ListConRanker: A Contrastive Text Reranker with Listwise Encoding

Anonymous ACL submission

Abstract

Reranker models aim to re-rank the passages based on the semantics similarity between the given query and passages, which have recently received more attention due to the wide application of the Retrieval-Augmented Generation. Most previous methods apply pointwise encoding, meaning that it can only encode the context of the query for each passage input into the model. However, for the reranker model, given a query, the comparison results between passages are even more important, which is called listwise encoding. Besides, previous models are trained using the cross-entropy loss function, which leads to issues of unsmooth gradient changes during training and low training efficiency. To address these issues, we propose a novel **List**wise-encoded **Con**trastive text re**Ranker** (**ListConRanker**). It can help the passage to be compared with other passages during the encoding process, and enhance the contrastive information between positive examples and between positive and negative examples. At the same time, we use the circle loss to train the model to increase the flexibility of gradients and solve the problem of training efficiency. Experimental results show that ListConRanker achieves state-of-the-art performance on the reranking benchmark of Chinese Massive Text Embedding Benchmark, including the cMedQA1.0, cMedQA2.0, MMarcoReranking, and T2Reranking datasets.[1]

1 Introduction

Given a query and a few passages that are semantically related or partially related to the query, the goal of the ranking task is to sort these passages based on their degree of semantic similarity. The reranker model is one of the most important parts in the Information Retrieval (IR) systems (Guo et al., 2020; Pang et al., 2020; Padaki et al., 2020). Recently, due to the trend of Retrieval-Augmented Generation (RAG) and limited context length of Large Language Models (LLMs), reranking models have been widely studied and rapidly developed (Lewis et al., 2020; Zhao et al., 2024; Glass et al., 2022), which can filter out noisy passages retrieved by embedding models.

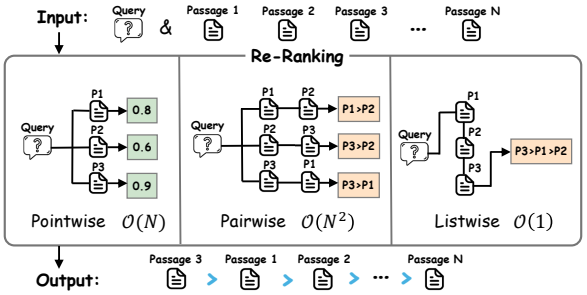

Figure 1: Pointwise rerankers receive the query and a passage as input and output the similarity score of them. Pairwise rerankers receive the query and two passages as input and output which passage is more similar to the query. Listwise rerankers receive the query and all passages as input and directly output the final ranking results. The complexity in the figure represents input times.

As shown in Figure 1, there are three main types of reranking models, which are pointwise (Nogueira et al., 2020b; Liang et al., 2023; Sachan et al., 2022; Schlatt et al., 2025), pairwise (Qin et al., 2024), and listwise (Sun et al., 2023; Ma et al., 2023). The main difference between them is that a pointwise reranker accepts a query and one passage as input at a time, while a pairwise reranker takes two passages, and a listwise reranker takes multiple passages at a time.

Most previous rerankers based on BERT-like Cross-Encoder are pointwise (Lu et al., 2022), because of the limited context length and the need to align with the two-sentence input format used during pre-training (Devlin et al., 2019; Zhuang et al., 2021). However, pointwise rerankers can only obtain the context of the query and a passage, when

[1]The weights and codes of ListConRanker will be released after acceptance.

models encode the feature of passage. The most important aspects are the relative ordering of passages and the comparison of similarities between passages. This results in the suboptimal performance of pointwise rerankers. Pairwise and listwise encoding reranker are two solutions to this problem. Due to the high input times and unstable comparison results (e.g., passage 1 > 2 and passage 2 > 3, but passage 3 > 1) of pairwise methods, their practical application value is low. In contrast, listwise methods represent a more realistic and valuable direction for exploration.

Recently, LLMs have demonstrated excellent performance on natural language tasks. Some work has attempted to use LLMs as listwise rerankers (Pradeep et al., 2023; Liu et al., 2024). They allow the LLM to directly output the predefined sequence numbers of passages as the final ranking result. However, it will still exceed the context length limit when there are hundreds of passages, leading to the failure of ranking (Sun et al., 2023). Besides, LLMs can not output exact similarity scores between the query and passages. Moreover, different input orders may also lead to instability in the results.

Based on the problems of the pointwise reranker and the listwise reranker based on LLMs, we explore the listwise reranker based on BERT-like embedding models, which is an area that has not been fully explored before. We propose a **List**wise-encoded **Con**trastive text re**Ranker** (**ListConRanker**). It first inputs query and passages into the embedding model. After getting the original features of the query and each passage, we combine these features into an input sequence, which is then fed into the proposed ListTransformer. The ListTransformer can facilitate global contrastive information learning between passage features, including the clustering of similar passages, the clustering between dissimilar passages, and the distinction between similar and dissimilar passages. Besides, we propose ListAttention to help ListTransformer maintain the features of the query while learning global comparative information.

At the same time, most of the previous pointwise rerankers apply cross-entropy (CE) loss function during training. However, for the ranking task, there is usually more than one similar (positive) passage. If the CE loss function is used, for multiple passages of the same query, models can only sample one positive passage per training step. This leads to low training efficiency for positive samples. Besides, it hinders the learning of contrastive information between positive samples.

To this end, we propose to apply Circle Loss (Sun et al., 2020). It can improve the data efficiency by taking multiple positive and negative passages as input at the same time. Besides, its self-adaptive weights can smooth out gradient changes during the training process and accelerate training. Specifically, it can reduce the gradient when close to the optimal space while increasing the gradient when far from it. This helps the model find the optimal space more quickly.

The main contributions of our work can be summarized as follows:

- We propose a novel BERT-based reranker model with listwise encoding named ListConRanker, which has not been fully explored before. It contains ListAttention and ListTransformer, which can utilize the global contrastive information to learn representations.
- We propose to use the Circle Loss as the loss function. Compared with CE loss and ranking loss, it can solve the problems of low data efficiency and unsmooth gradient change.
- Experimental results on the reranking benchmark of Chinese Massive Text Embedding Benchmark (C-MTEB) demonstrate that ListConRanker is state-of-the-art. The ablation study shows the effectiveness of ListTransformer and Circle Loss.

2 Related Work

There are three main encoding types of rerankers: pointwise encoding, pairwise encoding, and listwise encoding. As shown in Figure 1, the main differences between them are the number of passages input at a time and the output format. Due to the high input times of pairwise rerankers, which is $O(N^2)$ for ranking N passages, there has been less related work in the past. In the following sections, we will mainly introduce these three rerankers.

2.1 Pointwise Rerankers

Pointwise rerankers receive the query and a passage as input, and output the similarity between them. Dai and Callan (2019) and Gao et al. (2021) were the first to propose using the BERT model in ranking tasks and referred to this type of model as the cross-encoder architecture. This allows

for interaction between the query and the passage. However, they used the binary cross-entropy loss function during training, which prevented interaction between query-passage pairs. Based on this, Nogueira and Cho (2019) proposed using contrastive loss from a new perspective. Recently, due to the huge success of generative language models, Nogueira et al. (2020b) proposed to input the query and passage into the model directly and then let the model generate a "true" or "false" token to indicate whether they are similar. Furthermore, Sachan et al. (2022) proposed to use LLMs to compute the probability of the input query conditioned on the passage as the similarity between them.

However, these pointwise rerankers can only learn the context of one passage, which results in suboptimal performance. Listwise rerankers can provide global contrastive information, making it superior in architecture.

2.2 Pairwise and Listwise Rerankers

Pairwise Rerankers take a query and two passages as input and output which of the two passages is more similar to the query. Qin et al. (2024) proposed using an LLM as a judge. After obtaining results for all passage pairs, a traditional ranking algorithm is used to produce the final passage ranking.

Listwise rerankers receive the query and all corresponding passages as input. It outputs the ranking of passages directly. Most previous methods are based on LLMs. For example, some methods first proposed to let LLMs generate the reordered list (Ma et al., 2023; Pradeep et al., 2023; Zhang et al., 2023). To address the issue of exceeding the context length of LLMs in some extreme cases, Sun et al. (2023) proposed a listwise method based on sliding windows. Furthermore, Liu et al. (2024) encoded the passage into an embedding before inputting it into the LLM. This helps to address the lack of global contrastive information in the methods based on sliding windows.

Due to the limited context length of LLMs, the rerankers based on LLMs can not provide complete global contrastive information, which is the most important advantage of listwise rerankers.

3 Method

In this section, we mainly describe ListConRanker, which applies listwise encoding to learn global contrastive information. It uses the Circle Loss (Sun et al., 2020) to improve the data efficiency and smooth out gradient changes. The structure of ListConRanker is shown in Figure 2.

3.1 Original Features

Given a query q and N passages $P = \{p_1, p_2, ..., p_N\}$, we first input them to an embedding model to obtain their features $H = \{h_q, h_1, h_2, ..., h_N\}$.

$$h_q = \text{Embedding}(q) \quad (1)$$

$$h_i = \text{Embedding}(p_i) \quad (2)$$

where Embedding is a BERT-based embedding model, h_q is the feature of query, and h_i is the feature of passage i.

We get the original features by using an embedding to encode the context of the query and passage. However, these features do not contain any information of other passages, which means these passages are unable to be compared with other passages to optimize the ranking result.

3.2 Listwise Encoding by ListTransformer and ListAttention

After obtaining the features of query and passages, we concatenate these features into a sequence and input them into the ListTransformer which is similar to a Transformer Encoder (Vaswani et al., 2017) without position embedding except for the self-attention module. In addition, we apply learnable embeddings to help ListTransformer distinguish between query feature and passage features.

$$Z^{(0)} = \{h_q + e_q, h_1 + e_p, ..., h_n + e_p\} \quad (3)$$

$$Q^{(l)} = Z^{(l-1)} W_Q^{(l)} \quad (4)$$

$$K^{(l)} = Z^{(l-1)} W_K^{(l)} \quad (5)$$

$$V^{(l)} = Z^{(l-1)} W_V^{(l)} \quad (6)$$

$$Z^{(l)} = \text{ListAttention}(Q^{(l)}, K^{(l)}, V^{(l)}) \quad (7)$$

where e_q and e_p are learnable embeddings, $W_Q^{(l)}$, $W_K^{(l)}$, and $W_V^{(l)}$ are learnable parameters, and l is the l-th layer of ListTransformer.

The bidirectional self-attention in ListTransformer will make the query feature obscured by unrelated passages when there are a large number of unrelated passages. When the number of unrelated passages is small, the query can ignore the

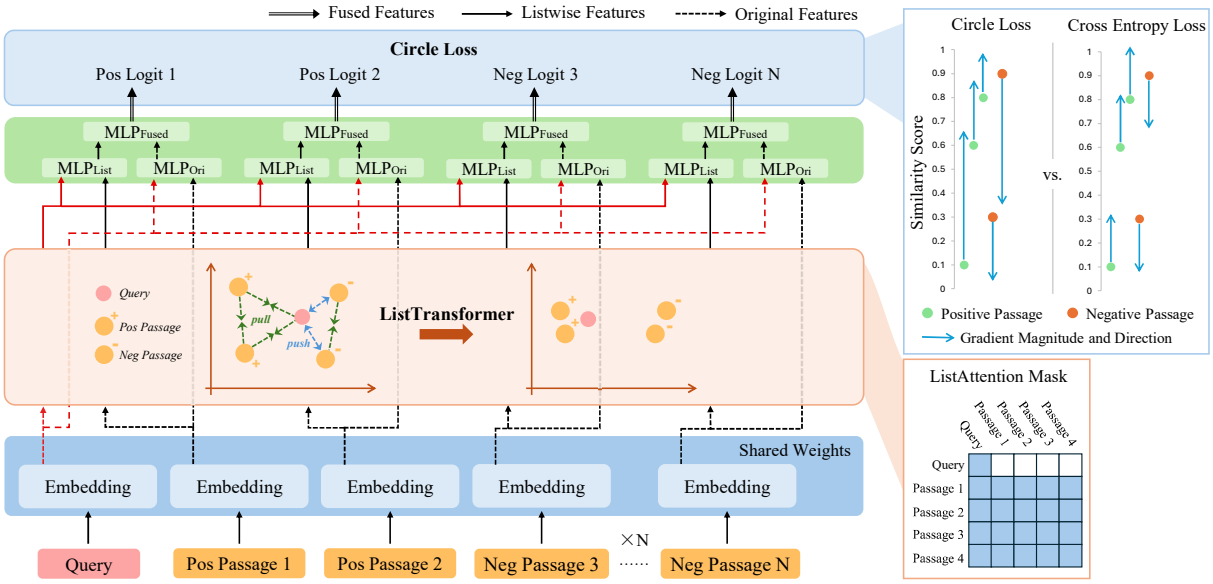

Figure 2: The overall architecture of the ListConRanker.

unrelated passages by attention weights. However, when the number is large, the noisy information dominates self-attention.

To this end, we propose the ListAttention in the ListTransformer. The attention mask details of ListAttention are shown in Figure 2. Specifically, we make the query can only get its own attention to preserve its original features. As for passages, we use the bidirectional self-attention. Passages can recognize the query features by query embedding and learn pair features between query and passage. Besides, the attention among passages can facilitate the learning of global contrastive information between passages. For example, it can reduce the distance between positive examples and between negative examples while increasing the distance between positive and negative examples. This global contrastive information reflects the concept of sequencing in ranking tasks.

After obtaining the features with global contrastive information (i.e., listwise features), we combine the listwise features with original features and use MLPs to determine the final similarity between the query and passage.

$$s_i^{origin} = \text{MLP}_{\text{Ori}}(h_q, h_i) \quad (8)$$

$$s_i^{list} = \text{MLP}_{\text{List}}(z_q^{(l)}, z_i^{(l)}) \quad (9)$$

$$s_i^{final} = \sigma(\text{MLP}_{\text{Fused}}(s_i^{origin}, s_i^{list})) \quad (10)$$

where $S^{final} = \{s_1^{final}, s_2^{final}, ..., s_n^{final}\}$ is the similarity between the query and passage p_i, MLP_{Ori}, MLP_{List}, and $\text{MLP}_{\text{Fused}}$ are all MLPs, σ is the sigmoid activation function.

Finally, we can sort all passages by their similarity to the query S^{final} in descending order to obtain the final ranking result.

3.3 Circle Loss

Most of the previous rerankers apply cross-entropy loss function to train the model. However, cross-entropy loss function has several disadvantages. First, its data efficiency is low. It can only sample one similar (positive) passage from all the passages per training step. This also prevents global contrast information learning between positive examples. Second, it does not have the feature of adaptively adjusting loss weights. Specifically, when the predicted values are close to or far from having the optimal space, the cross-entropy loss function can only implicitly control the size of parameter updates through the magnitude of the gradient. At the same time, the ordering is a relative result in ranking tasks. It only requires that positive samples be ranked higher than negative samples. The cross-entropy loss function requires the predictions for positive cases to be 1 and for negative cases to be 0. This is too strict for ranking tasks.

Therefore, we propose using Circle Loss (Sun et al., 2020) as the loss function for ListConRanker. It can customize the optimal prediction values for positive and negative cases. At the same time, it can adaptively adjust the gradient weights for each sample based on the customized optimal prediction values, which helps the model achieve smoother

gradient changes. Ultimately, this makes it easier for the model to find the optimal space. The calculation method for Circle Loss is as follows:

$$L = \log(1 + r_{neg} r_{pos}) \tag{11}$$

$$r_{neg} = \sum_{j=1}^{J} \exp(\gamma \alpha_{neg}^{j} (s_{neg}^{j} - \Delta_{neg})) \tag{12}$$

$$r_{pos} = \sum_{i=1}^{I} \exp(-\gamma \alpha_{pos}^{i} (s_{pos}^{i} - \Delta_{pos})) \tag{13}$$

$$\Delta_{neg} = m,\ \Delta_{pos} = 1 - m \tag{14}$$

$$O_{neg} = -m,\ O_{pos} = 1 + m \tag{15}$$

$$\alpha_{neg}^{j} = \max(0, s_{neg}^{j} - O_{neg}) \tag{16}$$

$$\alpha_{pos}^{i} = \max(0, O_{pos} - s_{pos}^{i}) \tag{17}$$

where m and γ are hyper-parameters, I is the number of positive samples in all passages, J is the number of negative samples in all passages.

3.4 Recursive-Funnel Inference

Due to the limited memory of GPUs, we input about 20 passages at a time for each query during training. However, during actual use, there may be situations where far more than 20 passages are input at the same time. For example, each query corresponds to approximately 1,000 passages that need to be ranked in the MMarcoReranking (Bonifacio et al., 2021) test set. The differences between the training and inference processes can cause self-attention weights to become dispersed in ListTransformer, which prevents the passages from learning effective global contrastive information. This has been fully demonstrated in the context length extension problem of large language models (Chen et al., 2023; Press et al., 2022). Finally, it leads to a drop in performance.

However, we find that ListConRanker still maintains a basic ranking capability when a large number of passages are input simultaneously through case studies. Specifically, for some clearly dissimilar passages, ListConRanker can still rank them after partially similar samples (i.e., hard negative samples) or similar samples (positive samples). When a large number of passages are input, ListConRanker is hard to distinguish between partially similar samples or similar samples. On the contrary, when only dozens of passages are input, ListConRanker can easily distinguish between them through global contrastive information.

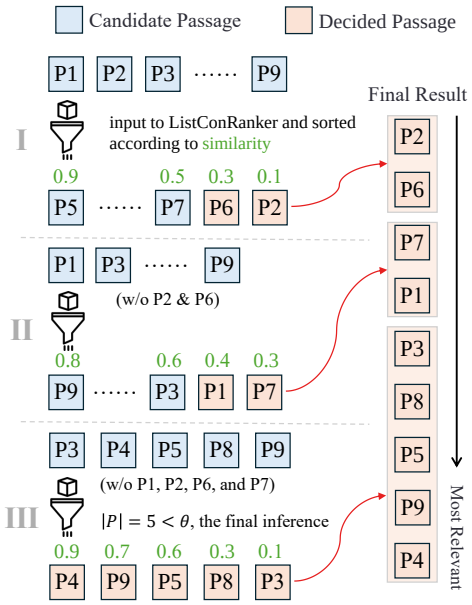

Figure 3: The process of Recursive-Funnel Inference. For simplicity, we do not show the query in the figure. The query will be input during each step of the inference.

Based on the above findings, we propose a novel Recursive-Funnel Inference for ListConRanker. For each inference, it can act like a funnel with different granularities and filter out irrelevant passages from coarse-grained to fine-grained. The specific inference process is shown in Algorithm 1 and Figure 3. For each inference step i, we input all N_i passages and then determine the ranking positions for the bottom $(\beta \times N_i)$ passages in the final results. The remaining $N_{i+1} = (1 - \beta) \times N_i$ passages are re-input into the ListConRanker. The iteration continues until the number of remaining passages is less than θ. The final positions for all passages are obtained.

4 Experiments

4.1 Datasets and Evaluation Metrics

We evaluate ListConRanker on the reranker section of Chinese Massive Text Embedding Benchmark (C-MTEB)[2] (Xiao et al., 2024), including the test set of cMedQA1.0 (Zhang et al., 2017), test set of cMedQA2.0 (Zhang et al., 2018), development set of MMarcoReranking, and development set of T2Reranking (Xie et al., 2023). We report the mean Average Precision (mAP) on each dataset to show the effectiveness of reranker models.

[2] https://huggingface.co/spaces/mteb/leaderboard

Model	LLM?	# Params	cMedQA1.0	cMedQA2.0	MMR	T2Reranking	Avg.
monoT5	✔	783M	76.19	81.69	24.65	67.70	62.55
ListT5	✔	783M	78.29	78.82	29.06	58.35	61.13
piccolo-large-zh-v2	✘	API	89.31	90.14	33.39	67.15	70.00
360Zhinao-1.8B-Reranking	✔	1.88B	86.75	87.92	37.29	68.55	70.13
ternary-weight-embedding	✘	327M	88.74	88.38	35.04	68.39	70.14
LdIR-Qwen2-reranker-1.5B	✔	1.54B	86.50	87.11	39.35	68.84	70.45
zpoint-large-embedding-zh	✘	327M	91.11	90.07	38.87	**69.29**	72.34
xiaobu-embedding-v2	✘	327M	90.96	**90.41**	39.91	69.03	72.58
Conan-embedding-v1	✘	327M	**91.39**	89.72	41.58	68.36	72.76
ListConRanker	✘	401M	90.55	89.38	**43.88**	69.17	**73.25**
- w/ Traditional Inference			90.19	89.93	37.52	69.17	71.70
- w/ Sliding Window Inference			90.47	89.48	42.26	69.17	72.85

Table 1: The results comparison with baselines on the reranking benchmark of C-MTEB. MMR stands for MMarcoReranking. We select the top 7 open-source models as of April 1, 2025, based on the average metrics as the baselines. In addition, we reproduced the monoT5 and ListT5 that performed well on non-Chinese benchmarks on C-MTEB. For more details of the reproduction, please refer to the Appendix I. The evaluation metric for all datasets is mAP. The best performance is in **bold**.

4.2 Implementation Details

We initialized the embedding model using the Conan-embedding-v1 model (Li et al., 2024). Since ListTransformer and MLPs are trained from scratch, we trained the model in two stages. Firstly, we freeze the embedding model and only train the ListTransformer and MLPs for 4 epochs using the training sets of cMedQA1.0, cMedQA2.0, MMarcoReranking, T2Reranking, huatuo(Li et al., 2023), MARC(Keung et al., 2020), XL-sum(Hasan et al., 2021), and CSL(Li et al., 2022) with a batch size of 1024. Secondly, we do not freeze any parameter and use the training sets of cMedQA1.0, cMedQA2.0, and T2Reranking to train for 2 epochs with a batch size of 256. Besides, we respectively set the hyperparameters l, γ, θ, and β to 2, 10, 20, 0.2. In the first stage of training, we set m to -0.2. In the second stage of training, we set m to 0.1. The experiments are run on 8 NVIDIA A800 40GB GPUs with about 260 A800 GPU hours.

4.3 Overall Results

Table 1 shows the results of cMedQA1.0, cMedQA2.0, MMarcoReranking, and T2Reranking. Compared to other models, ListConRanker demonstrated a significant advantage, particularly on the MMarcoReranking and T2Reranking datasets. Although some previous methods are based on LLMs with larger parameter sizes (i.e., 360Zhinao-1.8B-Reranking and LdIR-Qwen2-reranker-1.5B), they use pointwise encoding, which leads to suboptimal performance. It is worth noting that we do not use the MMarcoReranking dataset in the second stage of training. The significant improvement of ListConRanker on the MMarcoReranking can be attributed to the listwise encoding introduced by the ListTransformer. Additionally, the MMarcoReranking is unique compared to the other three datasets. Each query in the MMarcoReranking corresponds to 1,000 passages. This large number of passages allows for extensive global contrastive information and interaction within the ListTransformer, resulting in a performance boost.

In addition, we reproduced 3 models that perform well on non-Chinese benchmarks (i.e., monoT5 and ListT5). However, due to the mismatch between these models and the variable passage number input characteristic of Chinese benchmarks, their performance is suboptimal. This further highlights the current lack of exploration in Chinese reranking tasks.

4.4 Ablation Study

4.4.1 The Effect of ListAttention

To verify the effectiveness of ListAttention, we conducted experiments with different attention masks. The results, as shown in Table 2, indicate that bidirectional self-attention performs worse than ListAttention. The only difference between them lies in whether the query needs to compute attention for the passages and whether the query features are influenced by the passages. This decline in performance highlights the importance of maintaining the semantic features of the query.

Additionally, we explored a PassageAttention (see details in Appendix H). Specifically, in Pas-

Model	cMedQA1.0	cMedQA2.0	MMR	T2Reranking	Avg.
ListAttention	90.55	89.38	**43.88**	69.17	**73.25**
Bidirectional Self-Attention	**90.79**	**89.59**	42.12	**69.20**	72.93
PassageAttention	89.73	89.46	41.08	69.04	72.33

Table 2: The results of ablation study using different attentions on the reranker section of C-MTEB. All results are based on Recursive-Funnel Inference. The best performance is in **bold**.

Model	cMedQA1.0	cMedQA2.0	MMR	T2Reranking	Avg.
Fusing Original and Listwise Features	**90.55**	**89.38**	**43.88**	**69.17**	**73.25**
Only Listwise Features	90.36	**89.38**	41.48	68.91	72.53
Only Original Features	89.41	89.13	38.66	68.72	71.48
Embedding Model Continue Training	89.02	88.54	38.12	69.11	71.20

Table 3: The results of ablation study using different features on the reranker section of C-MTEB. The results of Fusing Original and Listwise Features and Only Listwise Features are based on Recursive-Funnel Inference. Recursive-Funnel Inference will not change the results of Only Original Feature and Embedding Continue Training, as the features of each passage are not influenced by other passages. Thus, there is no need to use Recursive-Funnel Inference on them. The best performance is in **bold**.

sageAttention, the query has bidirectional self-attention with all passages, but each passage only computes attention between itself and the query. Passages rely on the query as an anchor to learn global comparative information. As a result, query features are influenced by all passages, regardless of their similarity to the query. This causes the query to lose its own semantic meaning. Meanwhile, it also reduces the efficiency of passages learning global contrastive information. Notably, PassageAttention resulted in the lowest performance, further highlighting the importance of maintaining the semantic features of query.

4.4.2 The Effect of Fusing Original and Listwise Features

To verify the effect of fusing listwise features with original features, we conducted experiments where we used only listwise features and only original features separately. The results, shown in Table 3, demonstrate that using only listwise features results in only a slight performance drop compared to ListConRanker. However, when the model uses only original features, there is a significant drop in performance, especially on the cMedQA1.0 and MMarcoReranking datasets. This is because the original features lack global comparative information, as they are pointwise features. This underscores that listwise features play a dominant role in ListConRanker, as well as the importance of global comparative information.

Additionally, to rule out the impact of data and training strategies, we further train the embedding model using the second-stage training strategy. We do not use the first-stage strategy, because the embedding model is frozen in the first stage. Since similarity calculation uses inner products between vectors, there is no feature interaction between the query and passage, meaning it is neither a pointwise nor a listwise model. As observed, its performance is the lowest, further emphasizing the importance of query-passage interaction in the reranker.

4.4.3 The Effect of Circle Loss

To verify the effectiveness of Circle Loss, we explored the experimental results using different loss functions, as shown in Table 4. Firstly, when using the cross-entropy loss, the model achieved the worst performance due to inefficient data sampling. Secondly, when the loss function was switched to Triplet Loss (Balntas et al., 2016) and CoSENT Loss[3], which are designed specifically for ranking tasks, the models are able to sample all positive and negative samples of query in each training step. This not only improved the data sampling efficiency but also enabled the ListTransformer to bring positive samples closer together, which obtains more comprehensive global contrastive information. Finally, when the model used Circle Loss, compared to Triplet Loss and CoSENT Loss, the model has smoother gradient changes during training. Specifically, Circle Loss increases the gradient when the model is far from the optimal space and reduces the gradient as it approaches the optimal space. This allows the model to find the optimal space more

[3] https://spaces.ac.cn/archives/8847

Model	cMedQA1.0	cMedQA2.0	MMR	T2Reranking	Avg.
Circle Loss	**90.55**	89.38	**43.88**	**69.17**	**73.25**
CoSENT Loss	90.48	**89.79**	42.64	68.99	72.98
Triplet Loss	90.13	88.71	42.04	68.85	72.43
Cross-Entropy Loss	89.05	88.95	35.39	66.65	70.01

Table 4: The results of ablation study using different loss functions on the reranker section of C-MTEB. All results are based on Recursive-Funnel Inference. The best performance is in **bold**.

easily, leading to the best performance.

4.4.4 The Effect of Recursive-Funnel Inference

To explore the effect of Recursive-Funnel Inference, we compared the results of ListConRanker using Recursive-Funnel Inference with other inferences. The results are shown in Table 1. In the traditional inference approach, we input all passages into the ListConRanker at once. And we directly sort the passages based on their output scores to obtain all the results. It can be observed that Recursive-Funnel Inference improves performance on both the cMedQA1.0 and MMarcoReranking datasets, especially on MMarcoReranking. This is due to the fact that each query in MMarcoReranking corresponds to a large number of candidate passages, as mentioned above. In contrast, Recursive-Funnel Inference has a slight negative effect on cMedQA2.0. This might be because all the negative passages in the cMedQA2.0 are very similar to the query, causing the positive passages to be ranked lower in the early iterations. Further, this prevents them from being input into the final iteration.

Besides, we attempted the traditional sliding window method. As different input orders of passages can lead to inconsistent output results, we randomly shuffled the passage order 10 times using different seeds and presented the average performance. It can be seen that compared with directly inputting all passages, sliding window inference is still better and surpasses the current state-of-the-art model. However, due to the instability of the sliding window method, its performance still lags behind the Recursive-Funnel Inference.

4.4.5 The Effect of Scaling Up ListTransformer

To explore whether ListConRanker has a scaling-up ability similar to LLMs (Kaplan et al., 2020), we conducted experiments with different numbers of ListTransformer layers. And the results are shown in Figure 4. However, as the number of layers increased, we do not observe a significant improvement in the performance of ListConRanker. In most cases, the number of passages corresponding to a query is small. Therefore, a smaller number of ListTransformer layers is already sufficient for effective comparison among passages and learning global comparative information. Moreover, this also demonstrates the robustness of ListConRanker to the layer of ListTransformer. ListConRanker outperformed the state-of-the-art model across all layer settings except for the 8-layer configuration, which might be due to the lack of an increase in the training data size alongside the training parameters. This caused the model to be undertrained.

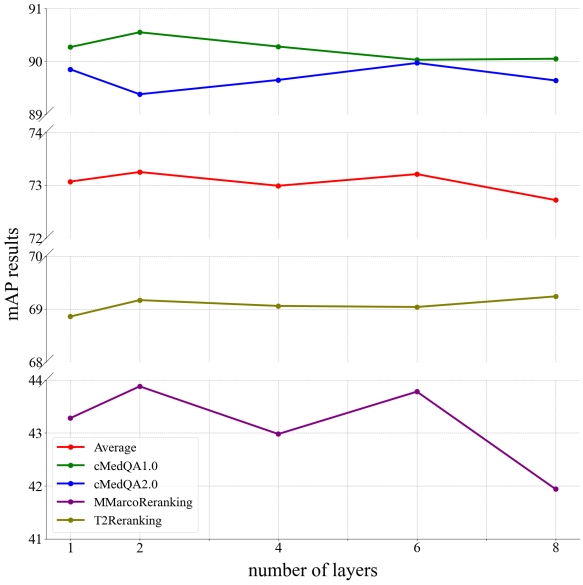

Figure 4: The influence of different layers of ListTransformer.

5 Conclusion

In this paper, we propose a novel reranker named ListConRanker by introducing listwise encoding through the use of the ListTransformer. The listwise encoding can help learn the global contrastive information between passages. In addition, we use ListAttention to help maintain the features of the query, which assist similarity calculations with passages. Finally, we propose to use the circle loss to replace the cross-entropy loss and solve the problem of data efficiency. Besides, circle loss can smooth the gradient and help the model to find the optimal space. The experimental results on the reranking benchmark of C-MTEB demonstrate the effectiveness of ListConRanker.

6 Limitations

We propose using Recursive-Funnel Inference to address the issue of disperse attention when inputting a large number of passages, especially in the MMarcoReranking dataset. This problem arises due to the lack of training samples with large numbers of passages. However, Recursive-Funnel Inference leads to the need for multiple inferences on some passages, which increases time complexity. For datasets where each query corresponds to only a small number of passages, the impact of the increased time complexity is subtle. We have other methods to address the issue of large numbers of passages while reducing time complexity. For example, we can sample a small number of passages from the passage set P. We remove these samples from P after obtaining the similarity scores. And we repeat the process multiple times to obtain all similarity scores and get the final order. However, the randomness of sampling can cause instability and uncertainty in the results. Therefore, we need to explore a low-time-complexity inference method for simultaneously inputting a large number of passages in the future.

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A The Algorithm of Recursive-Funnel Inference

To better understand Recursive-Funnel Inference, we present the algorithm in Algorithm 1.

B How does Circle Loss Smooth the Gradients

In Equations 11-17, we have shown the calculation method of Circle Loss. We show how it smooths the gradient changes during the training process through predicted logits here. It is mainly related to four variables: s, O, α, and m. The γ is a scaling factor and has nothing to do with gradient smoothing. The Δ_{neg} and Δ_{pos} are the between-class and within-class margins respectively, which is similar to the margin value in Triplet Loss.

First, Circle Loss uses m and O to control the upper and lower bounds of the predicted logits. We take the training process of positive passages as an example. In the first-stage training phase, we set $m = -0.2$. When the positive logit is greater than

Algorithm 1 Recursive-Funnel Inference

Input: Query q, Passage $P = \{p_1, p_2, ..., p_N\}$, Termination condition of the iteration θ, Passage reduction rate per iteration β

Output: Ranked result $R = \{r_1, r_2, ..., r_N\}$, where r_i is the order of p_i

while $|P| > \theta$ **do**
  $nums \leftarrow \text{ceil}(|P| \times \beta)$
  $scores \leftarrow \text{ListConRanker}(q, P)$
  $orders \leftarrow \text{argsort}(scores)$ // Descending
  for each $i \in [1, nums]$ **do**
    $last\_one \leftarrow orders[-i]$
    $r_{last\_one} \leftarrow |P|$
    P.remove(p_{last_one})
  end for
end while
$scores \leftarrow \text{ListConRanker}(q, P)$
$orders \leftarrow \text{argsort}(scores)$ // Descending
for each $i \in [1, |P|]$ **do**
  $last\_one \leftarrow orders[-i]$
  $r_{last\_one} \leftarrow |P|$
  P.remove(p_{last_one})
end for
return R

$O_{pos} = 1 + m = 0.8$ in Equation 15, Circle Loss will set α_{pos} through Equation 17. At this time, the loss and gradient of this positive passage is 0.

In addition, when the predicted logit of a positive passage increases from the lower bound to the upper bound, the gradient can also change from large to small through α. This enables the model to accelerate training at the beginning and prevent missing the optimal space by reducing the gradient in the later stage of training. We still take the training of a positive passage as an example. In the early stage of training, when the predicted logit of the positive passage is close to 0, the value of α_{pos} in Equation 17 will be a positive value close to O_{pos}. In the later stage of training, when the predicted logit of the positive passage approaches the upper bound O_{pos}, α_{pos} will be a positive value close to 0. Eventually, α_{pos} will act as a weight for both the loss and the gradient on r_{pos} in Equation 13.

C Comparison between Circle Loss and Other Ranking Loss

In Section 4.4.3 and Table 4, we have demonstrated the differences between Circle Loss and other loss functions (i.e., CoSENT Loss, Triplet Loss, and Cross-Entropy Loss). In addition to these loss functions, there are also some traditional listwise ranking loss functions (e.g., ListNet (Cao et al., 2007) and ListMLE (Xia et al., 2008)). We will compare them in the following.

ListNet and ListMLE are designed for ranking tasks with multiple similarity labels (e.g., A > B > C > D). Only a small number of passages may have the same rank. ListNet and ListMLE can ensure that each passage is finally ranked in the correct position. In this case, the binary cross-entropy (BCE) loss function can not achieve a similar goal. However, since the training and testing data in C-MTEB only have two labels, similar and dissimilar (i.e., A = B = C > D), the training objectives of ListNet and binary cross-entropy loss are quite similar in this case. Their training objectives are both to make the predicted values of positive passages approach 1 and those of negative passages approach 0. And the performance of the BCE loss function can be referred to in Table 4. Finally, Circle Loss is preferred over BCE loss function because it has the property of smoother gradient changes, making it a better choice.

D Dataset Details

We train ListConRanker using the training sets of cMedQA1.0 (Zhang et al., 2017), cMedQA2.0 (Zhang et al., 2018), MMarcoReranking (Bonifacio et al., 2021), T2Reranking (Xie et al., 2023), huatuo(Li et al., 2023), MARC(Keung et al., 2020), XL-sum(Hasan et al., 2021), and CSL(Li et al., 2022). The details of these datasets are presented in Table 5.

- **cMedQA1.0 and cMedQA2.0:** We use the original datasets without any pre-processing.
- **MMarcoReranking:** We use the Simplified Chinese subset of MMarcoReranking. Due to the large number of queries in the Chinese subset (about 40M queries), training on the full dataset risks domain overfitting. Therefore, we randomly selected 400,000 samples from the Chinese subset. Additionally, since each query in the original dataset corresponds to only one positive passage and one negative passage, which differs from the reranking task format, we applied a hard negative mining method to increase the number of negative passages per query to 20.

Dataset	Number of query	Avg. number of passages per query
cMedQA1.0	5,000	31.87
cMedQA2.0	10,000	51.88
MMarcoReranking	400,000	21.00
T2Reranking	105,668	8.11
huatuo	177,703	21.00
MARC	200,000	21.00
XL-sum	37,362	21.00
CSL	395,927	21.00
Total	1,331,660	20.25

Table 5: The details of all training datasets.

- **T2Reranking:** Since the T2Reranking dataset has four similarity labels for passages (ranging from 0 to 3, where 0 is the least similar and 3 is the most similar), but the test set is evaluated with only two similarity labels, we treat passages with labels 1 to 3 as positive examples and passages with label 0 as negative examples in the training set. Additionally, we filter out queries that do not have both positive and negative examples, using the remaining queries as the final training set.
- **huatuo and CSL:** Since the original datasets have only one positive passage and no negative passage per query, we applied a hard negative mining method to increase the number of negative passages to 20.
- **MARC and XL-sum:** We use their Simplified Chinese subsets. Similar to huatuo and CSL, since the original datasets have only one positive passage per query and no negative passage, we applied a hard negative mining method to increase the number of negative passages to 20.

The number of passages obtained through hard negative mining has not been verified through detailed experiments. It was determined empirically.

E The Reason of Two-stages Training

Both the MLPs and ListTransformer are trained from scratch. Since they don't have any meaningful information in the first stage, to prevent the embedding model from being influenced by the MLPs and ListTransformer and learning incorrect information, we freeze the embedding model. Besides, we select a value of m that is easier to learn, so as to enhance the generalization ability of the model and prevent the model from falling into the local optimal space. In the second stage, after the ListTransformer and MLPs have developed semantic discrimination capabilities, we select a more aggressive value of m to enable the ListConRanker to learn domain knowledge.

F Hyperparameters Selections

- l**:** The choice of the l hyperparameter is discussed in Section 4.4.5.
- γ**:** The selection of γ was not specifically tuned but was based on empirical experience.
- θ**:** We set θ to 20 because the average number of passages per query is around 20. The model performs well in terms of ranking when the number of passages is less than or equal to 20, so we decided to stop the Recursive-Funnel Inference at this point.
- β**:** Setting β to 0.2 is the result of balancing the computational complexity of Recursive-Funnel Inference and the ranking performance. Setting it too small would require multiple rounds of Recursive-Funnel Inference to complete a single prediction, increasing computational cost. On the other hand, setting it too large would lead to some positive passages being filtered out, causing a decline in model performance.

G Additional Parameters and Computational Complexity

Compared to previous embedding-based baselines (e.g., Conan-embedding-v1, xiaobu-embedding-v2, and zpoint-large-embedding-zh), ListConRanker introduces the ListTransformer module for listwise encoding. This adds more parameters to the model. The embedding model has 327M parameters. ListConRanker adds an additional 74M parameters (including the ListTransformer and the upper-layer MLPs), bringing the total parameter count to 401M.

However, although a considerable number of parameters have been added, the input sequence length for ListTransformer is small due to the reranking task typically involving only a small number of candidate passages. This is favorable for the $O(N^2)$ computational complexity of attention in ListTransformer. For example, when inputting 1 query and 10 candidate passages, each with a token length of 256, the inference of the embedding model requires 7.18G FLOPS. In this case, the input sequence for ListTransformer has 11 tokens,

Model	cMedQa1	cMedQA2	MMR	T2Reranking
monoT5	712	717	538	1395
Conan-embedding-v1	110	107	74	393
ListConRanker w/ TI	148	144	176	404
ListConRanker	572	559	775	490

Table 6: The inference time using single NVIDIA A800 40GB GPU on the reranking benchmark of C-METB compared with the baselines. TI stands for Traditional Inference. The time unit is seconds.

and it only requires an additional 0.26G FLOPS, which is about a 3.6% increase compared to the embedding model. Therefore, we believe the added ListTransformer module is computationally efficient and worth trying.

To further verify the time efficiency of ListConRanker, we present its inference time compared with the baseline on each dataset in Table 6. Although Recursive-Funnel Inference will increase the inference time, in fact, as shown in Table 1 of the paper, it is unnecessary to use Recursive-Funnel Inference in most datasets. Recursive-Funnel Inference has almost no impact on the performance of cMedQA1.0, cMedQA2.0, and T2Reranking. In extreme cases (i.e., MMarocoReranking), although using Recursive-Funnel Inference requires more time, it also significantly improves its performance (+6.36%).

Besides, it is worth noting that the inference time of ListConRanker remains significantly shorter than that of monoT5, a typical generative pointwise reranker, even with the use of Recursive-Funnel Inference. This further demonstrates that ListConRanker has more efficient parameters and time utilization. It also indicates that BERT-based models still deserve research in the field of rerankers.

H PassageAttention Details

We introduced PassageAttention, an approach opposite to ListAttention, in Section 4.4.1. Its attention mask is shown in Figure 5.

In ListAttention, we allow passages to directly interact through attention and learn comparative information. Each passage learns similarity information from the query and compares itself to other passages. This does not alter the semantic information of the query, ensuring that enough semantic information remains for accurate similarity prediction.

However, the comparison between passages is mediated through the query in PassageAttention, which means the query representation contains information from all the passages. This additional information in query representation is redundant and inefficient for similarity computation. When the query information is lost, the final similarity calculated with the passages results in significant errors, leading to the worst performance.

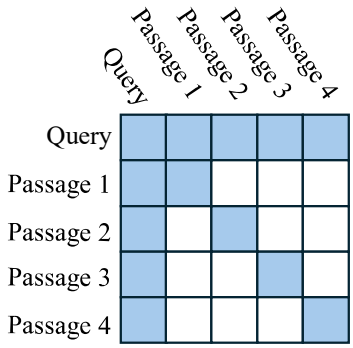

Figure 5: The attention mask of PassageAttention.

I Reimplementation details

To better demonstrate the effectiveness of ListConRanker, we reproduced and compared it with models that performed well on non-Chinese benchmarks in Table 1. We made some necessary modifications to the models due to adaptability reasons, which are described in detail below:

- **monoT5** (Nogueira et al., 2020a): Since the T5 (Raffel et al., 2020) used in the paper does not support Chinese, we replaced it with Flan-T5-large (Chung et al., 2024).
- **ListT5** (Yoon et al., 2024): We replaced the T5 used in the paper with Flan-T5-large for the same reason as monoT5. Additionally, since the Tournament Sort proposed in the paper only applies to input passages that are integer multiples of the window size, which does not match the characteristic of non-fixed input passage numbers in the C-MTEB, we replaced Tournament Sort with sliding window sorting, which has higher computational complexity and better performance.

J Baseline Links

Since most of the baselines do not have technical reports, we mainly provide the links to their open-source models here.

- **Conan-embedding-v1** (Li et al., 2024)**:** https://huggingface.co/TencentBAC/Conan-embedding-v1

- **xiaobu-embedding-v2:** https://huggingface.co/lier007/xiaobu-embedding-v2
- **zpoint-large-embedding-zh:** https://huggingface.co/iampanda/zpoint_large_embedding_zh
- **LdIR-Qwen2-reranker-1.5B:** https://huggingface.co/neofung/LdIR-Qwen2-reranker-1.5B
- **ternary-weight-embedding** (Chen et al., 2024)**:** https://huggingface.co/malenia1/ternary-weight-embedding
- **360Zhinao-1.8B-Reranking** (Team, 2024)**:** https://huggingface.co/qihoo360/360Zhinao-1.8B-Reranking
- **piccolo-large-zh-v2** (Huang et al., 2024): **:** https://huggingface.co/sensenova/piccolo-large-zh-v2