Rank1: Test-Time Compute for Reranking in Information Retrieval

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Abstract

We introduce RANK1, the first reranking model trained to take advantage of test-time compute. RANK1 demonstrates the applicability within retrieval of using a reasoning language model (i.e. OpenAI's o1, Deepseek's R1, etc.) for distillation in order to rapidly improve the performance of a smaller model. We gather and open-source a dataset of more than 600,000 examples of R1 reasoning traces from queries and passages in MS MARCO. Models trained on this dataset show: (1) state-of-the-art performance on advanced reasoning and instruction following datasets; (2) work remarkably well out of distribution due to the ability to respond to user-input prompts; and (3) have explainable reasoning chains that can be given to users or RAG-based systems. Further, we demonstrate that quantized versions of these models retain strong performance while using less compute/memory. Overall, RANK1 shows that test-time compute allows for a fundamentally new type of explainable and performant reranker model for search.[1]

1   Introduction

Reasoning language models (LMs) like OpenAI's o1, Deepseek's R1, and Gemini's Flash-Thinking have shown improved reasoning abilities through the use of test-time compute, i.e. generating a *reasoning chain* of tokens that allow the model to "think" before giving the final answer. Another large benefit to these style of models is that the reasoning chain can easily be distilled into smaller models. As shown by Deepseek's R1 (Guo et al., 2025) smaller models learn incredibly well from simple supervised fine-tuning on the larger model's reasoning chains.

The benefits that reasoning models bring to general text generation would also be valuable in an information retrieval (IR) context: allowing models additional time to reason why a passage could be relevant, while also allowing an auditable reasoning process to give to the user or RAG system. For this approach to be maximally effective, the model must be able to reason over both query and passage; if applied solely to the query, the reasoning model would not know the passage context and would have to try to infer it. This would be a form of query-expansion (Nogueira et al., 2019) and limits the model's ability to be precise. Thus, our work focuses on bringing test-time compute to IR in a *reranking* setting, where the model needs to compute the relevance of an initial top-k candidates.

To accomplish this goal, we sample 635,000 examples of R1's thought process on the MS MARCO dataset (Nguyen et al., 2016). We then fine-tune a suite of LMs on these reasoning chains and find that they show remarkable reasoning capabilities. Surprisingly, they also exhibit an ability to be prompted despite training from the base LMs only (without instruction fine-tuning) and while

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[1]Models, code, and data are available at https://github.com/orionw/rank1

? what county is colton in

Colton, California. Colton is a city in San Bernardino County, California, United States...

<think> The user is asking "what county is Colton in." ... So the first thing I notice is that the passage directly mentions San Bernardino County as the county where Colton is located.

The query is specifically about the county, and the answer is right there in the first sentence of the passage.

But wait, maybe I should check if there's any possibility that the passage isn't relevant. The rest of the passage talks ... but the key information about San Bernardino County is present ...

So the answer should be true because the passage answers the query directly.

</think> **true**

? do snow leopards change color

Snow leopards have long, thick fur, and their base color varies from smoky gray to yellowish tan, with whitish underparts ...

<think> The user is asking if snow leopards change color. The passage provided describes their fur color as varying from smoky gray to yellowish tan, with some patterns. Hmm, the key here is whether "varies" implies that they change color over time, like seasonally or due to some factors.

But wait, "varies" might just mean that different individuals have different base colors, not that a single leopard changes its color. The passage doesn't mention anything about changing color; it's just describing their appearance. ...

Therefore, the passage isn't directly relevant to the question of whether they change color. So the answer should be false.
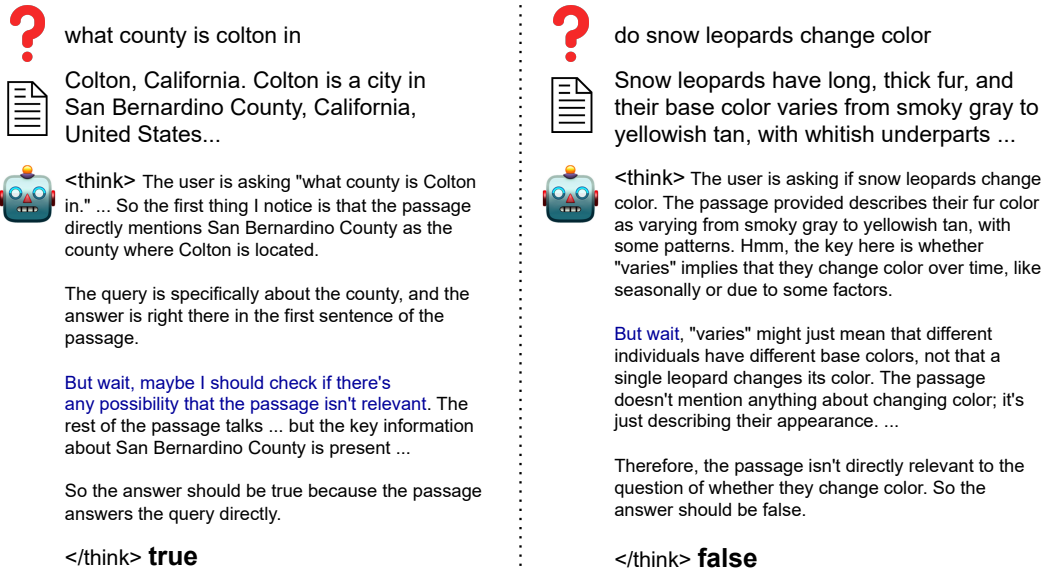
</think> **false**

Figure 1: Example reasoning traces from R1, used to train RANK1. Note the self-inquisitory reasoning (in blue) where the model questions is if it has the correct answer.

having no instruction-based IR training data (only MS MARCO). This includes state-of-the-art performance on the BRIGHT benchmark for reasoning (Su et al., 2024), the NevIR benchmark on complex negation understanding, and the mFollowIR dataset on multilingual instruction-following in IR despite having no non-English reasoning training data (Weller et al., 2025).

We also conduct a detailed analysis of performance on traditional IR benchmarks, such as TREC DL19 (Craswell et al., 2020) and BEIR (Thakur et al., 2021). We find that these datasets are likely model-saturated, as RANK1 surfaces an extremely large number of unjudged documents (364% more than RankLLaMA-14B). We argue these benchmarks are no longer helpful for distinguishing between the best performing rerankers and that focus should be put on benchmarks that examine advanced reasoning, instruction-following, and have more modern (e.g. post-ChatGPT) annotations.

Overall, RANK1 shows the many benefits that test-time compute can bring to the field of IR: **explainable reasoning chains** that can be audited by users or used by agentic RAG systems, **significantly improved reasoning** performance, and **adaptability from user-given prompts**.

2 Model Training

2.1 Data Preparation

In order to distil from R1, we first need to gather data to use to prompt it. We use the MS MARCO collection due to its diversity in topics and common use in previous work. We use kluster.ai as the API service to access R1 using their batch mode.

We generate data from an equal number (25% of the data) from each of the (1) positive examples in MS MARCO, (2) sampled negatives from Tevatron[2] (gathered from BM25 and CoCondenser), (3) rank 1-5 hard negatives from mT5-13B, and (4) rank 5-10 hard negatives from mT5-13B. However, we found that R1 classified roughly 80% of the mT5 hard negatives as positives. Thus we did another round of generation using only hard negatives from rank 5-10 and easy negatives from Tevatron. As the mined hard negatives do not have an official label, it is likely that many of them were false negatives and that R1 classified them correctly.

After all generation, our dataset has 635,264 examples of R1 generations, where R1 labeled 62.9% as relevant and 37.1% as non-relevant. We show a plot of these generation lengths in Figure 2 where we see a fairly normal distribution. Although we thought there may be length differences between these four subsets of data, we found that they all had the same rough distribution.

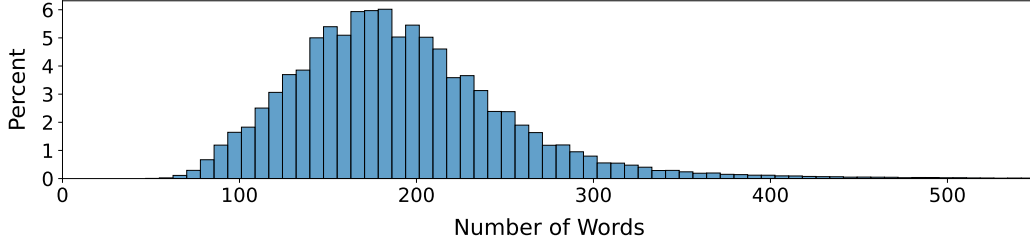[2]From https://huggingface.co/datasets/Tevatron/msmarco-passage-aug

Figure 2: Distribution of word lengths of the reasoning chains generated from R1. It has a slightly rightward skew but is generally normal shaped. Note that there is no noticeable difference in the distribution between passages that are predicted relevant vs non-relevant.

2.2 Data Mix and Quality Filtering

Since we had a surplus of documented judged relevant, we tried various methods to come to our final data mix. We initially tried using all the data, after balancing for the labels. We found that this performed significantly worse than filtering based on the labels we were most sure about (i.e. the positives from MS MARCO and the negatives from Tevatron). However, even on those subsets, 15% of R1's final prediction disagreed with the implied labels – thus we filtered out these instances.

Beyond being labeled as positives, we found that a large number of the mT5 mined hard negative samples were noisy. To alleviate this, we used a model trained on the first mix to self-filter the data.[3] This filtered approximately another 10% of the data, mostly false negatives. Since we still had a surplus of "relevant" labelled instances, we took all positives from the official MS MARCO positives and all negatives from the self-filtered set. This left us with a training set of 386,336 high quality training samples: 136k from the original MS MARCO positives, 154k from the Tevatron negatives, and 96k from the mT5 negatives. We note that having more negatives is standard: RankLLaMA (Ma et al., 2024) trained on a 15:1 ratio of negatives to positives for 7 million examples.

2.3 Training

We train three main models from the Qwen 2.5 family of models (Yang et al., 2024). These models have shown improved performance on recent LM benchmarks and have a wide range of models, allowing us to show the effects of scale. We use the 7B, 14B, and 32B parameter models. We show that alternate base models are also effective in Section 4. During initial experiments we found that the base models outperformed their instruction-tuned variants, so we start from the base versions.[4]

We train the models with LoRA using LLaMA-Factory (Zheng et al., 2024) for up to two epochs or for up to three days. We found that there was increased learning for roughly the 1.5 epochs but then performance saturated. For more details and hyperparameters configurations see Appendix A.

3 Experiments

We show the capabilities of the RANK1 through evaluation on advanced reasoning, instruction-following, and semantic-understanding datasets. We also demonstrate performance on traditional benchmarks. We use `mteb` (Muennighoff et al., 2022; Enevoldsen et al., 2025) to run all experiments except for DL19, which uses `rankllm` (Pradeep et al., 2023a). Inference is powered by `vllm` (Kwon et al., 2023) which makes it significantly faster than vanilla `transformers` (Wolf et al., 2020).

3.1 Baselines

We use BM25 (Robertson et al., 1994; Lù, 2024) and mE5-base (Wang et al., 2024) for our first stage models. For reranking models we show mainly other pointwise reranking models (e.g. models

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[3]We used the Mistral 24B version as it was the largest that fit on 1 GPU, filtering all instances where the model's prediction didn't agree with R1's prediction.

[4]This could be because instruct-versions are optimized for chat and math data, whereas we have a large amount of reranking-specific data that doesn't benefit from chat/math-based instructions.

	StackExchange							Coding		Theorem-based			Avg.
	Bio.	Earth.	Econ.	Psy.	Rob.	Stack.	Sus.	Leet.	Pony	AoPS	TheoQ.	TheoT.	
BM25	19.2	27.1	14.9	12.5	13.5	16.5	15.2	24.4	7.9	6.0	13.0	6.9	14.8
BM25 on GPT-4o CoT	53.6	53.6	24.3	38.6	18.8	22.7	25.9	19.3	17.7	3.9	18.9	20.2	26.5
MonoT5-3B	16.0	24.0	17.7	19.5	8.0	10.5	19.5	17.2	29.2	7.1	20.3	12.0	16.8
RankLLaMA-7B	17.5	15.5	13.1	13.6	17.9	6.9	16.9	8.4	**46.8**	2.2	4.5	3.5	13.9
RankLLaMA-13B	21.6	19.1	16.3	14.0	15.7	7.7	18.5	8.8	31.1	1.7	4.4	4.9	13.7
Rank1-7B	48.8	36.7	20.8	35.0	22.0	18.7	**36.2**	12.7	31.2	6.3	**23.7**	37.8	27.5
Rank1-14B	49.3	**37.7**	**22.6**	35.2	**22.5**	20.8	33.6	17.7	33.2	8.4	22.5	41.4	28.7
Rank1-32B	**49.7**	35.8	22.0	**37.5**	**22.5**	21.7	35.0	**18.8**	32.5	**10.8**	22.9	**43.7**	29.4

Table 1: The performance of retrieval models on BRIGHT. Numbers for ReasoningRank are taken from their paper (Ji et al., 2024) while BM25 scores are taken from the official BRIGHT paper. All models rerank from the BM25 on GPT-4o CoT top 100 documents, but are not given the GPT-4o CoT. **We find a large gap between similar sized rerankers and RANK1 models (sometimes 2x).** Bold indicates the best score for that subset in the reranker section.

that output a score per document): MonoT5-3B (Nogueira et al., 2019), mT5-13B fine-tuned on MMARCO for multilingual tasks (Jeronymo et al., 2023), and RankLLaMA 7 and 13B (Ma et al., 2024). For instruction following tasks we also include FollowIR-7B (Weller et al., 2024a) which was trained solely for instruction-following.

We show results for listwise models when those scores are available (Pradeep et al., 2023b; Niu et al., 2024; Sun et al., 2023), but we note that they are not comparable – listwise models take an order of magnitude more time at inference due to their sequential dependencies and have the advantage of seeing all documents in their context when reranking. We show them generally as a strong upper bound, as when state-of-the-art (SOTA) LMs (i.e. GPT-4o) are used.

3.2 Reasoning Capabilities

We show results on the reasoning intensive BRIGHT benchmark (Su et al., 2024) in Table 1. All reranker models judge the top 100 documents found using BM25 on the query plus GPT-4o's Chain of Thought (CoT) reasoning, which performed significantly better than BM25 without the query expansion (thus including more relevant documents in the top 100). However, at inference time, the rerankers are not given the CoT. We see a large gap between RANK1 and other models: in many cases near double the nDCG@10 score (e.g. 48.8 vs 24.3 for RANK1-7B vs ReasoningRank GPT-4o on Biology, or 18.7 vs 7.7 for RANK1-7B vs RankLLaMA-13B on Stackoverflow).

These results are especially notable when you consider that RANK1 models were **trained on an order of magnitude less data** than models like RankLLaMA (7 million vs 600k) **while using the same training dataset** (MS MARCO). We also find that performance scales with model size, with the 32B model outperforming the smaller models. Thus, RANK1 is SOTA when reasoning is needed.

3.3 Semantic Understanding

We also evaluate on the NevIR benchmark which requires reasoning over negation in Table 2. Models rerank all documents, and we report scores for listwise models from van Elsen et al. (2025).

We again find that RANK1 performs extremely well, even matching GPT-4o and coming 15+ points higher than the next closest model. We see that even o3-mini in a listwise setup only performs 7 points higher.

3.4 Instruction-Following

We show results on the mFollowIR dataset (Weller et al., 2025) as it illustrates both instruction-following and mul-

	Model	Score (%)
Listwise	RankGPT 4o-mini	64.1
	RankGPT 4o	70.1
	RankGPT o3-mini	**77.3**
Pointwise	RankLlama 7B	31.6
	RankLlama 13B	43.2
	MonoT5 base	34.9
	MonoT5 3B	50.6
	Rank1-7B	65.1
	Rank1-14B	67.5
	Rank1-32B	**70.1**

Table 2: Pairwise acc. on NevIR

tilingual capabilities. Table 3.3 shows results on the cross-lingual setup (En-XX) and Table 3.3 on the XX-XX task. We have all models rerank the top 100 scores of a strong but small base model mE5-base. We find that RANK1 has much higher nDCG@20 scores (from 0.586 to 0.611 on

Model	Persian		Chinese		Russian		Average	
	nDCG@20	p-MRR	nDCG@20	p-MRR	nDCG@20	p-MRR	nDCG@20	p-MRR
mE5-base	0.289	-3.9	0.316	+3.4	0.307	-2.1	0.304	-0.9
MonoT5-3B	0.118	-2.4	0.231	+5.0	0.240	+6.8	0.196	+3.1
FollowIR-7B	0.225	+1.8	0.375	+8.7	0.376	+0.4	0.325	+3.7
mT3-13B	0.453	-0.7	0.474	+2.3	0.505	-0.6	0.477	+0.4
RankLLaMA 7B	0.229	+0.8	0.272	+1.1	0.248	+0.1	0.250	+0.7
RankLLaMA 13B	0.256	+0.8	0.287	+1.8	0.320	-0.6	0.288	+0.6
Rank1-7B	0.564	+7.0	0.582	+3.1	0.511	-0.0	0.552	+3.4
Rank1-14B	**0.572**	**+11.9**	**0.611**	+4.6	0.516	+5.4	**0.567**	**+7.3**
Rank1-32B	0.555	+3.9	0.598	**+4.9**	**0.521**	**+6.6**	0.558	5.2

Table 3: mFollowIR Cross-Lingual scores across three language subsets. Bold indicates best score.

Model	Persian		Chinese		Russian		Average	
	nDCG@20	p-MRR	nDCG@20	p-MRR	nDCG@20	p-MRR	nDCG@20	p-MRR
mE5-base	0.493	-4.2	0.441	+0.3	0.417	-3.5	0.450	-2.5
MonoT5-3B	0.130	-3.8	0.233	+1.4	0.254	+2.2	0.206	-0.1
FollowIR-7B	0.163	-0.1	0.404	+6.6	0.379	+7.7	0.315	+4.8
mT5-13B	0.498	+0.1	0.548	+4.2	0.506	+1.9	0.517	+2.0
RankLLaMA-7B	0.248	-0.9	0.397	+1.3	0.396	-0.1	0.347	+0.1
RankLLaMA-13B	0.333	-2.0	0.448	+1.0	0.484	+0.5	0.422	-0.2
Rank1-7B	0.564	+2.4	0.665	+5.9	0.528	+4.7	0.586	+4.4
Rank1-14B	0.605	+11.1	0.647	+0.8	0.530	-1.0	0.594	+3.6
Rank1-32B	**0.619**	**+12.1**	**0.678**	**+10.2**	**0.535**	**+8.1**	**0.610**	**+10.1**

Table 4: Results for mFollowIR multilingual across three language subsets (Persian, Chinese, Russian). All models rerank the top 100 docs found from the mE5-base model. **We see a wide gap between RANK1 and other models, despite it not having any multilingual reranking training data.**

the multilingual average) compared to the next best model (mT5-13B trained on Multilingual MS MARCO) with 0.517. Furthermore, when considering just instruction following metrics there is a wide gap, especially in the multilingual setting (+10.1 vs +4.8 p-MRR on the custom instruction-trained FollowIR-7B). Other models are closer on the cross-lingual version, but there still remains a notable gap between the best RANK1 and the closest other model (+7.3 vs +3.7 p-MRR).

We again find this especially notable considering that mT5-13B is a similar size and was trained on multilingual data. RANK1 significantly outperforms it solely with English reasoning data.

3.5 "Traditional" Benchmarks

DL19 We also evaluate DL19 scores in Table 5. All models rerank the top 100 passages found using Re-pLLaMA. We found that our models performed significantly worse on the initial qrels and our analysis quickly showed this was due to the number of un-judged documents that our

Model	Original		Fixed
	Judged@10	nDCG@10	nDCG@10
RankLlama 7B	96.1	76.2	76.9
RankLlama 13B	96.1	77.2	76.9
MonoT5 3B	91.2	72.0	74.8
Rank1-7B	83.5	66.1	78.6
Rank1-14B	82.3	64.8	77.6
Rank1-32B	81.9	66.0	**80.1**

Table 5: Results on TREC DL19

models ranks higher. As seen in Table 5, the top 10 lists of existing pointwise rerankers is almost entirely judged passages (i.e. 96.1%), whereas RANK1 finds 10-15% less (down to 81.9%).

To remedy this, we annotated all top 10 documents that each model (baseline or RANK1) got wrong or were unjudged. We show examples of incorrectly labeled instances in Appendix C. We found that unjudged documents were mostly relevant, e.g. 70.6% of the unjudged documents for RankLLaMA 14B were relevant and 86.8% were relevant for Rank1-14B, etc.[5] After this annotation fix, we find

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[5]We release our new judged qrels in the Github above to help facilitate future work.

Model	ArguA	ClimF	DBP	FiQA	NFCorp	SciDoc	SciFact	Touche	TrecC	Avg.
BM25S	47.2	18.6	32.0	25.4	34.3	16.5	69.1	34.7	68.8	38.5
MonoT5-3B	42.5	25.4	44.5	46.5	37.8	19.3	76.1	30.7	79.6	44.7
RankLLaMA-7B	54.4	23.2	43.7	42.1	27.0	16.6	71.1	41.4	80.2	44.4
RankLLaMA-13B	49.3	24.5	44.9	44.1	28.1	18.1	72.7	39.2	80.8	44.6
Rank1-7B	42.8	15.0	38.9	39.5	36.2	17.2	77.2	22.8	81.9	40.9
Rank1-14B	45.3	16.2	37.4	37.9	35.8	17.9	77.0	27.1	78.2	41.0
Rank1-32B	57.6	15.8	40.7	41.8	36.9	19.6	76.8	19.9	81.9	41.7

Table 6: nDCG@10 results on the BEIR evaluation benchmark. Models rerank the top 100 documents from BM25S (Lù, 2024). Best results on each dataset and the entire benchmark are boldfaced.

that RANK1 models are no longer penalized for finding new documents and that performance is generally better than all other models (e.g. 78.6 vs 76.8 nDCG for RANK1-7B vs RankLLaMA 7B).

Thus, it seems that the original DL19 benchmark is no longer suitable for discriminating between the top performing approaches. Although this was examined for some TREC collections in 2022 by Voorhees et al. (2022), the largest model used in their experiments was BERT. Thus, motivated by our analysis, we would encourage the community to re-evaluate old TREC collections.

BEIR We show results on BEIR as a comparison in Table 6, using the datasets with less than 2k queries. All models rerank the top 100 documents found using BM25s (Lù, 2024). We find comparable but worse performance with RANK1. Although out of scope for this work, we found a large number of similar issues in BEIR datasets as we do in DL19. We discuss each dataset individually in Appendix F. It appears that traditional reranking benchmarks like DL19 and BEIR – although extremely successful at driving the field forward and still useful for weaker models – are no longer as useful for distinguishing between the best performing rerankers.

3.6 Test-Time Scaling

Given the success of reasoning language models in *scaling* test time compute (i.e. getting better results with more tokens used), we also attempted several ways of using extra test-time compute to improve performance. However, using the simple budget-forcing method from s1 (Muennighoff et al., 2025) did not improve performance and actually hurt performance on average. We hypothesize this may be due to the lack of difficulty in the reranking task – after all, reasoning over BRIGHT requires significantly less reasoning than the typical AIME problems used for evaluation. Alternatively, perhaps new techniques are needed to carefully induce the desired results.

4 Model Releases

Alternate Base Models Our main base models use the Qwen 2.5 series due to their strong performance and varying parameter sizes. However, to show that this approach also works on other base models, we train a version with Llama 3.1 8B (AI@Meta, 2024) and Mistral Small 2501 24B.[6] Similar to the Qwen models, we start from the base versions, not the instruct versions. We show the results on selected benchmarks in Table 7 where we can see that our approach holds for other base models with performance generally increasing as they scale (i.e. 24B is better than 8B). We also see that Llama 3.1 8B slightly underperforms Qwen 7B.

Quantization IR models typically require a heavier inference workload compared to many other LLM applications due to the number of passages to rerank. However, many common rerankers (MonoT5, RankLLaMA) do not take advantage of modern inference capabilities such as quantization.

We quantize each of our models using AutoAWQ (Lin et al., 2023) and compare performance before and after. We see that although performance drops slightly, the model size is significantly smaller, enabling **all models** (including the 32B version) to be run on one 24GB GPU. Despite the performance loss, quantized RANK1 models still significantly outperform the baselines on reasoning and instruction-following while being 1/3rd of the size.

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[6]Mistral Small can be found at https://huggingface.co/mistralai/Mistral-Small-24B-Base-2501

Model	Size (G)	SciFact	NevIR	Biology	Eng-Zho
Rank1-7B	15.2	77.2	65.1	48.8	58.2
quantized	5.6	75.4	62.0	42.8	56.3
Rank1-Llama3-8B	16.1	73.2	61.9	45.8	58.1
quantized	5.8	72.9	57.1	41.5	54.8
Rank1-14B	29.6	77.0	67.5	49.3	61.1
quantized	10.0	75.6	66.4	44.6	58.8
Rank1-Mistral-24B	47.2	75.8	67.4	51.8	59.9
quantized	14.3	72.7	64.6	47.1	59.4
Rank1-32B	65.5	76.8	70.1	49.7	59.8
quantized	19.3	77.2	69.9	52.3	59.7

Table 7: Quantization results on subsets of various tasks (SciFact from BEIR, Biology subset from BRIGHT, Eng-Zho on mFollowIR-CrossLingual). We use AutoAWQ for the quantization into int4. We see that models retain most of their performance while being significantly smaller.

5 Related Work

5.1 Advanced Reasoning and Instruction Following in IR

In the last couple years, retrieval systems have started to move beyond simple phrase-based semantic matching, to more complex information retrieval tasks. This has included a focus on new benchmarks: such as reasoning in retrieval (Su et al., 2024), instruction-following capabilities (Weller et al., 2024a; Oh et al., 2024), and retrieval for RAG systems (Lawrie et al., 2024; Mayfield et al., 2024).

On the modeling side, we have seen a surge of interest in models that can understand the meaning behind the user's query rather than doing phrase-based matching: this includes models like Instructor (Su et al., 2022), TART (Asai et al., 2022), GritLM (Muennighoff et al., 2024), FollowIR (Weller et al., 2024a), Gecko (Lee et al., 2024), and Promptriever (Weller et al., 2024b). These models typically use instruction-based data in their training data, so that they learn to adapt to new user instructions. However, for RANK1 we do not provide any instruction-based training data and fine-tune from the base (non-instruct) version of the LMs – despite this our model shows SOTA ability in these tasks.

5.2 Reasoning Language Models

Reasoning language models were introduced by OpenAI with their o1 model (Jaech et al., 2024). These models showed significantly improved performance on tasks that needed reasoning, such as math, logic, and programming. Since their release, many others have trained similar style models, including Google's Gemini Flash Thinking and Deepseek's R1. Notably, R1 is the only reasoning model that provides reasoning chains through APIs and is the only open-weights model.

Other than the impressive performance gains of these models, one additional feature is that models can quickly learn to emulate stronger models through basic supervised fine-tuning, rather than the more complex reinforcement learning pipelines that are typically used. We take advantage of this capability to train RANK1 using a simple training process.

There have also been a flurry of works in the open-source space, both before and after o1 on reasoning language models and systems, focused on reproduction (Snell et al., 2024; Muennighoff et al., 2025), calibration and confidence (Jurayj et al., 2025), agentic capabilities with explainable reasoning traces (Weir et al., 2022, 2024), and much more. We expect this line of work to continue and continued collaboration will likely improve these models in retrieval as well.

6 Limitations and Future Work

Overthinking Like other reasoning models, RANK1 can make mistakes and it can be surprising to see the model's reasoning chain come close to a correct answer only to change it's mind. We

also found in particular that RANK1 can be particularly stringent in marking passages as true. For example, on a TREC COVID query about the origins of COVID-19 it marked every single passage as non-relevant, since none mentioned the specific wet market in Wuhan. However, when given a prompt to assume the user had no information about COVID-19, it was able to adapt better (although not perfectly). We observed this tendency to "overthink" when using the model interactively as it would already know the answer and was looking for a very specific phrase. We expect that this could be lessened with data that specifically trains the model to calibrate this.

Inference Speed As a reasoning model using test-time compute RANK1 is slower than a model with only a classification head (i.e. RankLLaMA). In practice this can be somewhat mitigated by the usage of modern paged attention libraries like vLLM (Kwon et al., 2023) which we use, and also quantization techniques. Nonetheless, there is no getting around the fact that using test-time compute requires spending more compute than non-test-time compute models. Despite this additional compute usage, we see that users are willing to wait longer for quality search results, as illustrated by the popularity of the Deep Research products from Google and OpenAI.[7]

Future Work RANK1 also brings many more exciting areas for future work. As highlighted in the experiments section, it does extremely well despite the relatively small and non-diverse training data. Some of the straightforward areas of future work include:

- Fine-tuning with RL: although supervised fine-tuning works, it does not optimize for the final answer. It is likely that RL-based approaches would be able to add additional rewards/penalties that could better align the final prediction to the label.

- Listwise reasoning rerankers: although pointwise models are more efficient and more parallelizable, listwise rankers typically are more performant since they can see many documents at once. Simply gathering new data should enable this to be very successful.

- Multilingual and instruction-tuned versions: RANK1 was solely trained on English and non-instruct data and still showed strong results in these settings. Training on a more curated set of datasets will likely significantly improve the performance on these tasks.

7 Conclusion

We build the first reasoning reranker model that uses test-time compute, RANK1. We do so by collecting 600k+ examples from the reasoning language model R1, fine-tuning on its reasoning traces. Despite only using English MS MARCO data and training from base (non-instruct-tuned) language models, RANK1 shows state of the art reasoning and instruction following capabilities, even in multilingual settings. Overall, RANK1 introduces a new category of reranking models that enable a wide variety of more complex information retrieval tasks.

Acknowledgments

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[7]https://openai.com/index/introducing-deep-research/ and https://blog.google/products/gemini/google-gemini-deep-research/

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A   Training and Hyperparameter Details

We use nodes of 4x80GB H100 machines for training. Models are trained for up to 2 epochs or until 3 days of training (for the 32B model).

We fine-tune with LLaMA-Factory, using LoRA on all parameters with rank 32 and alpha 64. We use a learning rate of 1e-4 and an effective batch size of 128. We use early stopping based on the Bright Biology and NevIR scores. Models use prompts for BEIR and non-stackexchange cases so that they can understand the task (Appendix D).

Inference is done on 1 H100 80GB GPU. Baselines use default hyperparameters for max length and fp16 (and there are no other parameters).

Prompt for Inference

Determine if the following passage is relevant to the query. Answer only with 'true' or 'false'.

Query: query

Passage: document

Figure 3: Prompt used to generate data with R1 and also for inference with RANK1.

Model	Unjudged→Relevant	Changed→Correct
MonoT5-3b	50.00% (19/38)	6.74% (29/430)
RankLLaMA-13B	70.59% (12/17)	6.28% (27/430)
RankLLAMA-7B	70.59% (12/17)	6.74% (29/430)
Rank1-7B	85.92% (61/71)	5.35% (23/430)
Rank1-14B	86.84% (66/76)	6.05% (26/430)
Rank1-32B	88.46% (69/78)	6.51% (28/430)

Table 8: Qrel changes in the DL19 annotations

B Prompt for R1

We use the following prompt (Figure 3) to generate data for R1 (and use the same template for RANK1).

C Examples of Unjudged and Incorrect DL19 Labels

We re-annotated the top 10 passages for each model that got an incorrect or unjudged label. This was 295 labels. We found that none of the labels changed from correct to incorrect, but some labels went from incorrect to correct (Table 8).

We also show some examples of these cases in Table 9. The incorrect labels affected all models roughly equally, as seen previous in Table 8 at around 6% of the top 10 documents, while the unjudged documents were mostly found by RANK1.

D Prompts for specific datasets

Table 10 shows the data-specific prompts used for BEIR and the non-stackoverflow BRIGHT subsets.

E Things we tried that didn't work

We tried a few other things that didn't work:

- We tried to calibrate the scores better by adding a ModernBERT model (Warner et al., 2024) on top of the outputs of the reasoning chain. However, this ended up performing worse. It is possible that with better curation this would be an effective approach however.

- We tried adding extra loss to the last token of the next token prediction loss in LLaMA-Factory. However, this resulted in sub-par performance, likely because predicting the last true/false token at the end of reasoning chain is fairly easy (as the model already states beforehand "the answer is X" leaving little room for doubt).

Example 1

Query: what is physical description of spruce
Passage: Spruces are large trees, from about 20–60 metres (about 60–200 feet) tall when mature, and can be distinguished by their whorled branches and conical form. The needles, or leaves, of spruce trees are attached singly to the branches in a spiral fashion, each needle on a small peg-like structure.
Original label: 0 (non-relevant)
New label: 3 (relevant)

Example 2

Query: causes of left ventricular hypertrophy
Passage: High blood pressure may also bring on heart failure by causing left ventricular hypertrophy, a thickening of the heart muscle that results in less effective muscle relaxation between heart beats. This makes it difficult for the heart to fill with enough blood to supply the body's organs, especially during exercise, leading your body to hold onto fluids and your heart rate to increase.
Original label: unjudged
New label: 3 (relevant)

Example 3

Query: what are the social determinants of health
Passage: © Zoltan Balogh. The social determinants of health (SDH) are the conditions in which people are born, grow, work, live, and age, and the wider set of forces and systems shaping the conditions of daily life.
Original label: 1 (on topic)
New label: 3 (relevant)

Example 4

Query: example of monotonic function
Passage: Overview of the exponential function. The exponential function is one of the most important functions in mathematics (though it would have to admit that the linear function ranks even higher in importance). To form an exponential function, we let the independent variable be the exponent. A simple example is the function $f(x) = 2^x$. ...
Original label: unjudged
New label: 3 (relevant)

Table 9: Examples of incorrect labels and unjudged documents in the DL19 annotations.

F   Noise in BEIR benchmarks

We discuss here a few of the issues with individual BEIR datasets which cause them to be noisy and less accurate at judging between highly effective systems.

SciFact   In the original SciFact work (Wadden et al., 2020) the authors have three labels: support, refute, or not enough information (NEI). However, when incorporated into BEIR, the NEI queries are still included. As there was not evidence to support these queries (as determined by the original authors) these queries are effectively noise. In practice, what it means is that tests model's ability to find the top ranked BM25 document, which is guaranteed to not have enough information to either refute or support the claim. The large number of these queries add a significant amount of noise.

FiQA2018   FiQA is scraped from Financial Stackexchange (Maia et al., 2018). However, during the original scrape the creators did not collect the post's details. Thus, the retrieval setup is to take the posts title and search for the top answer. Yet, in many cases the user clarified important details in the post that entirely changed the meaning of the query. Without this additional information for some queries it is impossible for someone to determine what the best answer is as the post details asked many other questions that were different from the title of the post.

DBPedia   DBPedia has many partially relevant labels, that give credit for finding non-relevant information. For example, the entire passage with a relevance of "1" for the query "Eiffel Tower"

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Dataset	Prompt
SciFact	Claim: FILL_QUERY_HERE\<newline>\<newline>A relevant passage would provide evidence that either **supports** or **refutes** this claim. A passage with any information on any related subpart should be relevant.
ClimateFEVER	Claim: FILL_QUERY_HERE\<newline>\<newline>A relevant passage would provide evidence that either **supports** or **refutes** this claim. A passage with any information on any related subpart should be relevant.
TRECCOVID	FILL_QUERY_HERE If the article answers any part of the question it is relevant.
ArguAna	I am looking to write an essay and need to find counterarguments against this statement:\<newline>\<newline>FILL_QUERY_HERE\<newline>\<newline>Does this passage have any counterargument or evidence that could be used to help me?
DBPedia	I am looking to write an essay on this topic and need as much related background information to help me. The topic is:\<newline>\<newline>FILL_QUERY_HERE\<newline>\<newline>If the passage provides any background information that could be connected it is relevant.
FiQA2018	FILL_QUERY_HERE Find a passage that would be a good answer from StackExchange.
NFCorpus	Topic: FILL_QUERY_HERE\<newline>\<newline>Given the above topic, I need to learn about all aspects of it. It does not need to be directly relevant, only tangentially informational. Please mark as relevant any passages with even weak connections. I need to learn fast for my job, which means I need to understand each part individually.\<newline>\<newline>Again remember, any connection means relevant even if indirect. So if it is not addressed, that is okay – it does not need to be explicitly.\<newline>\<newline>Find me passages with any type of connection, including weak connections!!!!
Touche2020	FILL_QUERY_HERE **any** arguments for or against
SCIDOCS	papers that could be cited in FILL_QUERY_HERE. Anything with even indirect relevance should be relevant. This includes papers in the same broader field of science
BrightRetrieval aops	Find different but similar math problems to FILL_QUERY_HERE\<newline>\<newline>A document is relevant if it uses the same class of functions and shares **any** overlapping techniques.
BrightRetrieval theoremqa questions	Find a passage which uses the same mathematical process as this one: FILL_QUERY_HERE
BrightRetrieval leetcode	I am looking to find different problems that share similar data structures (of any kind) or algorithms (e.g. DFS, DP, sorting, traversals, etc.). I am looking for problems that share one or both of these similarities to this:\<newline>\<newline>FILL_QUERY_HERE\<newline>\<newline>Does this passage share any similarities? e.g. if there was a textbook on leetcode problems, this would be in the same book even though it could be in a different chapter.
BrightRetrieval pony	I will use the programming language pony. Problem: FILL_QUERY_HERE\<newline>\<newline>But to solve the problem above, I need to know things about pony. A passage is relevant if it contains docs that match **any** part (even basic parts) of the code I will have to write for the above program.
BrightRetrieval	Can you find background information about the concepts used to answer the question:\<newline>\<newline>FILL_QUERY_HERE\<newline>\<newline>A passage is relevant if it contains background information about a **sub-concept** that someone might cite/link to when answering the above question.
BrightRetrieval theoremqa theorems	Find a passage which uses the same mathematical process as this one: FILL_QUERY_HERE

Table 10: Dataset-specific prompts used in the BEIR and non-Stackexchange subsets of BRIGHT.

is "The year 1989 in architecture involved some significant architectural events and new buildings." However, nothing about the Eiffel Tower is connected to 1989. After digging, the only connection is its the 100 year anniversary of it being built – but the passage does not mention this. There are many such examples in the dataset (and more documents judged "1" than "2"), contributing to the noise.

Touche2020 Touche2020 has been well examined by Thakur et al. (2024). They created a much cleaner version of the data, however, it is not the "standard" evaluation set in BEIR.

Other datasets with partial relevance Many of the other datasets give credit for partial relevance in a similar manner to DBPedia. This includes TREC COVID (which has so many real positives that it is a non-issue for the top-10), NFCorpus, and SciDocs. For many of these datasets, it is very difficult for even a human to match relevance: e.g. on NFCorpus you would have to guess any potential link that had been on that website and was even ancillarily related to the title. An example is the query "How Fruits and Vegetables Can Treat Asthma" which matches a document with the title "Effect of a single high-fat meal on endothelial function in healthy subjects." and does not discuss asthma at all. The reranker would have to assume that any passage discussing food or asthma separately in any context would be relevant. Although one intution is that these documents should rank higher than completely non-relevant documents, for RANK1 it treats them as the same (as they are both equally non-relevant to the query). This may be suboptimal for some approaches, but for today's RAG use cases returning only actual relevant documents seems more useful.