

Prompt-Based Document Modifications In Ranking Competitions

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ABSTRACT

We study prompting-based approaches with Large Language Models (LLMs) for modifying documents so as to promote their ranking in a competitive search setting. Our methods are inspired by prior work on leveraging LLMs as rankers. We evaluate our approach by deploying it as a bot in previous ranking competitions and in competitions we organized. Our findings demonstrate that our approach effectively improves document ranking while preserving high levels of faithfulness to the original content and maintaining overall document quality.

1 INTRODUCTION

In competitive search settings [10], document authors might respond to rankings induced for queries of interest by modifying their documents. The goal is to improve future ranking. These modifications are often referred to as search engine optimization (SEO) [8]. Our focus, as that of prior work on competitive search [6, 10, 19], is on white hat SEO [8]: legitimate document modifications which do not hurt document quality nor the search ecosystem.

We present novel ranking incentivized document modification methods for ad hoc retrieval that are based on prompting large language models (LLMs). The desiderata of the modifications are (cf., [6]): (i) potentially improving future ranking for a query at hand, (ii) maintaining “faithfulness” to the original document, and (iii) producing a document of high (content) quality. Some of our methods are inspired by recent work on using prompting techniques to have LLMs induce rankings in response to queries [11, 12, 18]. For example, some of the prompts include information induced from past rankings to provide the LLM with implicit information about the undisclosed ranking function.

We evaluate the document modification methods using datasets that resulted from past ranking competitions [13, 19]. In addition, we organized ranking competitions and used our modification methods as bots competing against humans¹. The empirical evaluation demonstrates the merits of the most effective methods we studied with respect to humans and to a highly effective feature-based approach for ranking-incentivized document modification [6].

¹The dataset of the competition we organized, and the accompanying code, will be made public upon publication of this paper. They are available for reviewing purposes at <https://github.com/promptdriven2025>.

Related work. We refer the reader to [10] for a survey on competitive search. The work most related to ours is that of Goren et al. [6] who devised a supervised feature-based ranking-incentivized document modification method. We discuss the method in Section 3 and use it as a baseline.

There is recent work on performing SEO for Web pages by prompting LLMs [3]. The prompts are designed for commercial search engines such as Google and are not well suited to the general ranking functions we use for evaluation. In addition, the prompts, in contrast to ours, do not include examples of past rankings and are mainly zero shot.

There is work on attacks (not necessarily white hat) on BERT-based document rankers (e.g., [23]) and on LLM-based document and product rankers, conversational agents and question answering systems (e.g., [9, 14, 17]). Our focus, in contrast, is on white hat content modification for document ranking which is not committed to a specific ranking function. We focus on dense and sparse retrieval in our evaluation.

2 DOCUMENT MODIFICATION METHODS

We present methods utilizing a large language model (LLM) that modify a document so as to have it highly ranked in the next ranking induced for a query by an undisclosed ranking function. We assume that past rankings for the query and other queries can be observed. We post two additional goals for the modification: having the resultant document of high quality (in terms of discourse) and as “faithful” as possible to the original document in terms of the content it contains [6].

The modification methods are based on prompting an LLM. The prompts have two parts: (i) a general shared part which describes the task (document modification for improved ranking) with a directive to maintain similarity to the original document (i.e., faithfulness); and, (ii) context-specific part, specific to a prompt, which provides information about past rankings. We assume that the LLM produces high quality content in terms of discourse. The general shared part is:

Edit the candidate document to improve its search engine ranking for the candidate query, aiming for the highest rank (1 being the highest). Use the black box search engine’s past rankings over various queries, provided as context by the user, to guide your edits. Focus on editing the most impactful sentences to enhance ranking potential.

Target an edited document length of around «median length of context document corpus» words, not exceeding 150 words. Ensure the edited document is very similar to the candidate document. Generate only the edited document, without additional comments or titles.

Input:

- Candidate Query: <query>
- Candidate Document: <current document>

The placeholder: «median length of context document» is the median number of words in documents provided in the context-specific part of the prompt that follows the general part.

Context-specific part. The goal of this part of the prompt is to provide the LLM with “hints” about the undisclosed ranking function; specifically, past rankings. We present four types of context, most of which are inspired by work on using LLMs to induce ranking [12, 15, 18].

- **Pointwise:** The context includes pairs of a query and a document which was the highest ranked in the past for the query. This context is inspired by pointwise approaches to LLM ranking which provide the LLM with a query and examples of relevant and non-relevant documents (e.g., [11]). Including the documents most highly ranked in the past for the query at hand is conceptually reminiscent of a prevalent document modification strategy in competitive search [7, 19]: mimicking content in the most highly ranked documents in the past.
- **Pairwise:** Inspired by work on using pairwise approaches to prompt an LLM to induce ranking [18], the context includes queries accompanied with pairs of documents and an indication about which was ranked higher.
- **Listwise:** Inspired by listwise prompting approaches for LLM ranking [12], the context includes queries and ranked document lists.
- **Temporal:** The context includes a query and versions of the same document and their ranks in past rankings induced for the query. The goal is to provide the LLM with information about how modifications of a document affected its ranking along time.

Prompt configurations. There are numerous configurations of the context-specific part that we study. These are determined by the following factors and parameters: (i) the number of queries used; (ii) the number of examples used per query: number of the most highest ranked documents in the past (Pointwise), number of pairs (Pairwise), number of ranked lists (Listwise) and number of documents with their temporal changes and ranks (Temporal); (iii) whether the rank of the document to be modified in the last ranking induced for the query is included; (iv) whether the query at hand is included in the prompt, or alternatively only other queries; (v) for the pairwise approach (Pairwise) we consider a random selection of the pair of documents or the highest ranked document and an additional randomly selected document; and, (vi) for the Temporal approach (Temporal), we vary the number of past ranks of the example document.

3 EXPERIMENTAL SETTINGS

Datasets. We use datasets which are reports of ranking competitions [13, 19]. In these competitions, students were assigned to queries and had to produce documents that would be highly ranked. Before the first round the students were provided with an example of a document relevant to the query. In each of the following rounds, the students observed past rankings for their queries and could modify their documents to potentially improve their next round ranking.

The first dataset, **LambdaMARTComp**, is the result of ranking competitions held for 31 queries from the TREC9-TREC12 Web tracks [19]. Five to six students competed for each query. The undisclosed ranking function was LambdaMART [4] applied with various hand-crafted features. Following Goren et al. [6], whose document modification approach, **SentReplace**, serves as a baseline², we use round 7 for evaluation [19]. SentReplace is a state-of-the-art feature-based supervised method for ranking-incentivized document modification. It replaces a sentence in the document with another sentence to improve ranking and to maintain content quality and faithfulness to the original document.

The second dataset, **E5Comp**, is a report of ranking competitions [13] where the undisclosed ranking function was the cosine between the E5 embedding vectors [22] of a document and a query³. The competitions were run for 7 rounds with 15 queries from the Web tracks of TREC9-TREC12; 4 players were competing for each query [21]. We used round 4 for evaluation to allow the document modification methods to have enough history of past rankings.

For both datasets just described, we apply the different document modification methods, henceforth referred to as **bots**, upon each of the documents in the ranked list for a query in the specified round (except for the highest ranked document). For each selected document, we induce a ranking using the same ranker used in the competitions over its modified version and the original next-round versions of the other documents (of students) from the round. We use the evaluation measures described below upon the resultant ranking. We average the evaluation results across all documents we modified per round and over queries.

Evaluation measures. To evaluate rank promotion (demotion) of documents as a result of modification, we follow Goren et al. [6] and report **Scaled Promotion**: the increase (decrease) of rank in the next round with respect to the current round normalized by the maximum possible rank promotion (demotion).

To evaluate the faithfulness of a modified document (d_{mod}) to its original (current) version (d_{curr}), we compare the two documents using Gekhman’s et al. [5] natural language inference (NLI) approach. Specifically, we estimate whether one document (denoted *hypothesis*) is entailed from the other document (denoted *premise*) while preserving factual consistency. The estimate is the TT (TrueTeacher) measure: $TT(premise, hypothesis)$ is the output of the model in the range [0,1]; higher scores indicate stronger factual alignment.

²We found that using LambdaMART instead of SVMrank as originally proposed [6] yields improved performance.

³The intfloat/e5-large-unsupervised version from the Hugging Face repository (<https://huggingface.co/intfloat/e5-large-unsupervised>).

To apply the TrueTeacher model, we first compute the average number of sentences in the modified document that are entailed⁴ by the current document, which we refer to as raw faithfulness (RF): $RF(d_{mod}, d_{curr}) \stackrel{def}{=} \frac{1}{n} \sum_{i=1}^n \delta[TT(d_{curr}, d_{mod}^i) \geq 0.5]$; d^i is the i 'th sentence in document d ; δ is Kronecker's indicator function. Since $RF(d_{curr}, d_{curr})$ is not necessarily 1, we normalize the raw faithfulness to yield our **OrigFaith** measure: $\frac{RF(d_{mod}, d_{curr})}{RF(d_{curr}, d_{curr})}$.

Using LLMs to modify documents raises a concern about hallucinations [20]. We hence measure the extent to which the content in the modified document is "faithful" to that in the entire corpus⁵. To that end, we treat the current document as a query, and retrieve the top- k ⁶ documents in the corpus; T denotes the retrieved set. Retrieval is based on using cosine to compare a query embedding and the document embedding. We use two types of embeddings: E5 [22] and TF.IDF. We define raw corpus faithfulness (RCF) as: $RCF(d_{mod}) \stackrel{def}{=} \frac{1}{2k} \sum_{d \in T} (RF(d_{mod}, d) + RF(d, d_{mod}))$. The normalized corpus faithfulness measure we use is: $CF(d_{mod}) \stackrel{def}{=} \frac{RCF(d_{mod})}{RCF(d_{curr})}$. Using the E5 and TF.IDF embeddings results in the **CorpFaith(E5)** and **CorpFaith(TF.IDF)** normalized corpus faithfulness measures, respectively.

Statistically significant differences are determined using the two-tailed paired permutation test with 100,000 random permutations and $p < 0.05$.

Instantiating bots. For LLM we use Chat-GPT 4o [2]. As described in Section 2, there are a few parameters affecting the instantiation of specific prompts. The number of queries is set to a value in $\{1, 2\}$. The number of examples per query is selected from $\{1, 2, 3\}$. The number of past ranks (i.e., rounds) in the Temporal prompt is selected from $\{2, 3\}$. Using these parameter values, and the other binary decision factors that affect instantiation (see Section 2), results in 192 different bots (prompts). In addition, we set the LLM's temperature parameter which controls potential drift to values in $\{0, 0.5, 1, 1.5, 2\}$ [16].

Rank promotion performance of bots. In terms of Scaled Promotion, we found⁷ that the Pairwise bots (with random selection of document pairs) and the Listwise bots were the best performing for both the LambdaMARTComp and E5Comp datasets; the same specific instantiation of each of these two bots was always among the top-3 performing bots for both datasets. This finding attests to the rank-promotion effectiveness of these types of bots (prompts) for different rankers (LambdaMART and E5). The Temporal bots (prompts), which provide rank-changes information along rounds, were less effective (in terms of Scaled Promotion) than the Pairwise and Listwise bots, but were more effective than the Pointwise bots.

In what follows, we present the evaluation of the two bots which posted for both datasets Scaled Promotion among the best three:⁸

- Pairwise, where only the given query is included, one random pair of documents for each of the three last rounds is provided as examples, the current rank of the document is not used, and the temperature is set to 0.5.
- Listwise, where only the given query is included, two previous rounds are used, the current rank is not used, and the temperature is set to 0.

Appendix A provides the prompts for these bots.

Online evaluation. The evaluation performed over the LambdaMART-Comp and E5Comp datasets is offline and therefore spans a single round: the students who competed in the competition did not respond to rankings induced over the documents we modify here. We therefore also performed online evaluation where our instantiated prompts competed as bots against students. We organized a ranking competition⁹ similar to that of Mordo et al. [13] using 15 queries from TREC9-TREC12¹⁰. In contrast to Mordo et al.'s competitions [13], each game included 5 players: two-three students, one of the two bots discussed above (Pairwise or Listwise), and one or two static documents were created using a procedure similar to the one in Raifer et al. [19]: first, we used the query in the English Wikipedia search engine and selected a highly ranked page. We then extracted a candidate paragraph from this page, with a length of up to 150 words. Three annotators assessed the relevance of the passages, and we repeated the extraction process for each query until at least two annotators judged a paragraph as relevant. The selected paragraph was then used as a static document for the query for all students.

The students were not aware that they were competing against bots. We applied our bots in rounds 5¹¹, 6 and 7 and report the average performance over these three rounds.

We had documents in the online evaluation judged for relevance and quality using crowdsourcing annotators on the Connect platform of CloudResearch [1]. Following past work on ranking competitions [6, 19], a document's quality grade is set to 1 if at least three out of five English-speaking annotators marked it as valid (as opposed to keyword stuffed or useless) and to 0 otherwise. The relevance grade was 1 if the document was marked relevant by at least three annotators and 0 otherwise.

4 EXPERIMENTAL RESULTS

Table 1 presents the evaluation over the LambdaMARTComp. We let one of our bots, or the baseline bot, SentReplace [6], modify a single document at a time. We then analyze the resultant ranking over the single modified document and the next-round students' documents from the dataset. The performance numbers are averages over the different selected documents to be modified (all but the highest ranked one) and over queries. Note that the Students' faithfulness values are not block dependent as they are the same in all three cases in the next round. Their Scaled Promotion is affected by the bot used to modify the selected document.

⁴Entailment is determined by a threshold of 0.5 for the TT score [5].

⁵For a corpus we use all the documents in all rounds prior to the round on which evaluation is performed.

⁶We set $k = 10$ in our experiments.

⁷Actual numbers are omitted due to space considerations and as they convey no additional insight.

⁸These bots were also the best performing in the online evaluation presented below.

⁹The competition was approved by institution and international ethics committees.

¹⁰These are different queries than those used in the E5Comp dataset: 21, 55, 61, 64, 74, 75, 83, 96, 124, 144, 161, 164, 166, 170, 194.

¹¹Due to technical issues, we could not run the bots at round 4 as in the offline evaluation.

Table 1: Evaluation over the LambdaMARTComp dataset which resulted from competitions using a LambdaMART ranker [19]. The baseline (SentReplace [6]), Pairwise and Listwise blocks correspond to a round where a document was modified by the respective bot, and all other documents were of students. Boldface marks the best result in a column. Statistically significant differences of our bots with SentReplace and the students are marked with 'r' and 's', respectively.

	Scaled Promotion	OrigFaith	CorpFaith(E5)	CorpFaith(TF.IDF)
SentReplace [6]				
SentReplace	0.309	0.786	0.468	0.381
Students	0.313	0.727	0.544	0.504
Pairwise				
Our bot	0.345^s	0.57 ^s _r	0.507	0.437
Students	-0.095	0.727	0.544	0.504
Listwise				
Our bot	0.315 ^s	0.616 ^s _r	0.497	0.427
Students	-0.09	0.727	0.544	0.504

Table 1 shows that our Pairwise and Listwise bots outperform SentReplace and the students in terms of Scaled Promotion. The faithfulness of both of our bots is lower than that of the students and SentReplace but is still quite high. Note that SentReplace modifies a single sentence in a document and, hence, the modified document is quite faithful to the original document. The corpus faithfulness of both our bots (for both TF.IDF and E5) is higher than that of SentReplace. Thus, although our bots use an LLM (as opposed to SentReplace and the students), their corpus faithfulness is relatively high.

Table 2 presents the evaluation for the E5Comp dataset¹². The results presented above for LambdaMARTComp show that the bots were not better than the students in terms of corpus faithfulness. Over the E5Comp, our bots outperform the students with respect to Scaled Promotion and corpus faithfulness and underperform them in terms of faithfulness to the original document, although this faithfulness is still relatively high. All in all, Tables 1 and 2 attest to the effectiveness of our bots for both ranking functions: LambdaMART and E5.

Table 3 presents the evaluation for the online competitions (our bots vs. students) which used the E5 ranker. Q and R are the average quality and relevance grades, respectively. The Pairwise and Listwise blocks correspond to competitions where one of the two bots participated. Boldface marks the best result in a column. Statistically significant differences of our bots with the students are marked with 's'.

All in all, the findings presented above attest to the clear merits of our bots with respect to students and the SentReplace baseline

¹²We do not use here and after the SentReplace baseline as it was defined for sparse ranking functions.

Table 2: Evaluation over the E5Comp dataset which resulted from competitions using an E5 ranker. The Pairwise and Listwise blocks correspond to a round where a document was modified by the respective bot and all other documents were of students. Boldface: the best result in a column. Statistically significant differences of our bots with the students are marked with 's'.

	Scaled Promotion	OrigFaith	CorpFaith(E5)	CorpFaith(TF.IDF)
Pairwise				
Our bot	0.241 ^s	0.623 ^s	0.589	0.603
Students	-0.107	0.788	0.531	0.542
Listwise				
Our bot	0.341^s	0.711	0.573	0.592
Students	-0.128	0.788	0.531	0.542

Table 3: Online evaluation. Q and R are the average quality and relevance grades, respectively. The Pairwise and Listwise blocks correspond to competitions where one of the two bots participated. Boldface marks the best result in a column. Statistically significant differences of our bots with the students are marked with 's'.

	Scaled Promotion	OrigFaith	CorpFaith(E5)	CorpFaith(TF.IDF)	Q	R
Pairwise						
Our bot	0.098_b	0.839 _b	0.663 _b	0.735 _b	0.822	0.8_b
Students	0.029	0.821	0.675	0.726	0.925	0.642
Listwise						
Our bot	0.05	0.875_b	0.717_b	0.756_b	0.911 ^s	0.8_b
Students	-0.013	0.865	0.685	0.754	0.732	0.66

along various dimensions; specifically, rank promotion, document quality and relevance, and faithfulness to the corpus.

5 CONCLUSIONS

We presented novel methods for ranking incentivized document modifications: modifying a document so it will be highly ranked by an undisclosed ranking function for a query. Our methods are based on prompting large language models (LLMs). Some of our methods are inspired by prompting approaches for inducing LLM-based ranking over documents.

We conducted extensive empirical evaluation using past ranking competitions (for two different rankers). In addition, we organized ranking competitions where our document modification methods competed as bots against students.

The empirical evaluation demonstrated the merits of our best performing modification methods with respect to students and a previously proposed highly effective feature-based document modification approach.

A PROMPTS

```
PAIRWISE_PROMPT = "\n\nquery: <QUERY>\n\n* document: <
DOCUMENT a>\n\nlatest ranking: <RANK r(a)>\n\n\n*
document: <DOCUMENT b>\n\nlatest ranking: <RANK r(b)
>\n\n\n\nquery: <QUERY>\n\n* document: <DOCUMENT c
>\n\nsecond to latest ranking: <RANK r(c)>\n\n\n*
document: <DOCUMENT d>\n\nsecond to latest ranking:
<RANK r(d)>\n\n\n\nquery: <QUERY>\n\n* document: <
DOCUMENT e>\n\nthird to latest ranking: <RANK r(e)>\n
\n\n* document: <DOCUMENT f>\n\nthird to latest
ranking: <RANK r(f)>"
```

Figure 1: Context-specific part of the Pairwise prompt which includes document pairs from the last three rankings. For each ranking, two documents, (a,b), (c,d), (e,f), were randomly selected and their rank is specified: r(a), r(b), r(c), r(d), r(e), r(f).

```
LISTWISE_PROMPT = "\n\nquery: <QUERY>\n\n* documents
ordered by latest ranking from highest to lowest in
relation to the query: \n\n\n* <DOCUMENT a>\n\n\n* <
DOCUMENT b>\n\n\n* <DOCUMENT c>\n\n\n* <DOCUMENT d>\n
\n\n\n\n* documents ranked by second to latest
ranking from highest to lowest in relation to the
query:\n1. <DOCUMENT e>\n2. <DOCUMENT f>\n3. <
DOCUMENT g>\n4. <DOCUMENT h>\n5. <DOCUMENT i>\n\n\n\n
"
```

Figure 2: Context-specific part of the Listwise prompt which includes the latest ranking over documents: a, b, c, d (excluding the current document) and the previous ranking of the entire document list: e, f, g, h, i.

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