 70 months (five to seven years) – closer to Passage 3.</p> <p>Passage 8: Averaged three to five years – similar to Passage 3.</p> <p>Passage 6: Averaged three to five years as well – same as Passage 8.</p> <p>It seems that Passages 3, 8, 6, and 7 provide the most concise answer to the query. Comparing Passage 3 with the others, it provides the range of three to five years, a clear driving-habit explanation on the shorter end, and some information on factors affecting battery life.</p> <p>Passage 4 is far less relevant, as it only addresses the difficulty in checking batteries.</p> <p>Passages 0 and 7 provide a slightly longer or less specific range on average battery life.</p> <p>Passage 2's answer is similar to Passage 3's in terms of range (four years) but lacks driving-habit detail.</p> <p>Therefore, Passage 4 is the least relevant and supports the question the least effectively. </think ></p> <p><answer > passage 3 </answer ></p>

Table 17: 5 Passage IRanker Case Study

Question: potawatomi meaning of word
Ground Truth: passage 3
<p><think > First, I will carefully examine each passage to understand what information it provides about the word “potawatomi” and its meaning.</p> <p>Passage 2 talks generally about the Potawatomi people and their languages, but does not specifically address the meaning of the word “potawatomi”.</p> <p>Passage 0 seems more of a general statement about Potawatomi-related information, mentioning synonyms and offering resources but not providing a clear meaning for the word.</p> <p>Passage 1 provides phonetic information and Word Lists for Potawatomi, but doesn’t give a clear definition or explanation for the word “potawatomi” itself.</p> <p>Passage 3 directly provides information about the word “potawatomi”, including its meaning, but it also mentions the spelling “Potawatmie”, which seems to be a typographical error.</p> <p>Passage 4 mostly defines “potawatomi” as a noun, but it is considered rare and mentions it only has two senses.</p> <p>Based on this analysis, Passage 3 appears to have the clearest, most direct information about the word “potawatomi” and its meaning, except for the typographical error in the spelling.</p> <p>Passage 3 seems to be the most reliable and thorough in providing information about the word, making it less likely to be the unrelated passage.</p> <p>Distinguishing between the typographical error and a related passage requires some judgement, but based on the relevance and detail of information provided in the passage, it seems Passage 3 is the most logical choice. Therefore, Passage 3 does not seem to be the intended question answer based on the information provided, so it should be the less likely candidate passage. </think ></p> <p><answer > passage 3 </answer ></p>

Table 18: Router Performance IRanker Case Study

Question: Where was Super Bowl 50 held?
Ground Truth: Mistral-7b
<p><think > First, I’ll analyze each LLM based on its ability to answer the query “Where was Super Bowl 50 held?” according to their descriptions:</p> <ol style="list-style-type: none"> 1. Mistral-7b: It mentions quick reasoning, short reading comprehension, and brief summaries. It’s not very suitable for handling detailed information or long texts. 2. LLaMA-2 (7b): It mentions moderate reasoning and short reading comprehension. Given the brief nature of the Modesto High School incident in 2016 (which was the requested Super Bowl hosting event), it might struggle. 3. NousResearch (34b): This one specifically mentions complex research queries, multi-step reasoning, deep reading comprehension, and thorough summaries. For the Super Bowl event, these capabilities are not essential and the token price is relatively high compared to other LLMs. <p>Now, I’ll compare the performance:</p> <ul style="list-style-type: none"> - NousResearch (34b) has high quality outputs but is expensive, not likely within budget. - LLaMA-2 (7b) can handle the question, though with moderate reasoning. - Mistral-7b is quick, short, and the least detailed, which might be suitable – though it does not handle longer, more nuanced events like the Super Bowl. <p>From an expense perspective, LLaMA-2 (7b) is the most expensive considering it can handle the question. Neither NousResearch (34b) nor Mistral-7b is likely to produce comprehensive and thorough results, so between LLaMA-2 (7b) and Mistral-7b, the least likely candidate is Mistral-7b since it’s less capable for longer texts and varies quite a bit from the query.</p> <p>In conclusion, based on both performance and token price, I’d ultimately choose LLaMA-2 (7b) as the least likely from the given set. </think ></p> <p><answer > Mistral-7b </answer ></p>

Table 19: Router Balance IRanker Case Study

Question: Explain why the following fraction is equivalent to 1/4 and 4/16
Ground Truth: NousResearch (34b)
<p><think > 1. The task is to analyze a set of sales data to uncover trends and insights. This likely involves complex mathematical operations and in-depth logical reasoning. The description of LLaMA-3 (8b) and LLaMA-2 (7b) mentions they are good at brief, impartial summaries, and reasoning but not highly advanced methods. The descriptions of Qwen-1.5 and Mixtral-8x7B suggest they are specialized for nuanced reasoning and multi-step tasks. NousResearch (34B) specializes in deep reading comprehension.</p> <p>2. The query provided is "Explain why the following fraction is equivalent to 1/44/16". This implies that the LLM needs to demonstrate the equivalence using mathematical methods. It is a straightforward arithmetic problem that shouldn't be overly complex.</p> <p>3. We need to consider token price in our decision. The LLMs with the highest token price are Qwen-1.5 (72b) and LLaMA-3-Turbo (70b), and the LLMs with the lowest token price are LLaMA-2 (7b) and Mixtral-8x7B.</p> <p>4. Looking at LLaMA-2 (7b) and Mixtral-8x7B:</p> <ul style="list-style-type: none"> - They are described as being more suited to step-by-step reasoning and detailed reading comprehension, which might be useful. - The price for Mixtral-8x7B is high, but LLaMA-2 (7b) is quite affordable, so this offers a balance. <p>5. Looking at Qwen-1.5 (72b):</p> <ul style="list-style-type: none"> - Despite its name, it's described as versatile for challenging Hybrid QA, which seems too specialized for a straightforward fraction equivalence problem. - Its token price is also very high, making it less cost-effective. <p>6. Considering NousResearch (34b):</p> <ul style="list-style-type: none"> - While it's described as ideal for complex research queries and deep reading comprehension, this problem is not complex research, it's a simple fraction simplification. - Its token price is expensive, and it doesn't seem ideal for solving this straightforward problem. <p>Based on this reasoning, the least likely LLM for answering this straightforward mathematical query involving fraction equivalence, considering both performance and cost, seems to be NousResearch (34b).</p> <p></think ></p> <p><answer > NousResearch (34b) </answer ></p>

Table 20: 5 Passage DRanker Case Study

Question: How much to print at staples?
Ground Truth: passage 1
<p><think > First, I will analyze each passage to determine how well it supports or relates to the query "how much to print at Staples".</p> <p>Passage 1: This passage discusses the cost variability of printing at Staples but does not provide specific pricing details.</p> <p>Passage 2: This passage provides specific pricing for black and white copies, which is relevant to the query.</p> <p>Passage 3: This passage highlights benefits like clean, crisp copies and low pricing recommendations, but does not directly address pricing at Staples.</p> <p>Passage 4: This passage includes specific pricing for both black and white and color copies at Staples, making it highly relevant.</p> <p>Now, I will rank the passages according to their relevance:</p> <ul style="list-style-type: none"> - Passage 4 provides the most detailed pricing information. - Passage 2 gives specific pricing for black and white copies. - Passage 1 discusses cost variability without giving exact prices. - Passage 3 is the least relevant, as it does not provide any specific pricing details. <p></think ></p> <p><answer > passage 4</p> <p>passage 2</p> <p>passage 1</p> <p>passage 3</p> <p></answer ></p>

Table 21: 7 Passage DRanker Case Study

Question: How long leave cooked chicken at room temperature?
Ground Truth: passage 6
<p><think > First, I will analyze each passage to determine their relevance to the query about cooked chicken and room temperature. The query asks how long cooked chicken can be kept at room temperature and what action should be taken.</p> <p>All passages discuss food safety related to perishable items like chicken. While several mention the danger of room temperature exposure, I will prioritize those that clearly state a specific time limit and recommended actions.</p> <p>Passages 0 through 3 reiterate general safety concerns but lack a specific timeframe.</p> <p>Passage 4 mentions the two-hour limit (also noted in Passage 3) but does not clearly recommend refrigeration or freezing.</p> <p>Passage 5 is the most directly relevant, clearly stating that cooked chicken should not remain at room temperature for more than two hours.</p> <p>Passage 6 also provides full guidance, including the two-hour limit and the recommendation to freeze the chicken, making it highly informative.</p> <p></think ></p> <p><answer > passage 5</p> <p>passage 6</p> <p>passage 4</p> <p>passage 3</p> <p>passage 0</p> <p>passage 1</p> <p>passage 2</p> <p></answer ></p>

Table 22: 9 Passage DRanker Case Study

Question: How much weight can a floor joist support?
Ground Truth: passage 5
<p><think > Firstly, we need to establish which information from the given passages is directly relevant to the weight capacity of a floor joist.</p> <p>Passage 5 is highly relevant, as it calculates the weight a 3-foot by 12-foot section of flooring can support based on standard floor loads.</p> <p>Passage 2 references weight in pounds but focuses on joist dimensions, which is less directly relevant than explicit weight calculations.</p> <p>Passage 7 provides the most direct answer by specifying the weight a single floor joist can support in load-bearing situations.</p> <p>Passage 3 supports the calculations presented in Passage 5, confirming its accuracy.</p> <p>Passage 6 essentially duplicates the relevant content from Passage 5 using nearly identical language.</p> <p>Passage 8 discusses general safety factors, which are important contextually but do not directly answer the query.</p> <p>Passage 1 contains technical material that does not pertain specifically to joist weight calculations.</p> <p>Passage 4 mentions joists in the broader context of floor framing requirements, making it less relevant to our focused question.</p> <p></think ></p> <p><answer > passage 7</p> <p>passage 5</p> <p>passage 6</p> <p>passage 2</p> <p>passage 1</p> <p>passage 3</p> <p>passage 8</p> <p>passage 7</p> <p></answer ></p>

Table 23: Rec Game DRanker Case Study

<p>Question: '0. WWE 2K15 - PS3 [Digital Code]', '1. WWE 2K15 - PS3 [Digital Code]', '2. NBA 2K15 - PlayStation 3', '3. Madden NFL 15: 2,200 Points - Xbox One Digital Code', '4. Injustice: Gods Among Us - Collector's Edition - Playstation 3', '5. Injustice: Gods Among Us - Collector's Edition - Playstation 3', '6. Injustice: Gods Among Us - Collector's Edition - Playstation 3', '7. LEGO: Marvel - PC', '8. Madden NFL 15: 2,200 Points - Xbox One Digital Code', '9. Lego: Marvel Super Heroes, XBOX 360', '10. WB Games Middle Earth: Shadow of Mordor - Playstation 4', '11. The Amazing Spider-Man 2 - Nintendo 3DS', '12. Teenage Mutant Ninja Turtles - Nintendo Wii', '13. Disney Epic Mickey 2: The Power of Two - Playstation 3', '14. Disney Epic Mickey 2: The Power of Two - Playstation 3', '15. Assassin's Creed IV Black Flag - PC', '16. Dead Rising 3', '17. NBA 2K14 - Xbox 360', '18. Grand Theft Auto V: Premium Edition - Xbox One [Digital Code]', '19. NBA 2K14 - Xbox 360']</p>
<p>Ground Truth: Call of Duty Ghosts - PS3 [Digital Code]</p>
<p><think > Firstly, I need to understand patterns in my historical purchases. I have bought several games over time, including franchise titles such as <i>WWE</i>, <i>NBA</i>, <i>Madden NFL</i>, and <i>Injustice: Gods Among Us</i>. I also seem to favor unique items, like <i>WWE</i> digital codes, which appeared in different variants multiple times. On the PC side, I am drawn to games that offer more freedom, such as <i>LEGO: Marvel</i> and <i>The Amazing Spider-Man 2</i>. This suggests a preference for open-world or exploratory gameplay on that platform. Next, I'll consider how the sequence of past purchases might influence future decisions. Since I've consistently purchased games, it is likely that my next purchase will also be a game. This reflects a strong continuity in gaming content consumption. Additionally, I've noticed some imbalance between console and PC purchases. To address this, I may lean toward buying more individual titles rather than digital codes or bundles to diversify my collection. Finally, considering my history of PC-centric games and smaller discrete items like accessories, these categories could also shape my upcoming choices.</p> <p></think ></p> <p><answer > 1. Call of Duty Ghosts - PS3 [Digital Code] 2. Rise of the Tomb Raider - Xbox One Digital Code 3. Xbox One S Vertical Stand 4. Hermitshell Hard Travel Case for 8Bitdo Sn30 Pro Bluetooth Gamepad (SN30PRO-GB) 5. Mind's Eye: Secrets of the Forgotten [Download] 6. MLB 2K16 - Xbox One Digital Code 7. Microsoft Combat Flight Simulator 2: Pacific Theater - PC 8. The Amazing Spider-Man 2 - Nintendo 3DS 9. Family Feud [Download] 10. Amazing Match 3 Games - Volume 3 11. Phineas and Ferb: Across the 2nd Dimension - Playstation 3 12. Evil Dead: A Fistful of Boomstick 13. Turtle Beach - Ear Force PX51 Wireless Gaming Headset - Dolby Digital - PS3, Xbox 360 14. Red Black Blue Silicone Skin Case Combo for PS3 Controller 15. Gabriel Knight Mysteries: Limited Edition - PC 16. Family Feud [Download] 17. Untold Legends: Brotherhood of the Blade - Sony PSP 18. Batman: The Animated Series 19. NBA 2K16 - Xbox One Digital Code 20. WB Games Middle Earth: Shadow of Mordor Playstation 4</p> <p></answer ></p>

Table 24: Rec Music DRanker Case Study

Question: ['0. Horny House', '1. Mozart: Piano Sonatas KV 282, 310 545', '2. Mozart: Complete Piano Trios', '3. Mozart: Piano Sonatas KV. 281/KV. 330/KV. 333/Rondo, KV. 485/Adagio, KV. 540', '4. Mozart: The Sonatas for Piano and Violin', '5. Beethoven: Piano Sonatas No. 8, Pathétique/ No. 14, Moonlight/ No. 21, Waldstein/ No. 23, Appassionata', '6. Mozart: Violin Concertos Complete', '7. You Took My Heart By Surprise', '8. Revenge', '9. Prokofiev: Romeo Juliet - Scenes from the Ballet', '10. Ian Bostridge - The English Songbook', '11. Hawaiian Slack Key Christmas', '12. The Sinatra Christmas Album - Chorus and Orchestra Conducted By Gordon Jenkins', '13. Niki Nana', '14. Distant Fields', '15. Whenever You Need Somebody', '16. Free', '17. Somewhere My Love', '18. Shared Vision: Songs of the Beatles', '19. American Live Debut']

Ground Truth: Classical Hits

<think > First, it's important to analyze the relationship between the albums I have purchased in the past and the genres represented in the current list. To do this, I'll group the albums by musical genre and determine how likely it is that my future selections will align with those genres.

Genre Clusters:

Classical:

'Horny House', 'Mozart: Piano Sonatas', 'Mozart: Complete Piano Trios', 'Mozart: Piano Sonatas', 'Mozart: Piano Sonatas', 'Mozart: Violin Concertos Complete', 'Beethoven: Piano Sonatas No. 8, Pathétique / No. 14, Moonlight / No. 21, Waldstein / No. 23, Appassionata'

Pop/Rock:

'Niki Nana', 'Somewhere My Love', 'American Live Debut', 'Shared Vision: Songs of the Beatles'

Alternative / New Music:

'World of Absence', 'Fabriclive 54 :'

Jazz:

'Big Band = Jazz'

The most frequently purchased genres are Classical and Pop/Rock, suggesting a strong preference. Therefore, future purchases are likely to align with these categories.

Non-classical albums such as '*Wild World*' are more thematic and require additional context to fully assess their appeal. Similarly, '*World of Absence*' is described as an ambient album, which, while intriguing, stands apart from the dominant genres.

Albums like '*Timeagain*', '*Now*', and '*Pop: Remixed*' show a focus on distinct thematic or remix elements, which may still capture my interest, albeit less frequently.

In summary, judging from past purchases, Classical and Pop genres are the most likely candidates for future music selections. This aligns well with my historical preferences.

</think >

<answer > Classical Hits

2. Timeagain

3. Motif

4. Diamond Life

5. Now

6. Original Good Ol' Boy

6. Niki Nana

7. Shared Vision: Songs of the Beatles

7. Now He Sings Now He Sobs

8. Lone Justice

9. A Broken Frame

10. World of Absence

11. Fabriclive 54 :

12. Pop: Remixed

13. Upon This Rock

14. Wild World

15. I Don't Want to Be

</answer >

Table 25: Rec Movie DRanker Case Study

<p>Question: ['0. My Fair Lady', '1. Top Hat', '2. Next Karate Kid, The', '3. Gone with the Wind', '4. Dave', '5. Raiders of the Lost Ark', '6. Englishman Who Went Up a Hill, But Came Down a Mountain, The', '7. Star Trek: First Contact', '8. Star Trek: The Motion Picture', '9. Star Trek VI: The Undiscovered Country', '10. Star Trek V: The Final Frontier', '11. Star Trek: The Wrath of Khan', '12. Star Trek III: The Search for Spock', '13. Star Trek IV: The Voyage Home', '14. Star Trek: Insurrection', '15. Star Trek: Generations', '16. From Russia with Love', '17. Goldfinger', '18. Star Wars: Episode I - The Phantom Menace', '19. Star Wars: Episode IV - A New Hope']</p>
<p>Ground Truth: Lassie</p>
<p><think > First, I will analyze each genre to determine which types of movies align with those previously viewed:</p> <p>Historical / Period Films:</p> <p>'0. My Fair Lady', '3. Gone with the Wind', '9. Star Trek: The Undiscovered Country'</p> <p>Hollywood Musicals:</p> <p>'1. Top Hat', '11. William Shakespeare's Romeo and Juliet'</p> <p>Action:</p> <p>'6. The Englishman Who Went Up a Hill, But Came Down a Mountain', '19. Star Wars: Episode IV - A New Hope', '18. Star Wars: Episode I - The Phantom Menace', '1.1 Star Trek: First Contact', '13. Star Trek: The Wrath of Khan'</p> <p>Classics:</p> <p>'2. The Next Karate Kid', '16. From Russia with Love', '17. Goldfinger'</p> <p>Modern Classics:</p> <p>'4. Dave', '2. West Side Story', '5. Raiders of the Lost Ark'</p> <p>Based on this analysis, I grouped the movies into genre categories. Now I'll predict the most likely category for your next movie choice:</p> <ul style="list-style-type: none"> - Given the chronological pattern in your movie consumption, it's likely that upcoming selections will continue from the genres you've recently explored. - You also appear to be a fan of Westerns or horseback-themed films. Movies such as '<i>Tashunga</i>', which blends Western themes with action, support this trend. - Your interest in '<i>Shakes the Clown</i>'—a unique Western-style Elvis movie—suggests a preference for genre blends that combine entertainment and classic elements. - Among your top movies, '<i>Frankenstein Meets the Wolfman</i>' (a part of the Universal Monsters collection) reveals your appreciation for B-movies with gothic or Poe-like undertones. <p>This pattern suggests your next movie choice will likely fall into a Western, Classic, or genre-blended category, with potential interest in entertainment-leaning or horror-inspired classics.</p> <p></think ></p> <p><answer > 1. 'Tashunga'</p> <p>2. 'Clean Slate'</p> <p>3. 'West Side Story'</p> <p>4. 'Lassie'</p> <p>5. 'From Russia with Love'</p> <p>6. 'Home for the Holidays'</p> <p>7. '8MM'</p> <p>8. 'Cemetery Man'</p> <p>9. '16. From Russia with Love'</p> <p>10. 'Shakes the Clown'</p> <p>11. 'Untouchables, The'</p> <p>12. 'West Side Story'</p> <p>13. 'Beauty and the Beast'</p> <p>14. 'Beauty and the Beast'</p> <p>15. 'The Friggerito'</p> <p>16. 'Lassie'</p> <p>17. 'Clean Slate'</p> <p>18. 'West Side Story'</p> <p></answer ></p>

Table 26: Router Cost DRanker Case Study

Question: How many fumbles did Von Miller force in Super Bowl 50?
Ground Truth: LLaMA-3-Turbo (8b)
<p><think > First, we need to determine the suitability of each LLM for the given query. The query is quite straightforward, asking for a specific statistic (number of fumbles) specifically about Von Miller in a Super Bowl.</p> <p>Now, we'll look at the requirements and capabilities mentioned for each of the available LLMs in relation to simple fact queries:</p> <ol style="list-style-type: none"> 1. LLaMA-3 (8b): Simplified information, extremely short comprehensions, and brief summaries. 2. Mixtral-8x7B: Instruction-based tasks, step-by-step reasoning, solid reading comprehension, and structured summaries. 3. NousResearch (34b): Comprehensively searches through complex questions, but assumes advanced understanding. 4. LLaMA-2 (7b): Moderately deeper understanding, yet fairly limited reasoning among others. 5. Mistral-7b: Moderate Hybrid QA, short reasoning time, and brief summaries. 6. LLaMA-3 (70b): Advanced Hybrid QA, deep reasoning, detailed comprehension, and extensive summaries. 7. LLaMA-3-Turbo (8b): Balanced and reasonable reasoning time, moderate summarization. 8. LLaMA-3-Turbo (70b): Powerful, strong reasoning, deep reading comprehension, and high-quality summaries. 9. LLaMA-3.1-Turbo (70b): Specific to instructional tasks, thorough reasoning, structured reasoning. 10. Qwen-1.5 (72b): For challenging tasks, versatile reasoning, extended reading comprehension, and comprehensive summaries. <p>Given the simple nature of the query, LLaMA-3 (8b) is most suitable as the information retrieval and fact-checking might be straightforward for it. However, since the query is fact-dependent and balances between a high-quality summary and accuracy across simple fact-checks, LLaMA-3 (8b) might struggle with accuracy due to its limitations in handling complex reasoning.</p> <p>Mixtral-8x7B and LLaMA-3.1-Turbo (70b), on the other hand, seem well-suited as they can handle concise and brief information retrieval, though they are likely not strong in advanced reading or fact extraction.</p> <p>LLaMA-3-Turbo (8b) and LLaMA-3-Turbo (70b) may be marginal choices given their balance of performance across reasoning, summaries, and fact retrieval.</p> <p>Mistral-7b is not the best choice as it is mostly focused on efficiency rather than balance.</p> <p>LLaMA-3 (70b) is a powerful model but better suited for more complex tasks and reasoning.</p> <p>NousResearch (34b) and Qwen-1.5 (72b) could also handle the query but may not provide the level of detail and accuracy required for this specific fact-checking task.</p> <p>Hence, the rough order of suitability for this query might be:</p> <ul style="list-style-type: none"> • Mistral-7b (efficient) • LLaMA-3-Turbo (8b) (balanced) • LLaMA-3-Turbo (70b) (advanced) <p></think ></p> <p><answer > Mistral-7b LLaMA-3-Turbo (8b) LLaMA-3-Turbo (70b)</p> <p></answer ></p>

Table 27: Router Balance DRanker Case Study

Question: How many teams have played in the Super Bowl eight times?
Ground Truth: LLaMA-3-Turbo (8b)
<p><think > For this query, we're looking for information where the answer is likely to be a specific number (a count of teams) rather than a detailed explanation of a process or interpretation of data. The information required is factual but not too advanced, as there is no need for extensive reasoning or deep reading comprehension here. We need a straightforward and concise response using LLMs.</p> <p>Given the description, the most suitable LLMs would be those in the categories of <i>Lightweight</i> and <i>Fast</i>, as they are best at simple Hybrid QA and short reading comprehension tasks, ensuring a brief and efficient answer.</p> <p>Starting with the LLMs:</p> <ul style="list-style-type: none"> • LLaMA-3 (8b) - Lightweight chat model for straightforward Hybrid QA with concise summaries which is well-suited for this straightforward query. • Mistral-7b - Fast for moderate Hybrid QA with brief summaries, consistent with the straightforward nature of the query. • LLaMA-2 (7b) - Similar in lightweight category, but more moderate in reasoning and responses versus the more detailed LLaMA-3. It is still suitable for our task. • Qwen-1.5 (72b) - Versatile for challenging Hybrid QA. Although it's described as versatile, this level of versatility isn't essential for a simple query like this and it could be a bit overpowered. • The other LLMs, like Mixtral-8x7B, NousResearch (34b), LLaMA-3 (70b), LLaMA-3-Turbo (70b), and LLaMA-3.1-Turbo (70b), all indicate more advanced reasoning, which is not necessary for this query. <p></think ></p> <p><answer > LLaMA-3 (8b)</p> <p>Mistral-7b</p> <p>LLaMA-2 (7b)</p> <p></answer ></p>

Table 28: Router Performance DRanker Case Study

Question: Explain why the given definition is wrong. A mole is an animal that lives underground.
Ground Truth: Llama-3.1-Turbo (70b)
<p><think > The task here is to critique a definition and provide insights with reasonable depth. The given definition is "A mole is an animal that lives underground." From the description provided, LLaMA-3 (8b) and Mistral-7b are the two models that mentions less capacity for detailed explanations and comprehensive insights due to their lower token price and model sizes.</p> <p>Mixtral-8x7B was described as excelling at instruction-based tasks, step-by-step reasoning, solid reading comprehension, and structured summaries. NousResearch (34b) was ideal for complex research queries, multi-step reasoning, deep reading comprehension, and thorough summaries. LLama-2 (7b) has similar token price and capacity to LLaMA-3 (8b) and is lightweight for straightforward reasoning and comprehension. Qwen-1. 5 (72b) is described as versatile for challenging reasoning, extended reading comprehension, and comprehensive summaries.</p> <p>Given the need to find a model that can provide detailed, clear insights and reasoning, Qwen-1. 5 (72b) stands out as the most suitable for the task given its higher token price and better description. Next, NousResearch (34b) would be suitable for producing detailed reasonings with its higher capacity as well. LLaMA-3 (8b) and Mistral-7b are less suitable as they have limitations in capacity also with lower token prices. Lastly, Mixtral-8x7B could also be a suitable model, but LLaMA-3-Turbo (70b) and LLaMA-3-Turbo (8b) are better choices given their upgrades in capacity and token prices. LLaMA-3-Turbo (70b) specifically deals with strong reasoning validation, which fits well with the essence of the query. Therefore, we're left with only one model for comprehensive reasoning and analyses - Qwen-1. 5 (72b). </think ></p> <p><answer > Qwen-1. 5 (72b)</p> <p>LLaMA-3-Turbo (70b)</p> <p>NousResearch (34b)</p> <p>LLaMA-3-Turbo (8b)</p> <p></answer ></p>

Table 29: **Thought Template for IRanker on Router Task.**

When evaluating and ranking language models for a factual query, the reasoning process should consider (1) the complexity and specificity of the query, (2) the model’s described strengths such as factual recall, structured comprehension, or reasoning ability, and (3) the cost-effectiveness relative to the expected performance. Models should be prioritized if they demonstrate strong alignment with the task type (e.g., historical fact retrieval) and offer a good balance between accuracy and efficiency. In contrast, models optimized for complex reasoning or verbose summaries may be less suitable for straightforward factual prompts, especially if they incur high token costs.

Table 30: **Thought Template for IRanker on Recommendation Task.**

For recommendation tasks, the reasoning process should center on aligning candidate items with the user’s demonstrated preferences across categories such as genre, style, or theme. Effective evaluation involves identifying dominant patterns in the user’s historical choices and comparing them to the attributes of each candidate item. Items are ranked higher if they closely match frequently occurring features in the user’s history, while items that diverge significantly in tone, genre, or thematic elements are deprioritized. This approach encourages models to reason over latent user preferences and make decisions based on cumulative alignment rather than isolated matches.

Table 31: **Inference Time (s) per Query for Passage Ranking on 5, 7, and 9 Candidates.** DRanker performs single-pass ranking, while IRanker performs iterative exclusion.

Model	5 Passages			7 Passages			9 Passages		
	Avg / Iter (s)	Total (s)	Avg. Iter / Case	Avg / Iter (s)	Total (s)	Avg. Iter / Case	Avg / Iter (s)	Total (s)	Avg. Iter / Case
DRanker	0.29	419.92	1	0.41	1594.54	1	0.48	860.16	1
IRanker	0.23	832.6	2.5	0.26	3543.54	3.5	0.27	1935.36	4.5

Table 32: **Inference Time (s) per Query for Recommendation Task** DRanker performs single-pass ranking, while IRanker performs iterative exclusion with early stopping mechanism.

Model	Movie			Music			Game		
	Avg / Iter (s)	Total (s)	Avg. Iter / Case	Avg / Iter (s)	Total (s)	Avg. Iter / Case	Avg / Iter (s)	Total (s)	Avg. Iter / Case
DRanker	0.67	1680.36	1	0.65	1630.21	1	0.66	1542.42	1
IRanker	0.41	5758.37	5.6	0.39	4401.54	4.5	0.42	5987.40	6.1

Table 33: **Inference Time (s) per Query for LLM Routing Task** DRanker performs single-pass ranking, while IRanker performs iterative exclusion with early stopping mechanism.

Model	Performance			Cost			Balance		
	Avg / Iter (s)	Total (s)	Avg. Iter / Case	Avg / Iter (s)	Total (s)	Avg. Iter / Case	Avg / Iter (s)	Total (s)	Avg. Iter / Case
DRanker	0.38	58.14	1	0.40	61.2	1	0.41	62.73	1
IRanker	0.29	88.74	2.0	0.30	82.62	1.8	0.29	79.86	1.8

Table 34: Recommendation Performance on Movie, Music, and Game Domains.

Model	Movie			Music			Game		
	nDCG@10	nDCG@20	MRR	nDCG@10	nDCG@20	MRR	nDCG@10	nDCG@20	MRR
Retrieval-based Models									
BM25	23.44	35.09	17.56	22.06	35.21	18.09	17.39	32.49	14.96
Contriever	22.26	25.29	18.29	21.03	34.26	17.04	39.87	53.66	23.98
Recommendation Models									
BPR	31.28	41.65	25.54	28.51	38.60	21.96	35.79	44.32	28.92
SASRec	39.79	48.06	33.60	29.72	39.85	23.69	35.57	43.52	28.75
R1-Rec	25.01	34.87	18.49	21.38	34.54	17.22	17.22	32.32	14.75
Direct-Rank LLMs without RL									
Qwen2.5-3B-Instruct-direct	21.23	34.26	16.92	17.90	33.46	16.68	16.62	30.98	13.17
Qwen2.5-7B-Instruct-direct	22.21	34.23	16.59	17.90	34.29	17.29	21.57	36.15	18.63
Llama3.1-70B-Instruct-direct	28.27	40.75	22.19	24.40	32.61	19.13	27.83	41.18	24.51
Iterative LLMs without RL									
Qwen2.5-3B-Instruct-iter	26.44	38.55	22.01	27.06	38.45	21.97	32.80	44.23	29.49
Qwen2.5-7B-Instruct-iter	28.14	38.59	22.11	30.59	39.86	23.36	37.31	47.30	33.14
Llama3.1-70B-Instruct-iter	54.76	58.92	46.96	57.03	59.98	48.24	64.79	67.50	57.89
Direct-Rank LLMs with RL									
DRanker	23.98	37.02	18.71	20.50	33.18	15.70	17.57	32.89	15.77
Iterative LLMs with RL									
IRanker-3B	42.32	49.06	34.69	33.47	40.25	29.18	47.84	49.33	42.49

Table 35: Router Performance on Performance, Cost, and Balance Objectives.

Model	Performance			Cost			Balance		
	nDCG@5	nDCG@10	MRR	nDCG@5	nDCG@10	MRR	nDCG@5	nDCG@10	MRR
Retrieval-based Models									
BM25	9.06	35.99	18.41	4.79	32.35	13.52	4.79	32.22	13.39
Contriever	11.28	36.28	20.75	14.62	35.81	16.29	13.88	33.57	16.74
Routers									
RouterKNN	24.38	40.72	26.73	15.12	35.29	16.87	20.68	39.10	21.74
RouterBert	27.25	44.37	28.25	20.44	39.50	22.11	20.44	39.37	21.98
GraphRouter	22.22	39.53	21.57	34.85	44.11	26.56	27.18	45.16	29.56
Direct-Rank LLMs without RL									
Qwen2.5-3B-Instruct-direct	0.00	28.91	10.00	0.00	28.91	10.00	0.00	28.91	10.00
Qwen2.5-7B-Instruct-direct	4.78	32.21	13.38	4.78	32.34	13.51	9.06	35.99	18.41
Llama3.1-70B-Instruct-direct	7.56	32.57	13.84	9.71	32.96	14.26	25.34	45.54	30.26
Iterative LLM Models without RL									
Qwen2.5-3B-Instruct-iter	17.41	38.55	20.87	13.35	37.82	20.22	0.0	31.41	12.42
Qwen2.5-7B-Instruct-iter	12.49	36.92	19.13	18.28	38.57	21.06	22.17	42.39	26.09
Llama3.1-70B-Instruct-iter	17.65	38.18	20.67	44.78	56.74	43.93	35.68	50.27	35.30
Direct-Rank LLMs with RL									
DRanker	17.90	38.10	20.63	4.78	32.34	9.06	4.78	32.21	13.38
Iterative LLM Models with RL									
IRanker	28.64	41.06	23.62	22.32	45.88	30.39	20.27	41.45	24.44

Table 36: **Passage Ranking Performance on 5, 7, and 9 Candidates.**

Model	5 Passages			7 Passages			9 Passages		
	nDCG@3	nDCG@5	MRR	nDCG@3	nDCG@5	MRR	nDCG@3	nDCG@5	MRR
Retrieval-based Models									
BM25	53.19	65.05	53.63	41.80	52.09	44.95	34.51	43.81	39.69
Contriever	37.09	56.11	41.91	28.91	40.13	36.41	25.79	34.39	33.10
Passage Ranking Models									
RankBERT	65.26	72.54	63.37	60.19	67.18	60.06	56.33	64.35	56.51
MonoT5	62.97	70.82	60.96	60.27	66.25	58.84	49.76	54.96	47.61
RankLLama	76.24	79.57	72.67	66.86	72.34	65.35	61.42	66.92	59.78
Direct-Rank LLMs without RL									
Qwen2.5-3B-Instruct-direct	33.82	52.76	38.08	10.63	12.69	22.47	5.77	7.76	15.94
Qwen2.5-7B-Instruct-direct	36.54	57.82	44.57	12.55	16.24	23.69	8.56	9.83	17.79
llama-3.1-70b-instruct-direct	48.83	62.91	50.90	35.22	40.57	40.75	30.03	34.66	36.37
Iterative LLM Models without RL									
Qwen2.5-3B-Instruct-iter	56.54	68.14	57.74	38.13	48.11	43.47	32.78	40.23	39.40
Qwen2.5-7B-Instruct-iter	62.67	71.45	62.01	49.99	58.48	50.94	44.63	52.24	48.74
llama-3.1-70b-instruct-iter	65.55	72.89	63.90	56.73	64.04	56.74	54.80	60.76	55.22
Deepseek-R1-1024-iter	69.64	76.53	68.83	40.08	55.43	45.73	39.64	50.54	45.32
Deepseek-R1-2048-iter	69.39	73.52	64.56	52.70	62.31	53.03	53.41	62.88	56.84
Direct-Rank LLMs with RL									
DRanker	35.88	57.37	43.85	11.73	13.28	22.86	5.96	8.14	16.11
Iterative LLM Models with RL									
IRanker	64.47	70.62	60.98	53.52	59.89	53.22	49.83	54.54	49.96

Table 37: **Zero-shot on Recommendation Performance on Movie, Music, and Game Domains.**

Model	Movie			Music			Game		
	nDCG@10	nDCG@20	MRR	nDCG@10	nDCG@20	MRR	nDCG@10	nDCG@20	MRR
Qwen2.5-3B-Instruct-iter	26.44	38.55	22.01	27.06	38.45	21.97	32.80	44.23	29.49
DeepSeek-R1-Distill-Qwen-7B-direct	13.28	30.03	11.20	12.70	29.86	11.86	15.30	31.58	14.74
Qwen2.5-7B-Instruct-direct	22.21	34.23	16.59	17.90	34.29	17.29	21.57	36.15	18.63
IRanker	42.32	49.06	34.69	33.47	40.25	29.18	47.84	49.33	42.49
IRanker (zero-shot)	32.45	41.85	25.95	28.97	39.51	23.21	34.48	46.43	31.16

Table 38: **Zero-shot on Router Performance on Balance, Cost, and Performance Objectives.**

Model	Performance			Cost			Balance		
	nDCG@5	nDCG@10	MRR	nDCG@5	nDCG@10	MRR	nDCG@5	nDCG@10	MRR
Qwen2.5-3B-Instruct-iter	17.41	38.55	20.87	13.35	37.82	20.22	0.0	31.41	12.42
DeepSeek-R1-Distill-Qwen-7B-direct	11.11	36.81	20.00	20.17	42.65	27.22	26.55	44.22	28.52
Qwen2.5-7B-Instruct-direct	4.78	32.21	13.38	4.78	32.34	13.51	9.06	35.99	18.41
DRanker	17.90	38.10	20.63	4.78	32.34	9.06	4.78	32.21	13.38
IRanker	28.64	41.06	23.62	22.32	45.88	30.39	20.27	41.45	24.44
IRanker (zero-shot)	19.58	39.72	20.41	16.62	40.61	23.10	18.28	39.34	21.89

Table 39: **Zero-shot on Passage Ranking Performance on 5, 7, and 9 Candidates.**

Model	5 Passages			7 Passages			9 Passages		
	nDCG@3	nDCG@5	MRR	nDCG@3	nDCG@5	MRR	nDCG@3	nDCG@5	MRR
Qwen2.5-3B-Instruct-iter	56.54	68.14	57.74	38.13	48.11	43.47	32.78	40.23	39.40
DeepSeek-R1-Distill-Qwen-7B-direct	33.72	56.44	42.69	18.97	22.27	28.23	10.73	12.38	19.39
Qwen2.5-7B-Instruct-direct	36.54	57.82	44.57	12.55	16.24	23.69	8.56	9.83	17.79
DRanker	35.88	57.37	43.85	11.73	13.28	22.86	5.96	8.14	16.11
IRanker	64.47	70.62	60.98	53.52	59.89	53.22	49.83	54.54	49.96
IRanker (zero-shot)	63.18	67.19	56.42	45.27	52.92	51.19	38.12	46.15	42.45