RaCT: Ranking-aware Chain-of-Thought Optimization for LLMs

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Abstract

Large language models (LLMs) have shown significant promise in text reranking tasks by leveraging their advanced language understanding and reasoning capabilities. However, traditional supervised fine-tuning (SFT) approaches by ranking utilities can compromise LLMs' general-purpose abilities. To address this challenge, we propose a novel LLM-based reranking algorithm – RaCT – that implements SFT with Chain-of-Thought prompting, followed by a ranking preference optimization (RPO). The proposed RaCT aims to enhance ranking performance for LLMs while preserving their inherent language modeling abilities. Experimental evaluations on the three public ranking benchmarks (TREC DL, BEIR, and BRIGHT) and one LLM benchmark demonstrate the superior ranking performance of RaCT with a retained language understanding and reasoning capacity.

1 Introduction

Text reranking is a vital task in information retrieval (Liu, 2009; Hasanain, 2018), crucial for search engines (Li et al., 2024), conversational AI (Becker et al., 2012), and recommendation systems (Zhao and Liu, 2024). Large language models (LLMs) excel in reranking due to their reasoning and human-like thinking capabilities, enabling them to handle complex queries and ambiguous contexts. RankGPT (Achiam et al., 2023) has set a high standard in listwise reranking (Ma et al., 2019), leveraging its systematic reasoning (Brown et al., 2020) to advance reranking technologies.

Building on top of RankGPT, several models have sought to distill its output into smaller, task-optimized models through supervised fine-tuning (SFT). To name a few, RankVicuna (Pradeep et al., 2023a) uses distilled data generated exclusively from GPT-3.5 and focuses on efficient fine-tuning to improve ranking performance with a lightweight

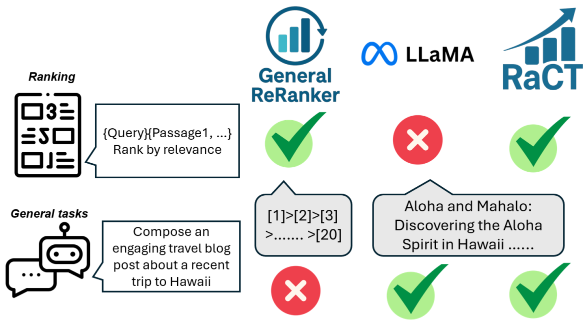

Figure 1: General text reranking LLMs excel at ranking tasks but struggle with general tasks such as open-ended text generation. General LLMs (e.g., LLaMA) perform well on diverse tasks but lack strong ranking capabilities. RaCT effectively integrates both, achieving high performance in ranking while maintaining general language generation abilities.

architecture. RankZephyr (Pradeep et al., 2023b) develops a more comprehensive approach that utilizes distilled data from GPT-3.5 and GPT-4, ensuring the quality and reliability of training data to achieve superior ranking results. While these models exhibit state-of-the-art ranking performance, they pose a new challenge for LLM rerankers: *the trade-off between optimizing ranking utility and preserving the inherent language modeling capabilities*. Empirically, over-emphasizing ranking through SFT could significantly degrade LLM in general-purpose language understanding tasks, hindering its practical deployment as a reranking agent in real-world scenarios.

General rerankers achieve strong performance on listwise ranking tasks after SFT, but often lose their ability to follow general instructions. As shown in Figure 1, models like LLaMA may output incomplete or irrelevant results, such as numeric lists, when asked to write a travel blog. This suggests that SFT for ranking can reduce a model's general text generation ability.

In this study, we introduce a novel LLM reranking algorithm, namely RaCT, by implementing SFT through a chain-of-thought (CoT) prompt (see Fig. 2) to guide sequential passage ranking without undermining the LLM's general language understanding ability. To enhance the reasoning ability, we further incorporate CoT prompting into ranking preference optimization (RPO) (Rafailov et al., 2024), proposing a new step-wise ranking preference learning framework RaCT. The framework utilizes overlapping ranking orders as the reward function, enabling efficient and flexible error correction.

We summarize the contributions of this work as follows:

- To the best of our knowledge, this is the first research study to investigate the trade-off between ranking utility and language modeling for the recent emerging LLM re-rankers.
- We propose a novel chain-of-thoughts instruction (reranking) tuning algorithm – RaCT – that enables LLMs to rank passages based on relevance step by step, and RPO to enable further ranking preference optimization.
- Empirical evidence on three ranking benchmarks, TREC Deep Learning Tracks (Craswell et al., 2021a, 2020), BEIR (Thakur et al., 2021), and BRIGHT (Su et al., 2025), and the Massive Multitask Language Understanding (MMLU) benchmark (Hendrycks et al., 2020) suggests that our approach achieves state-of-the-art LLM re-ranking performance with the preservation of intrinsic language modeling capabilities.

USER: I will provide you with {num} passages, each indicated by a numerical identifier []. Rank the passages based on their relevance to the search query: {query}.
[1] {passage 1}
[2] {passage 2}
...
[{num}] {passage {num}}
Search Query: {query}.
Rank the {num} passages by selecting the most relevant passage at each step from the remaining passages. After choosing the most relevant passage, remove it from the pool and continue ranking until all passages are ordered.
Instructions:
Start with the most relevant passage and select it from the full list.
For each following step, pick the most relevant passage from the remaining passages only.
List the selected passages by their identifiers at each step, one after the other, until all passages are ranked.
Example Output:
Step 1: [4]
Step 2: [4, 2]
Step 3: [4, 2, 3]
...
step {num}: [4,2,3,15,...,14]
Final Answer: [4, 2, 3,..., 14]
Only respond with each step and the final answer, ensuring each passage is included once and ranked in descending relevance.

Figure 2: RaCT Chain-of-Thought (CoT) reranking prompt guiding the model to rank passages based on relevance to a query iteratively. The prompt ensures step-by-step selection, removal, and ordering of passages, with an example illustrating the expected output format.

2 Methodology

2.1 CoT Reranking Prompt and Dataset

RaCT formulates listwise reranking as a chain-of-thought (CoT) reasoning task, where the model iteratively selects the most relevant passage until all are ranked. The prompt (Figure 2) guides LLaMA to output ranked indices given a query and a set of passages. This builds on prior zero-shot reranking methods such as RankVicuna and RankZephyr (Pradeep et al., 2023a,b; Liu et al., 2024), which use template-based prompts to optimize ranking metrics like nDCG (Järvelin and Kekäläinen, 2002).

We train RaCT on 40k examples from Pradeep et al. (2023b), with 20 BM25-retrieved passages per query labeled by $\text{RankGPT}_{3.5}$ or RankGPT_4. The dataset includes three prompt formats: standard RankGPT-style prompts,RaCT CoT prompts, and RaCT CoT prompts where the model outputs the ranked list directly without explanation. We split 90% for supervised CoT tuning and 10% for RPO. Denoted as CoT tuning data and RPO data. The dataset is publicly available.[1]

2.2 RaCT: Two-Stage Training

Training Stage 1: CoT Tuning As shown in Figure 3, during the Stage 1, we use CoT Tuning data with mixed prompt templates, maintaining a zero-shot setup since RankGPT and RaCT do not rely on human-labeled data.

Before fine-tuning, the LLaMA3.1-8B-Instruct model (Grattafiori et al., 2024) failed to perform CoT reranking, merely copying the example format without relevance. This highlights the need for fine-tuning. Model weights are available on Hugging

[1] https://huggingface.co/datasets/castorini/rank_zephyr_training_data

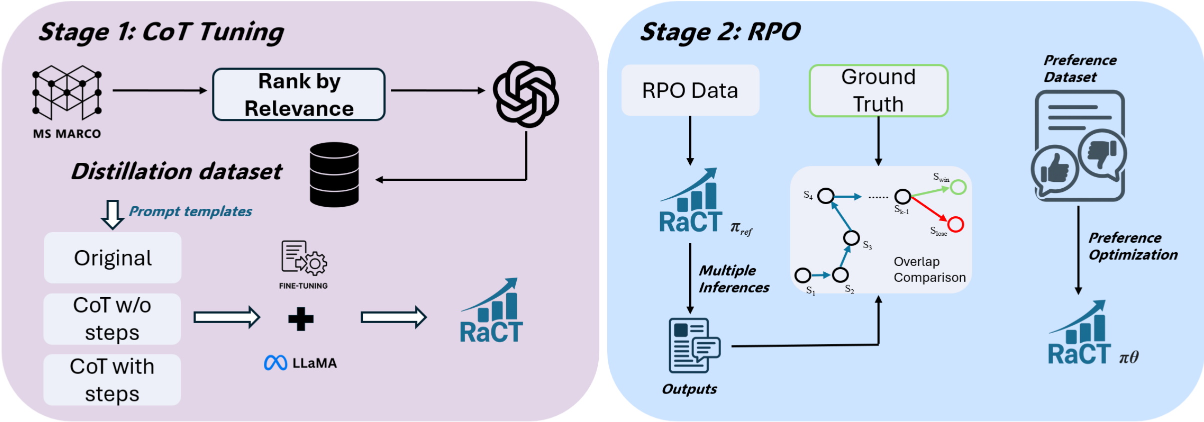

Figure 3: Training framework of our model. $Left$: Stage 1 aims to teach the student model to perform text reranking. $Right$: In stage 2, we use the same prompt format to generate multiple answers, then pick the chosen and rejected answers based on the number of overlapped steps, finally, we utilize the preference data to perform RPO training.

Face.[2]

We fully fine-tune the 8B parameter LLaMA3.1 model for three epochs with a batch size of 128, a 5×10^{-6} learning rate, and bfloat16 format. Training on four NVIDIA A100 80GB GPUs took approximately 20 hours. We use Maximum Likelihood Estimation (MLE) as our objective function, optimizing the model to generate the most probable ranking sequence given the input passages and queries.

Training Stage 2: RPO After Stage 1, the RaCT model generates three ranking predictions (y) on prompts (x) from RPO data. Predictions are evaluated by overlapping ranking orders with ground-truth labels, creating a preference dataset with prompts (x), chosen steps (s_w), rejected steps (s_l), and overlapping steps (s_o). Unlike prior methods, the final ranking y comprises a sequence of reasoning steps, $y = \{s_1, s_2, \ldots, s_n\}$, where each step is conditioned on prior steps $\pi(s_k|x; s_{1:k-1})$. Overlapping steps (s_o) are tracked until a divergence is found, after which only the initial contiguous overlaps are included in s_o, and later steps are categorized as chosen (s_w) or rejected (s_l). This results in a dataset of (x, s_w, s_l, s_o).

The objective maximizes the likelihood of correct steps (s_w) while minimizing incorrect ones (s_l), using the loss:

$$\mathcal{L}(\theta) = -\mathbb{E}_{(x,s_w,s_l,s_o)\sim D}\Big[\log\sigma\Big(\beta\log\frac{\pi_\theta(s_w \mid x; s_o)}{\pi_{ref}(s_w \mid x; s_o)} - \beta\log\frac{\pi_\theta(s_l \mid x; s_o)}{\pi_{ref}(s_l \mid x; s_o)}\Big)\Big],$$

where $\pi_\theta(s \mid x; s_o)$ represents the model's probabilities, optimized to favor correct steps while leveraging reference model probabilities (π_{ref}) for stable training and better generalization, especially in zero-shot scenarios. This improves CoT reasoning's sequential decision-making and model consistency. The RPO stage is trained on four NVIDIA A100 80GB GPUs over one epoch, taking approximately 6 hours.

3 Experiments

3.1 Evaluation Benchmarks

We evaluate ranking performance on standard academic benchmarks, including TREC DL19 and DL20 (Craswell et al., 2020, 2021a), each with 100 BM25-retrieved passages per query and human relevance labels. To assess generalization, we include additional cross-domain benchmarks: BEIR (Thakur et al., 2021), TREC DL21/DL22 (Craswell et al., 2021b, 2022), and BRIGHT (Su et al., 2025). Reranking is conducted using a sliding window strategy (Sun et al., 2023), details explained in Appendix C. To verify general-purpose capabilities, we also evaluate on MMLU (Hendrycks et al., 2020), testing 57 subject areas for text understanding post fine-tuning.

3.2 Results

Table 1 compares model performance on TREC and MMLU. Our 8B RaCT model outperforms all baselines, including the larger, closed-source RankGPT_4[3], despite using only 90% of the training

[2] https://huggingface.co/meta-LLaMA/Meta-LLaMA-3-8B-Instruct

[3] RankGPT is the only closed-source and largest model in the table.

Models	MSv1		MSv2		MMLU
	DL19	DL20	DL21	DL22	AVG.
RankGPT$_4$	0.750	0.704	0.684	0.509	0.864
BM25	0.506	0.480	0.446	0.269	N/A
Gemma-7B	0.533	0.530	0.446	0.269	0.649
LLaMA3.1	0.669	0.641	0.639	0.429	0.720
DeepSeek-R1-8B	0.565	0.503	0.558	0.380	0.530
RankZephyr	0.742	0.709	0.600	0.408	0.000
RankVicuna	0.668	0.655	0.608	0.421	0.373
LLaMA3.1 + SFT	0.707	0.635	0.660	0.441	0.628
RaCT (Ours)	**0.758**	**0.720**	**0.706**	**0.532**	**0.720**

Table 1: Performance of different models on TREC (nDCG@10) and MMLU (exact match score) benchmarks. All the reranking tasks are based on BM25 retrieval results. The **bold** values highlight the best performance.

data. It also surpasses *LLaMA3.1 + SFT*, confirming the benefit of our CoT reranking prompt. In the RPO stage, RaCT achieves further gains with just one epoch and shows strong robustness: performance drops only 0.004 under tighter sliding windows, compared to over 0.02 for others.

We also applied LoRA to fine-tune only the linear layers in Stage 1, reducing training time by 4 hours while achieving a competitive 0.747 on DL19. This surpasses RankZephyr and RankGPT, showing that a lightweight fine-tuning approach can still achieve strong ranking performance with our CoT prompting strategy.

Model	BEIR	BRIGHT
BM25	0.426	0.137
RankZephyr	0.422	0.130
RaCT	**0.545**	**0.178**

Table 2: Average performance comparison on BEIR and BRIGHT benchmarks (nDCG@10), see detailed scores in Appendix F and G

Table 2 presents the performance comparison of RaCT against BM25 and RankZephyr across various BEIR and BRIGHt benchmark datasets. Both LLM models are reranking based on BM25 retrieval results. The results show that RankZephyr, despite being a fine-tuned model, receives a lower average score than the traditional retriever BM25, indicating that its reranking effectiveness does not always surpass basic retrieval methods. Combined with the results from DL21 and DL22, these findings suggest that while traditional fine-tuning methods improve performance on in-scope datasets, they do not necessarily generalize well to out-of-scope datasets. In contrast, RaCT demonstrates stronger generalization across different retrieval tasks, reinforcing the effectiveness of incorporating CoT prompting and RPO in improving reranking capabilities beyond the training distribution.

On MMLU, RaCT matches LLaMA3.1's performance, while *LLaMA3.1 w/o CoT* shows a slight drop and RankVicuna performs poorly. RankZephyr has completely lost its ability to generate meaningful outputs, it receives a score of 0 on MMLU.

Although our model was trained using a mixed Chain-of-Thought (CoT) reranking prompt, we use the same concise prompt as RankGPT during inference and directly output the final ranked list. This ensures that inference time remains unchanged.

3.3 Ablation Study

Setting	nDCG@10 (DL22)
RaCT$_{\text{BM25}}$ (baseline)	0.532
– CoT	0.407
– RPO	0.504
– CoT&RPO	0.429
RaCT$_{\text{SPLADE++ED}}$	0.683

Table 3: Ablation study with LLaMA3.1-8B as the base model. Each row removes or modifies components from the full RaCT setup and reports performance on TREC DL22 (nDCG@10).

Table 3 presents an ablation study based on LLaMA3.1-8B. Removing CoT or RPO from the RaCT$_{\text{BM25}}$ baseline leads to performance drops, with CoT having a larger impact (0.407 vs. 0.504). Removing both results in 0.429, which is lower than using CoT alone but higher than using RPO alone, indicating that both components contribute and their combination is most effective. Using SPLADE++ED as the retriever further boosts performance to 0.683, showing the reranker's compatibility with stronger retrieval systems.

4 Conclusion and Future Work

In this paper, we introduced RaCT, a zero-shot listwise reranker based on LLaMA3.1, and showed the effectiveness of CoT prompting and CoT–RPO training. Our model outperforms both open- and closed-source baselines, including RankZephyr and RankGPT$_4$. For future work, we plan to adapt RaCT to other architectures (e.g., Mistral, Zephyr, QWEN) and train on more diverse, higher-quality datasets to enhance robustness and performance.

5 Limitations

While our model is based on LLaMA 3.1, which supports a 128k context window—significantly longer than RankVicuna (4k) and RankZephyr (8k)—we observe that using extremely long contexts by including all passages at once can negatively impact reranking performance. In some cases, this leads to worse results compared to a sliding window approach. This suggests that simply leveraging longer context lengths does not always yield better rankings, possibly due to attention dilution or ineffective utilization of distant context. In future work, we aim to explore strategies to better manage long-context inputs, such as adaptive passage selection or hierarchical attention mechanisms, to fully exploit the model's context capacity without compromising ranking quality

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A Baseline Selection

To illustrate the efficacy of RaCT, we select several baseline models, including the unsupervised retriever model BM25 (Robertson and Zaragoza, 2009); zero-shot prompt-based LLMs: RankGPT_4[4], Gemma-7B (Team et al., 2024), LLaMA3.1-8B-Instruct (Grattafiori et al., 2024) and DeepSeek-R1-Distill-Llama-8B (DeepSeek-AI et al., 2025); fine-tuned LLM-based models (RankVicuna, RankZephyr). To show the effectiveness of our CoT reranking prompt, we train a model with a similar paradigm to RankZephyr but use our base model LLaMA3.1-8B-Instruct, denoted as *LLaMA3.1 + SFT*.

B Evaluation Benchmarks (Expanded)

We evaluate ranking capabilities using TREC DL19 (Craswell et al., 2020) and DL20 (Craswell et al., 2021a) Tracks, derived from MS MARCO V1 (Bajaj et al., 2016), with human-annotated relevance labels. DL19 and DL20 contain 43 and 54 queries, respectively, each paired with 100 BM25-retrieved candidate passages. For broader generalization analysis, we include additional datasets not seen during training: (1) BEIR Benchmarks (Thakur et al., 2021), (2) TREC DL21 (Craswell et al., 2021b) and DL22 (Craswell et al., 2022) based on MS MARCO V2, and (3) BRIGHT: A Reasoning-Intensive Benchmark (Su et al., 2025). Reranking uses a sliding window strategy (Sun et al., 2023) with window size 20 and stride 10 to process long sequences. Rankings are computed independently for each segment and aggregated across the query.

To assess whether ranking fine-tuning affects broader model capabilities, we test on MMLU (Hendrycks et al., 2020), which covers 57 diverse academic and professional subjects. We compare performance before and after ranking fine-tuning to ensure the model retains general language understanding and generation abilities.

C Sliding Window Strategy

In the sliding window strategy commonly used in reranking models (e.g., RankZephyr, RankGPT, and our method), passages appearing in multiple overlapping windows are ranked multiple times based on the local context of each window.

Since most reranking evaluations focus on nDCG@10, only the top 10 passages from the final ranking are considered. This means that passages appearing in the final window retain their latest assigned ranking, while earlier rankings from overlapping windows are not explicitly reconciled. This approach follows the standard strategy used in previous works and provides a computationally efficient way to handle long passage lists.

[4] gpt-4-0613

D Base Model Selection

Models	DL19	DL20	DL21	DL22
LLaMA3-8B	0.752	0.710	0.693	0.502
LLaMA3.1-8B	**0.753**	**0.710**	**0.698**	0.504
LLaMA3.2-3B	0.718	0.697	0.690	**0.517**
LLaMA3.2-1B	0.713	0.682	0.673	0.465

Table 4: Performance Comparison of different base models on TREC Benchmarks (nDCG@10). All the models are trained with identical RaCT strategy. The bold values highlight the best performance across the respective datasets.

E Window Size

Models	Window/Stride Size		
	2/1	10/5	20/10
Gemma-7B	0.541	0.593	0.533
LLaMA3.1	0.549	0.660	0.641
RankZephyr	0.562	0.612	0.742
RankVicuna	0.551	0.655	0.668
LLaMA3.1 + SFT	0.567	0.663	0.666
RaCT w/o RPO	0.697	0.737	0.753
RaCT	0.702	0.754	0.758

Table 5: Performance of different models with different window size and step size, BM25 performs all of the retrieval stage, and all of the evaluations are performed on DL19

F BEIR Evaluation

Datasets	BM25	RankZephyr	RaCT
NFC	0.322	0.331	**0.392**
FEVER	0.651	0.618	**0.823**
COVID	0.595	0.592	**0.847**
NEWS	0.395	0.396	**0.471**
SciFact	0.679	0.679	**0.790**
HotPotQA	0.633	0.669	**0.762**
NQ	0.306	0.375	**0.600**
Qoura	0.789	0.719	**0.807**
FIQA	0.236	0.230	**0.435**
CFEVER	0.165	0.160	**0.237**
Arguana	**0.397**	0.295	0.310
Touche	**0.442**	0.434	0.414
SCIDOCS	0.149	0.148	**0.207**
Signal	0.330	0.316	**0.347**
DBPedia	0.318	0.395	**0.459**
Robust04	0.407	0.406	**0.492**
Avg.	0.426	0.422	**0.545**

Table 6: Performance Comparison on BEIR Benchmarks (nDCG@10). The bold values highlight the best performance across the respective subsets.

G BRIGHT Evaluation

Datasets	BM25	RankZephyr	RaCT
Bio.	0.182	0.219	**0.246**
Earth.	0.279	0.237	**0.331**
Econ.	0.164	0.144	**0.185**
Psy.	0.134	0.103	**0.228**
Rob.	0.109	0.076	**0.164**
Stack.	**0.163**	0.137	0.157
Sus.	0.161	0.166	**0.205**
Pony	0.043	0.065	**0.137**
Leet.	0.247	0.247	**0.253**
AOPs	0.065	0.068	**0.072**
TheoT	0.021	0.020	**0.082**
TheoQ	0.073	0.073	**0.081**
Avg.	0.137	0.130	**0.178**

Table 7: Performance Comparison on BRIGHT Benchmarks (nDCG@10). The bold values highlight the best performance across the respective subsets.

H Examples of General LLM Tasks

To illustrate the degradation in general text understanding and generation capabilities of RankVicuna and Rankzephyr, we provide two examples below. Due to the length of RaCT's response, we have omitted the middle portion of the answer.

H.1 Example 1

Prompt

Compose an engaging travel blog post about a recent trip to Hawaii, highlighting cultural experiences and must-see attractions.

RankVicuna

Ultimately, showcasing Hawaii's rich history and cultural significance.
Title: Embracing Hawaiian Culture: Discovering Historical Landmarks and Rich Traditions on the Big Island

RankZephyr

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Aloha and Mahalo: Discovering the Aloha Spirit in Hawaii
As I stepped off the plane in Honolulu, I couldn't help but feel a sense of excitement and anticipation wash over me. I had dreamed of visiting Hawaii for years, and finally, I was here. The warm tropical air enveloped me, and the sweet scent of plumeria filled my senses as I made my way to my hotel. Little did I know, this trip would be a journey not only to breathtaking natural wonders but also to a rich cultural heritage that would leave me feeling grateful and inspired.
Immersing in the Local Culture:
(Content omitted for brevity.)
Must-See Attractions:
(Content omitted for brevity.)
A Taste of Aloha:
(Content omitted for brevity.)
Conclusion:
(Content omitted for brevity.)
Practical Tips and Recommendations:

- Visit Pearl Harbor and USS Arizona Memorial in the morning to avoid the crowds.
- Try local specialties like poke, laulau, and shave ice.
- Take a surf lesson or snorkeling trip to explore the islands' stunning coastlines.
- Visit the Bishop Museum to learn about the history and geology of Hawaii.
- Explore the islands' many farmers' markets for fresh produce and local products.
- Learn traditional Hawaiian crafts, like leis and ukulele strings, from local artisans.

Mahalo (thank you) for joining me on this journey to the Aloha State. I hope my story has inspired you to plan your own trip to Hawaii and experience the warmth and beauty of this incredible destination.

H.2 Example 2

Prompt

Can you help me write a resignation letter to my current employer, while leaving on good terms and expressing gratitude for the opportunities provided?

RankVicuna

(Nothing was generated from the model.)

RankZephyr

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I'd be happy to help you write a resignation letter to your current employer. Here's a sample template you can use as a guide:

Dear [Recipient's Name],
I am writing to inform you of my decision to resign from my position as [Your Position] at [Company Name], effective [Date of Last Day of Work]. I want to express my deepest gratitude to you and the entire [Company Name] team for the opportunities I've had during my time here.
(Content omitted for brevity.)
Please don't hesitate to reach out to me if you need anything after my departure. I can be reached at [Your Email Address] or [Your Phone Number].
Sincerely,
[Your Signature]

Some tips to keep in mind when writing your resignation letter:

- Be professional and respectful: Use a formal tone and language throughout the letter.
- Express gratitude: Let your employer know how much you appreciate the opportunities you've had and the experience you've gained.
- Offer to help with the transition: Show that you're committed to making the transition as smooth as possible by offering to complete outstanding tasks and assist with the handover of your responsibilities.
- Keep it brief: Aim for a letter that is no more than one page in length.
- Proofread: Make sure to proofread your letter carefully to ensure it is free of errors and typos.

Remember to customize the letter to fit your own circumstances and experiences. Good luck with your resignation, and I hope it leads to a positive and successful transition for you!