# **Ranking-Incentivized Quality Preserving Content Modification**

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## ABSTRACT

The Web is a canonical example of a competitive retrieval setting where many documents' authors consistently modify their documents to promote them in rankings. We present an automatic method for quality-preserving modification of document content — i.e., maintaining content quality — so that the document is ranked higher for a query by a non-disclosed ranking function whose rankings can be observed. The method replaces a passage in the document with some other passage. To select the two passages, we use a learning-to-rank approach with a bi-objective optimization criterion: rank promotion and content-quality maintenance. We used the approach as a bot in content-based ranking competitions. Analysis of the competitions demonstrates the merits of our approach with respect to human content modifications in terms of rank promotion, content-quality maintenance and relevance.

## **1 BACKGROUND AND MOTIVATION**

Several research communities nurture work on adversarial attacks on algorithms. The motivation is to push the sate-of-the-art by identifying model and algorithmic weaknesses. The "attacked" algorithms are often used in real-life systems (e.g., face recognition [14]). Exposing their vulnerabilities is considered an accelerator for innovation more than a threat.

A classic example is the crypto community. Throughout the decades, publications of successful attacks on crypto mechanisms helped to push forward improved mechanisms [7]. Additional examples are the machine learning, natural language processing and vision communities. There has recently been much work on devising adversarial attacks on machine learning algorithms — specifically neural networks — that span different tasks: general machine learning challenges [20, 35, 40], reading comprehension [22], speaker identification [27], object detection [43], face recognition [14], and more. This line of work has driven forward the development of algorithms which are more robust to adversarial examples; e.g., Jia et al. [23], He et al. [19], Zhang et al. [47].

The Web search echo-system is, perhaps, the largest-scale adversarial setting in which algorithms, specifically search methods,

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operate. That is, many document authors consistently modify their documents to have them more highly ranked for specific queries. This practice is often referred to as search engine optimization (SEO) [18]. The incentive is quite clear: high ranks translate to high utility as most of the attention – and therefore engagement - of search engine users is focused on the documents most highly ranked [25]. Some SEO techniques are considered "illegitimate" (a.k.a., black hat [18]) as they are unethical and hurt the echosystem (e.g., search effectiveness and/or user experience); spamming is a prominent example. Other techniques are considered completely "legitimate" (a.k.a., white hat [18]) as they are intended to improve documents' representations with respect to queries to which they pertain. Thus, in the "ranking games" that take place on the Web [41], the documents' authors are "players" or "adversaries" whose adversarial actions can be "legitimate" (white hat) or "illegitimate" (black hat); the search engine's ranking function is the mediator.

Despite its importance as a large scale and highly evolved adversarial setting, and despite the research attention paid to adversarial attacks and defenses in other research communities as mentioned above, the adversarial effects in the Web search echo-system have attracted relatively little research attention [1, 8]. An important reason for this reality is that developing black hat SEO techniques is unethical, and can hurt the search echo-system in the short term. Yet, it can also potentially help to find vulnerabilities of search functions which is important for improving them in the long run. We subscribe to the stand that, despite the potential long term merits, such type of work should see no place in scientific publications.

Still, an important question is why there is not a much larger body of work on addressing adversarial effects. The vast majority of such work has been on spam identification [1, 8]. One part of the answer seems to be that many of the adversarial effects are due to, or involve, the dynamic nature of the Web — changes of pages, ranking function, indexing cycles, etc. For example, the fact that some authors are incentivized to compete for improved ranking yields, in white hat settings, negative impact on the search echo-system; specifically, degrading topical diversity in the corpus [4, 38]<sup>1</sup>. Studying such dynamics in terms of rankings seems to require access to query logs of large-scale commercial Web search engines. In other words, it is very difficult to impossible to replicate the dynamic search setting on the Web. In contrast, for example, devising and evaluating content-based spam classifiers can be done using a static snapshot of documents and regardless of rankings.

We claim that the state-of-affairs just described, in terms of the limited volume and scope of work on adversarial Web search, is

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<sup>&</sup>lt;sup>1</sup>Similar dynamics in recommendation systems was also studied [5].

nowadays being challenged to a major extent and there is a call to action. In the last few years there has been a dramatic change in terms of the potential ability to generate large scale and high quality black hat content effects. For example, advanced language modeling techniques such as BERT [10], GPT2 [37] and XLNet [44] can be used to automatically generate fake content at scale [45]. While fake content could be considered spam, it is way more difficult to identify than classic spam, especially when generated using the above mentioned state-of-the-art techniques [45]; as a case in point, fake content could still be of high quality. Another example for a modern threat on search engines is that for neural-based retrieval methods [34]. It could be the case that adversarial attacks on neural methods used for vision and NLP applications as mentioned above will soon be translated to attacks on ranking methods.

One of the important implications of the reality just described is that Web document authors who will not use automatic tools for content creation and manipulation, specifically for automatic white-hat SEO which will help their documents to be highly ranked when they deserve to, will not be competitive in the adversarial search setting. This implication, together with the fact that creating benchmarks that will allow to research dynamic and adversarial search settings remains highly difficult to impossible to achieve, motivate our work. That is, given the increased ability to hurt the search echo-system, we strive to counter balance it by developing legitimate, white hat, tools that can (i) help Web authors in the competitive search setting without hurting the search echo-system, and (ii) be used for creating publicly available benchmarks that will allow to study competitive and adversarial dynamic search settings.

## **2** CONTRIBUTION

We present the first, to the best of our knowledge, attempt to devise an automatic method of "legitimate", white hat, content modification of documents. The goal of the modification is promotion in rankings induced by a non-disclosed relevance ranking function for a given query. The method can observe past rankings for the query which are the only signals about the ranking function. By "legitimate" modification we mean a change that maintains the document's content quality in contrast to black hat SEO [18].

Our method replaces a short passage of the document with another short passage from a candidates pool. We cast this passage replacement task as a learning-to-rank (LTR) [32] problem over passage pairs: a passage in the document and a candidate passage for replacement. The optimization goal for training the LTR function is bi-objective: rank promotion and content-quality maintenance which we address via presumed coherence maintenance. The highest ranked passage pair is selected for the replacement.

We evaluated our approach by using it as a bot in content-based ranking competitions we organized between students<sup>2</sup>. The competitions were approved by international and institutional ethics committees. In the competitions, the bot produced documents which were promoted in rankings to a larger extent than the students' documents. Furthermore, the bot's content modifications did not hurt relevance in contrast to students' modifications of their documents, and maintained content quality to a large extent.

Hence, although simple, our approach constitutes a first scientific proof of concept for the feasibility of manipulating document content for rank promotion in search engines while maintaining the document quality. It is important to keep in mind that our focus in this paper is on the basic task of selecting passages of the document, and passages from some given pool, to perform the replacement. Creating the pool of candidates for replacement is an important task at its own right which we discuss as a future work; e.g., leveraging the recent significant progress in automatic language generation capabilities mentioned above. For the proof of concept in this paper, we simply used a pool of passages extracted from other documents which were highly ranked for the given query in past rankings. The motivation for this practice is based on some recent observations about SEO strategies employed by publishers [38]; namely, that they tend to mimic documents highly ranked in the past. Obviously, this is not a practical solution for pool generation due to copyright issues, but rather a means to our end of evaluating our proposed learning-based approach for passage replacement. In addition to devising methods for creating a pool of candidate passages, moving towards a practical application of our approach will call for introducing modifications which are not content-based. While content-based features are extremely important in Web ranking functions [32], there are other types of important features.

The line of research we pursue is important not only for document authors so as to "keep up" with the ranking game in a legitimate manner, but also for those who devise ranking functions in adversarial retrieval settings. That is, having document modification methods will allow to create a myriad of benchmarks which do not exist today for studying dynamic retrieval settings, even if in our case these are white hat.

## **3 RELATED WORK**

There is a body of work on identifying/fighting black hat SEO; specifically, spam [1, 8]. Our approach is essentially a content-based white hat SEO method intended to rank-promote *legitimate* documents via *legitimate* content modifications. We are not aware of past work on devising such automatic content modification procedures.

Our approach might seem at first glance conceptually similar to the black hat *stitching* technique [18]: authors of low-quality Web pages manually "glue" to their documents unrelated phrases from other documents. In contrast, our approach operates on descent quality documents and is optimized to maintain document quality.

Our approach can conceptually be viewed as ranking-incentivized paraphrasing: modifying the document to promote it in rankings, but keeping content quality and having the content remain faithful to the original content. Past work on paraphrasing (e.g., [2]) does not include methods intended to promote documents in ranking.

We use simple estimates (e.g., lexical and Word2Vec similarities) to measure the extent to which content coherence is maintained given the passage replacement. More evolved estimates can be used to this end [16, 28, 29, 31, 36]. Furthermore, one could modify the document using text-generation approaches that account for coherence [17, 21, 26], which we leave for future work.

<sup>&</sup>lt;sup>2</sup>The dataset is at: https://github.com/asrcompetition/content\_modification\_dataset; the code is at https://github.com/asrcompetition/content\_modification\_code.

Ranking-Incentivized Quality Preserving Content Modification

## 4 CONTENT MODIFICATION APPROACH

Suppose that the author of a document with descent content quality would like the document to be highly ranked for a query q by a search engine whose ranking function is not disclosed. More specifically, the author observes the current ranking,  $\pi_{cur}$ , induced for q, and her goal is to promote her document,  $d_{cur}$ , in the next induced ranking,  $\pi_{next}$ , assuming that  $d_{cur}$  was not the highest ranked in  $\pi_{cur}$ . We present an approach to automatically modifying  $d_{cur}$ 's content to this end, yielding a document  $d_{next}$ .<sup>3</sup>

There are three desiderata for the content modification: (i) maximizing the likelihood that  $d_{next}$  will be positioned in  $\pi_{next}$  at a higher rank than  $d_{cur}$ 's current rank in  $\pi_{cur}$ , (ii) maintaining content quality, and (iii) having  $d_{next}$  faithful to  $d_{cur}$  in terms of the provided information.

In reference to work on passage-based document paraphrasing (e.g., Barzilay and Lee [3]), we perform the content modification by replacing one of  $d_{cur}$ 's short passages with another short passage from a given pool of candidates,  $G_{pool}$ .<sup>4</sup> The goal is to optimize the replacement with respect to the desiderata mentioned above. We cast the task as a learning-to-rank challenge [32] over pairs of passages,  $(g_{src}, g_{target})$ , where  $g_{src} \in G(d_{cur})$  and  $g_{target} \in G_{pool}$ ;  $G(d_{cur})$  is the set of  $d_{cur}$ 's passages. The highest ranked passage pair is used for replacement.

Candidate passages in the pool Gpool can be created in various ways; e.g., from scratch using language generation techniques, or by paraphrasing passages in  $d_{cur}$  or those in other documents. However, our focus here is on the passage-pair ranking challenge, and more generally, on the first proof of concept for the contentmodification challenge we pursue. Hence, we used a simple approach to create G<sub>pool</sub> following recent findings about strategies employed by documents' authors to promote their documents in rankings [38]: authors tend to mimic content in documents that were highly ranked in the past for a query of interest. The merits of this strategy were demonstrated using theoretical and empirical analysis [38]. The simple motivation behind this strategy is that induced rankings are the only (implicit) signal about the ranking function, and documents highly ranked are examples for what the ranking function rewards. Accordingly, here,  $G_{pool}$  is the set of all passages in documents ranked higher than  $d_{cur}$  in  $\pi_{cur}$ . In practical applications, these passages will not be used directly to avoid copyright issues. As noted above, they can be paraphrased, or the passage pool creation can alternatively rely on automatic passage generation. We leave these challenges for future work.

## 4.1 Learning to Replace Passages

The ranking function for passage pairs,  $(g_{src}, g_{target})$ , should be optimized for the three desiderata described above. Here we focus on the first two — rank promotion and maintaining content quality. Since content quality is a difficult notion to quantify, we set as a goal to not significantly hurt "local coherence" in terms of the passage relations (e.g., semantic similarities) to its surrounding passages.

We do not directly address the desideratum of  $d_{next}$ 's faithfulness to  $d_{cur}$ . Yet, using the coherence-based features suggested

below and the fact that  $g_{src}$  and  $g_{target}$  are short passages help to keep  $d_{next}$  "semantically similar" to  $d_{cur}$ .

Our passage-pair ranking function is optimized, simultaneously, for achieving rank promotion and maintaining local coherence. This is a dual-objective optimization. Inspired by work on learning Web ranking functions with a dual objective: relevance and freshness [9, 12, 13], we use labels which are aggregates of rank-promotion and coherence labels.

Specifically, if  $d_{cur}$  is a document in the training data, and  $\pi_{cur}$  is the current ranking it is part of, we produce a rank-promotion label *r* with values in  $\{0, 1, \ldots, 4\}$  and a local-coherence maintenance label *c* with values in  $\{0, 1, \ldots, 4\}$  for each pair  $(g_{src}, g_{target})$  in  $G(d_{cur}) \times G_{pool}$ . Details about producing these labels are provided in Section 5. We then produce a single label  $l \ (\in \{0, \ldots, 4\})$  for  $(g_{src}, g_{target})$  by aggregating *r* and *c* using the (smoothed) harmonic mean  $[9]: l \stackrel{def}{=} \frac{(1+\beta^2)rc}{r+\beta^2c+\epsilon}$ , where  $\beta$  is a free parameter that controls the relative weight assigned to the rank-promotion and coherence labels, and  $\epsilon = 10^{-4}$  is a smoothing parameter.

We can now use these labels that quantify, simultaneously, rankpromotion and local coherence maintenance in any learning-torank approach [32] to learn a ranking function for passage pairs.

4.1.1 Features for Passage Pairs. The passage pair  $(g_{src}, g_{target})$  is represented by a feature vector with two types of features: those that target potential rank promotion as a result of moving from  $d_{cur}$  to  $d_{next}$ , and those that target the change of local coherence as a result of this move. None of the features is based on assuming knowledge of the ranking function for which promotion is sought.

Herein,  $\vec{x}^T$  denotes the TF.IDF vector representing text x (a document or a passage);  $\vec{x}^W$  denotes its Word2Vec-based vector representation [33]: we average the Word2Vec vectors of terms in a passage to yield a passage vector, and we average the resultant vectors of passages in a document to yield a document vector. We provide details of training Word2Vec in Appendix A. We measure the similarity between two vectors using the cosine measure.

## Rank-promotion features.

The QryTermSrc and QryTermTarget features are the fraction of occurrences of q's terms in  $g_{src}$  and  $g_{target}$ , respectively. The assumption is that document retrieval scores assigned by any retrieval method increase with increased query-terms frequency [15].

The SimSrcTop(T), SimTargetTop(T), SimSrcTop(W) and SimTargetTop(W) features are  $\cos(\vec{g}_{src}^T, cent_{\pi_{cur}}^T)$ ,  $\cos(\vec{g}_{target}^T, cent_{\pi_{cur}}^T)$ ,  $\cos(\vec{g}_{src}^N, cent_{\pi_{cur}}^W)$  and  $\cos(\vec{g}_{target}^W, cent_{\pi_{cur}}^W)$ , respectively;  $cent_{\pi_{cur}}^T$ , and  $cent_{\pi_{cur}}^W$  are the arithmetic mean (centroids) of the *m* TF.IDFbased and Word2Vec-based vectors, respectively, that represent the *m* most highly ranked documents in the current ranking  $\pi_{cur}$  that are also ranked higher than  $d_{cur}$ . We set the maximum value of *m* to 3. As the ranking function is unknown, similarity to top-retrieved documents can somewhat attest to increased retrieval score.

The next four features are based on the assumption that similarity of a passage to documents which were highly ranked in the past for the query can attest to improved retrieval score. Formally, we observe the *p* past and current rankings induced for  $q: \pi_{-1}, \pi_{-2}, ...,$  $\pi_{-p}; \pi_{-1}$  is the current ranking  $\pi_{cur}$  and  $\pi_{-2}$  is the previous ranking; *p* is a free parameter. Let  $d_{\pi_{-i}}$  be the document most highly

<sup>&</sup>lt;sup>3</sup>The "next ranking" is induced after the search engine indexed  $d_{next}$  instead of  $d_{cur}$ . <sup>4</sup>The approach does not depend on the passage markup technique.

ranked in  $\pi_{-i}$ ; we set  $cent_{\pi_{past}}^T \stackrel{def}{=} \sum_{i=1}^p w_i \vec{d}_{\pi_{-i}}^T$  and  $cent_{\pi_{past}}^W \stackrel{def}{=} \sum_{i=1}^p w_i \vec{d}_{\pi_{-i}}^T$ ;  $w_i$  is a time-decay-based weight:  $w_i \stackrel{def}{=} \frac{\alpha \exp(-\alpha i)}{\sum_{j=1}^p \exp(-\alpha j)}$ , which is inspired by work on time-based language models [30] with  $\alpha = 0.01$  [30]. Then, the features SimSrcPrevTop(T), SimTargetPrevTop(T), SimSrcPrevTop(W) and SimTargetPrevTop(W) are defined as  $\cos(\vec{g}_{src}^T, cent_{\pi_{past}}^T), \cos(\vec{g}_{target}^T, cent_{\pi_{past}}^T), \cos(\vec{g}_{src}^W, cent_{\pi_{past}}^W)$  and  $\cos(\vec{g}_{target}^W, cent_{\pi_{past}}^W)$ , respectively.

**Coherence-maintenance features**. The next features, all based on Word2Vec similarities, address local coherence. The SimSrcTarget(W) feature is:  $\cos(\vec{g}_{src}^W, \vec{g}_{target}^W)$ .

The next four features are similarities of  $g_{src}$  and  $g_{target}$  with the context of  $g_{src}$  in  $d_{cur}$ : its preceding and following passages in  $d_{cur}$  denoted  $g_{prec}$  and  $g_{follow}$ , respectively. Specifically, Sim-SrcPrecPsg(W), SimSrcFollowPsg(W), SimTargetPrecPsg(W) and SimTargetFollowPsg(W) are:  $\cos(\vec{g}_{src}^W, \vec{g}_{prec}^W)$ ,  $\cos(\vec{g}_{src}^W, \vec{g}_{follow}^W)$ ,  $\cos(\vec{g}_{target}^W, \vec{g}_{prec}^W)$  and  $\cos(\vec{g}_{target}^W, \vec{g}_{follow}^W)$ . If  $g_{src}$  is the first passage in  $d_{cur}$  then we use  $g_{follow}$  instead of  $g_{prec}$ ; if  $g_{src}$  is the last passage in  $d_{cur}$  we use  $g_{prec}$  instead of  $g_{follow}$ ; i.e., in both cases, the same feature is used twice.

## **5 EVALUATION**

Our document modification approach operates as follows. First, a ranking for a query is observed. Then, the approach is applied to modify a given document with the goal that the resulting document will be ranked higher in the next induced ranking. In real dynamic settings, other documents can change at the same time thereby affecting the next ranking. Accordingly, we devise two types of evaluation, online and offline, both based on a dynamic setting.

#### 5.1 Experimental Setting

To perform the online evaluation, we used our approach as a bot in live content-based ranking competitions that we organized. The competitions were inspired by those presented by Raifer et al. [38] who analyzed publishing strategies.

Our competitions were approved by an international and an institutional ethics committees. In the competitions, students in a course served as documents' authors and were assigned to queries. The students were incentivized via bonuses to the course grades to write and modify plain text documents of up to 150 terms so that the documents will be highly ranked for the queries. Students in the course could have attained the perfect grade without participating in the competitions. The students who participated signed consent forms and could have opted out at any point in time.

Our bot received a document to be modified so as to compete with the students for rank promotion. We organized a competition for each of 15 queries randomly sampled from the 31 used by Raifer et al. [38]<sup>5</sup>. These queries were originally selected from all topic titles for the Web tracks of TRECs 2009-2012 by the virtue of having a commercial intent that can stir up ranking competitions<sup>6</sup>.

Two students took part in each competition for a query. No two students competed against each other for more than one query, and no student competed for more than three queries. The two students competing for a query were provided at the beginning of the competition with the same example of a document relevant to the TREC topic the query represents. Some of these documents were adopted from the dataset in Raifer et al. [38]; others were created by the authors of this paper using a similar approach to that in Raifer et al. [38]. The students had no incentive to stick to these original documents. Hence, in contrast to our bot, they had more freedom in promoting their documents. Furthermore, all students had prior experience in participating in similar contentbased ranking competitions for queries other than those they were assigned to in our competitions.

In the first round of the competition, the students submitted their modified documents to the search engine. They were then shown a ranking induced over a set of five documents: their two documents and additional three **planted** documents which were randomly selected from the first round of Raifer et al.'s competitions. The students were not aware of the fact that other documents might not be written by students competing with them. The identities of all documents' authors were anonymized. Throughout the competition, the students had access to all documents in rankings. The ranking function, described below, was not disclosed to the students.

Having observed the induced ranking, the two students could then modify their documents to potentially promote them in the next ranking, and submit them for the second round of the competition. The most highly ranked planted document in the first round, which was not also the most highly ranked in the entire ranking, and which was marked by at least three annotators out of five in Raifer et al's competitions as of high quality, was provided as input  $(d_{cur})$  to our bot. Our approach modified the document and submitted it  $(d_{next})$  to the second round. For the other two planted documents, their second-round versions in Raifer et al.'s competition were submitted to our second round. As additional baseline which was not part of the actual competitions we use a simulated static bot: it receives the same document in the first round as our bot, and simply submits it to the second round with no modifications. Comparison with the static bot allows to evaluate the merit of using a dynamic bot which responds to ranking.

Our approach was designed for a single shot modification. Hence, our main evaluation is based on the ranking induced in the second round of the competition with respect to that induced in the first round. Furthermore, we used crowdsourcing via the Figure Eight platform (https://www.figure-eight.com) to assign quality and relevance labels to all documents in the competition as in Raifer et al.'s competitions, using their annotation guidelines. Each document was annotated by five annotators. A document was deemed relevant or of high content quality if it was marked as such by at least three annotators. Although not designed for iterative document modification, we let our bot participate in two additional rounds modifying its document in response to rankings. We did not bound the number of previous rankings the bot observes (i.e., the value of p in Section 4.1.1). The bot utilized in its rank-promotion features information about all rankings as from the first round to the current round. The students had access to the exact same information.

**Document ranking function**. Similarly to Raifer et al. [38], we used the state-of-the-art LambdaMART learning-to-rank (LTR)

<sup>&</sup>lt;sup>5</sup>Raifer et al.'s dataset is available at https://github.com/asrcdataset/asrc.

<sup>&</sup>lt;sup>6</sup>The topic IDs of the 15 queries are: 10, 13, 18, 32, 33, 34, 48, 51, 69, 167, 177, 180, 182, 193, and 195.

method [42] with 25 standard content-based features as the search engine's ranking function. These features were either used in Microsoft's learning-to-rank datasets<sup>7</sup>, or are query-independent document quality measures [6]. Further details regarding the ranking method are provided in Appendix A.1.

**Ranking passage pairs**. Our document modification approach is based on learning-to-rank passage pairs. As the documents are short (up to 150 terms), we used sentences for passages. We trained the approach using the rankings available for all 31 queries from round 6 of Raifer et al.'s competitions; RankSVM was the passagepair ranker [24]. Our training dataset contains 57 documents which serve for  $d_{cur}$  and 3399 passage pairs ( $g_{src}, g_{target}$ ). Additional details about the training are provided in Appedix A.2. We now describe the creation of rank-promotion (r) and local-coherence maintenance (c), henceforth coherence, labels for training.

For each document  $d_{cur}$  in a ranking  $\pi_{cur}$  in the training set, we create, as described in Section 4, passage pairs  $(g_{src}, g_{target})$  where  $g_{src} \in d_{cur}$  and  $g_{target}$  is any passage in documents ranked higher than  $g_{src}$  in  $\pi_{cur}$ . We replace  $g_{src}$  in  $d_{cur}$  with  $g_{target}$  to yield  $d_{next}$ , and induce a new ranking  $\pi_{next}$ .<sup>8</sup> The rank-promotion label, r, is 0 if  $d_{next}$ 's rank position in  $\pi_{next}$  is the same or worse than that of  $d_{cur}$  in  $\pi_{cur}$ ; otherwise, r is the difference between  $d_{next}$ 's rank in  $\pi_{next}$  and  $d_{cur}$ 's rank in  $\pi_{cur}$ . As there are 5 documents in each ranking, r is in  $\{0, 4\}$  as mentioned in Section 4.

To produce a coherence label for  $(g_{src}, g_{target})$ , we aggregated the labels assigned by human annotators in two different crowdsourcing tasks performed using Amazon's Mechanical Turk. In the first task, the annotators were shown  $d_{cur}$  and  $d_{next}$ , where  $g_{src}$ was highlighted in  $d_{cur}$  and  $g_{target}$  was highlighted in  $d_{next}$ . The annotators were asked to mark which of the two documents was the original. The coherence label is the number of annotators, among the 5 assigned, who failed identifying  $d_{cur}$  as the original.

The second coherence label was produced by showing  $d_{next}$  to annotators and telling them that it was obtained by replacing a passage in a document they did not see. The annotators were asked to point to the passage which presumably replaced a passage in that document; all passages in the document were marked. The number of annotators who did not identify  $g_{target}$  as the replacing passage is the coherence label.

We scale the arithmetic mean of the two coherence labels by  $\frac{4}{5}$  to have the resultant coherence label, *c*, in  $\{0, 1, \ldots, 4\}$  as is the case for the rank-promotion label. We then use the harmonic mean to aggregate the coherence and rank-promotion labels as described in Section 4.1. The resulting label, *l*, is a real number in  $\{0, 4\}$ . To *train* the bot for the competitions, we set  $\beta = 1$  in the harmonic mean; i.e., coherence and rank promotion are assigned the same weight for training. We demonstrate in the offline evaluation (Section 5.3) the merits of using this value of  $\beta$  with respect to alternatives.

**Offline evaluation**. As was the case for training the bot for our competitions (the online evaluation), we used the round-6 data from Raifer et al. [38] to train our approach for offline evaluation. Training is performed with the labeled (l) passage pairs as above. We experiment with l = c and l = r where only the coherence and

rank-promotion labels are used, respectively; and, with *l* being the harmonic mean of *c* and *r* as described in Section 4.1 with  $\beta = 1.9$ 

To test our approach, we let it modify each of the documents at ranks 2–5 in round 7 of Raifer et al.'s [38] competitions for each of the 31 queries. Each of these documents was written by a student. Thus, in total we have 124 different experimental settings for an instance of our approach: 4 ranks × 31 queries<sup>10</sup>. Specifically, in each setting, our approach modifies document  $d_{curr}$  into  $d_{next}^{bot}$ . The student who originally submitted  $d_{curr}$  in round 7 (potentially) modified it to  $d_{next}^{student}$  for round 8. Then, we contrast the rank position of  $d_{next}^{bot}$  and  $d_{next}^{student}$  in two rankings induced over five documents. Four of the documents are shared between the two rankings: those from round 8 which were submitted by the four students whose document is either  $d_{next}^{bot}$  or  $d_{next}^{student}$ .

In each setting we induce a ranking, using the ranker described above, over the document modified by our approach and the four round-8 documents of the students whose documents were not selected to be modified by our approach in round 7.<sup>11</sup> We also induce a ranking over all five original documents from round 8 of Raifer et al. [38]. We then contrast the rank position of our modified document in the first ranking with that of the student's modified document in the second ranking. The other four documents are the original student documents from round 8.

We also use five annotators as in the online competitions to evaluate the quality of documents produced by our approach. Quality annotations for all other documents are available from Raifer et al. [38] as described in Appendix A.2.

To summarize, the offline evaluation is based on contrasting our bot with a "human" agent (student): we let the two modify the same document which was written by the student. We then contrast the rank-promotion, quality and relevance of the two modified documents where all other documents in the same competition for the query at hand were modified by other students. In contrast to the online evaluation with our competitions described above, we cannot run this process for more than a single round. The reason is that the students in Raifer et al.'s competitions [38] did not respond to rankings that included the documents produced by our approach.

## 5.2 Online Evaluation Results

There are five "players" per query in each live competition round: two students from our competitions, two students from Raifer et al.'s competitions whose documents were planted, and the bot.

We analyzed the competitions using five evaluation measures. The first three measures quantify ranking properties, and are computed per player and her document for a query. The values for our students and Raifer et al.'s are averaged over the students. The averaged values, and the values for the bot and the static bot, are averaged over queries. The first measure, **average rank**, is the rank

<sup>&</sup>lt;sup>7</sup>https://tinyurl.com/rmslr

<sup>&</sup>lt;sup>8</sup>This procedure is challenging when using APIs of commercial search engines due to the time until the next indexing. We leave this challenge for future work.

<sup>&</sup>lt;sup>9</sup>Note that setting  $\beta$  to 0 or to a very high value does not result in the integrated labels *l* relying only on coherence (*c*) or rank-promotion (*r*), respectively. Hence, to emphasize these two extreme cases, we use *c* or *r* as the integrated label *l*.

<sup>&</sup>lt;sup>10</sup>In practice we have 113 different experimental settings for an instance as we do not apply our approach on documents deemed of low quality or keyword stuffed in [38]. <sup>11</sup>The ranker we use here is the base ranker Raifer et al. [38] utilized. Raifer et al. also added post-hoc rank penalties for low quality documents which we do not apply here. Additional details can be found in Appendix A.1.

Table 1: Online evalution: main result. The best result in a block for each round is boldfaced. Promotion is with respect to the previous round, and hence, there are no promotion numbers for the first round. Recall that positive values for raw and scaled promotion attest to actual promotion while negative values attest to demotion. The lower the values of average rank the better. (The highest rank is 1.)

		round 1	round 2
	students	3.200	3.400
average rank	planted	2.733	2.766
	static bot	3.133	3.399
	our bot	3.133	2.667
raw promotion	students	NA	-0.200
	planted	NA	0.000
	static bot	NA	-0.266
	our bot	NA	0.466
scaled promotion	students	NA	-0.136
	planted	NA	-0.002
	static bot	NA	-0.177
	our bot	NA	0.122
	students	0.867	0.900
quality	planted	0.400	0.766
	static bot	1.000	1.000
	our bot	1.000	0.933
relevance	students	0.933	0.866
	planted	0.900	0.966
	static bot	0.866	0.866
	our bot	0.866	0.866

of the player's document, averaged as described above; the highest rank is 1. The **raw promotion** and **scaled promotion** measures quantify the change of a document's rank between rounds 1 and 2. The documents at rank 1 are not considered as they can only be demoted. Raw promotion is the number of positions by which the document was promoted (demoted). The scaled promotion is the raw promotion normalized by the maximum potential for promotion/demotion with respect to the document's position.

The **quality** scores are assigned by crowdsourcing annotators (in our and in Raifer et al.'s competitions) and attest to the document's content quality. A document quality score is set to 1 if at least three out of five annotators marked it as of high content quality; otherwise, its quality score is 0. Using the same approach, we assigned documents with a 0/1 **relevance** grades for the TREC topic represented by the query. For the quality and relevance measures, we report the ratio of queries for which the player's document received a quality/relevance score of 1, and normalize with respect to the number of players where needed.

**Main results**. Table 1 presents our main results for the online evaluation (our competitions).<sup>12</sup> Recall that the document the bot (and the static bot) received per query in the first round was of high

quality. The static bot did not change the document for the second round in contrast to our bot.

We see in Table 1 that by all three ranking-based evaluation measures, our bot outperformed the two active students in our competitions ("students"), the two students from Raifer et al.'s competitions ("planted") and the static bot. It is the only player who has positive raw and scaled promotion values in the second round. Furthermore, the bot's documents started from an average rank slightly better than that of the active students' documents (3.133 vs. 3.2), and after the modifications for the second round they were promoted to a higher average rank (2.667 vs 3.4); in fact, on average, the students were demoted from average rank of 3.2 to 3.4 which is reflected in the negative raw and scaled promotion numbers. The documents the bot received in the first round were ranked higher than, or the same as, those of the active students for 53% of the queries. The percentage increased to 67% in the second round after the documents were modified by the bot and the students.

Comparison of our bot with the static bot in terms of average rank and rank promotion attests to the importance of a "live" bot which responds to rankings. We also see that the average quality of the documents of our bot in the second round (0.933) is higher than that of the documents of the two students from our competitions (0.9) and from Raifer et al.'s competitions (0.766). The quality of the static bot's document in the second round is 1 as it is the same document from the first round (and the same document our bot received) which by selection was of quality value 1.

Table 1 also shows that the document our bot received in round 1 from Raifer et al.'s competitions was not always relevant. (It was relevant in 86.6% of the cases.) The bot did not hurt relevance, on average, by its modifications (second round). This is in contrast to the two active students who had (on average) a lower fraction of relevant documents in the second round than in the first.

The competitions' results are encouraging. The bot won over the active students in terms of rank-promotion and did not hurt relevance in contrast to the students. There was some mild quality decrease as a result of the bot modifications, but the resultant quality still transcends that of the students' documents. In the offline evalution reported in Section 5.3, we show that there is no statistically significant difference between the quality of documents produced by the bot and that of documents produced by students.

Now, while the students had prior experience in ranking competitions, the bot learned from a past static snapshot of a competition. (See Section 5.1.) Moreover, the students could have modified their documents in round 2 without maintaining faithfulness to their documents from round 1. This was not the case for the bot by design.

*5.2.1 Repeated Competitions.* Our bot was designed for a single shot (modification) response to a ranking. Yet, we let the competitions run for additional two rounds with the bot and the two participating students. The two planted documents from round  $i \in \{2, 3\}$ ) were replaced with their round i + 1 versions from Raifer et al.'s competition. We also use as a baseline the static bot which did not change the document our bot received in round 1.

We see in Figure 1 that in terms of average rank, the bot wins over all other players and the static bot as from round 2. (This is the first round in which the bot modified the document it received.)

<sup>&</sup>lt;sup>12</sup>We do not present here statistical significance reports as only 15 queries were used and this is a too small number for computing statistical significance. We do report statistical significance for the offline evaluation in Section 5.1 where we use 31 queries.



Figure 1: Online evaluation: analysis of the four rounds of the competition. The curves for the quality and relevance of the static bot are horizontal lines with values of 1 and 0.867, respectively.

Table 2: Offline evaluation. Our bot was trained for coherence (c), rank-promotion (r) and both (l); l is the harmonic mean of c and r using  $\beta = 1$ . Statistically significant differences with the students and the static bot are marked with 's' and 'b', respectively. The best result in a column is boldfaced.

	average rank	raw promotion	scaled promotion	quality	relevance
students	3.327	0.212	0.034	0.991	0.796
static bot	3.248	0.292	0.094	<b>1.000</b>	0.823
our bot $(c)$	3.133	0.407	0.145	0.973	0.973 <sup>sb</sup>
our bot $(r)$	2.584 <sup>sb</sup>	<b>0.956<sup>sb</sup></b>	<b>0.340<sup>sb</sup></b>	0.973	0.982 <sup>sb</sup>
our bot $(l)$	2.673 <sup>sb</sup>	0.867 <sup>sb</sup>	0.309 <sup>sb</sup>	0.982	0.991 <sup>sb</sup>

Furthermore, the bot is the only player whose scaled-promotion values are always non-negative<sup>13</sup>. These findings attests to the merits of the bot in terms of rank promotion.

Figure 1 also shows that the quality of the bot's documents monotonically decreases. This is not a surprise as the bot was designed for a single modification rather than a chain of modifications; e.g., we did not prevent duplicate sentences in the modified documents, which the annotators penalized in terms of quality. Yet, we note that even in round 3, 85% of the documents produced by the bot were considered of high content quality by the annotators; and, in rounds 2 (the first round in which the bot started changing the document) and 3 the quality of the bot's documents was higher or equal to that of the documents of the two students who participated in the competitions. A similar, although less steep, drop of quality is observed as from round 2 for the documents produced by the students who participated in the competition. The increasing quality for the planted documents can be attributed to the fact that in Raifer et al.'s competitions there were heavy ranking-penalties for producing low-quality documents [38], which we did not impose in our competitions.

Finally, we see in Figure 1 that the bot did not cause a decrease in the fraction of relevant documents as a result of its modifications. In contrast, the average fraction of relevant documents of the students who participated in our competitions was lower in rounds 2-4 than in round 1.

## 5.3 Offline Evaluation Results

We now turn to describe the offline evaluation results. Recall from Section 5.1, which describes the experimental setting, that the evaluation is performed using the competitions of Raifer et al. [38]. Specifically, our approach, henceforth referred to as bot, is applied to documents in round 7. The approach is trained with three types of labels which results in three bots: one trained as in the online evaluation for both rank-promotion and coherence (*l* labels) with  $\beta = 1$  in the harmonic mean; the other two are trained either only for coherence (*c* labels) or only for rank-promotion (*r* labels).

Table 2 presents the average over (initial) ranks (2–5) and 31 queries of the rank-promotion, quality and relevance measures for the documents produced by our three bots and for the documents produced by the corresponding students. As in the online evaluation, we use for reference comparison a static bot which keeps the student document as is. Figure 2 presents the per initial rank measures when training the bot for both coherence and rank-promotion (*l*) with  $\beta = 1$  as was the case in the online evaluation<sup>14</sup>. Statistically significant differences for all measures are computed (over the 31 queries) using the two tailed permutation (randomization) test (with 100000 random permutations) at a 95% confidence level. Bonferroni correction was applied for multiple testing.

We see in Table 2 that all three versions of our bot outperform the students and the static bot for all three rank-promotion measures: average rank, raw promotion and scaled promotion. The improvements are substantial and statistically significant when using the r (only rank promotion) and l (rank promotion and coherence) labels for training the bot. Furthermore, the fraction of relevant documents produced by each of the three bot versions is statistically significantly higher than that for the students and the static bot. The fraction of quality documents produced by the three bot versions is slightly lower than that of the students, but the differences are never statistically significant.

Among the three versions of our bot, the one trained for both coherence and rank-promotion yields the highest quality and relevance results and posts very strong rank-promotion performance (the second best in the table); hence, it was selected for the online evaluation discussed above. We further see in Table 2 that, as expected, training for rank-promotion — alone (r) or together with coherence (l) — results in much better rank promotion than when

 $<sup>^{13}</sup>$  The trends for raw promotion are similar and hence these results are omitted as they convey no additional insight.

 $<sup>^{14}{\</sup>rm The}$  raw promotion graph is omitted as it conveys no additional insight: it shows the exact same patterns as in the scaled promotion graph.

Conference'17, July 2017, Washington, DC, USA



Figure 2: Offline evaluation: our bot (trained with the *l* labels and  $\beta = 1$ ) vs. the student(s). Both modify the same document at the same initial rank for a query. For reference comparison we use a static bot that receives the same document and does not modify it. The presented numbers are averages over 31 queries. Recall that lower rank means higher positioning.

training only for coherence (*c*). Furthermore, all the differences in average rank, raw promotion and scaled promotion between using *r* and *c* and between using *l* and *c* are statistically significant. The quality of the produced documents does not vary much with respect to the version used for training; indeed, none of the quality differences between the three versions is statistically significant. In terms of relevance, training for both rank-promotion and coherence (*l*) outperforms training only for promotion (*r*) and training only for coherence (*c*); however, none of the differences between the three, in terms of relevance performance, is statistically significant.

The averages over initial ranks reported in Table 2 for the *l*-label bot well reflects the per initial rank state-of-affairs shown in Figure 2: the documents produced by our bot are (i) more highly ranked, (ii) of quality that is statistically indistinguishable from, and (iii) more often relevant with respect to the students' documents. These findings are also aligned with those presented in Section 5.2 for the online evaluation. All in all, both the online and offline evaluations attest to the clear merits of our proposed approach.

#### 5.4 Feature Analysis

Table 3 presents the feature weights learned by the RankSVM passage-pair ranker which was used in the online and offline evaluations: training was performed with rank-promotion and coherence integrated labels (*l*) with  $\beta = 1$  in the harmonic mean. Appendix A.2 provides additional details of training the RankSVM. Feature weights are comparable as feature values are min-max normalized.

We see in Table 3 that the weight of the QryTermTarget feature, which is a measure of query-terms occurrences in the passage to be used for replacing another, is the highest. Indeed, using passages that contain many occurrences of query terms can help to improve retrieval scores and hence ranking. In accordance, the feature with the lowest negative weight is QryTermSrc which quantifies the query-terms occurrences in the passage that is candidate for being replaced. Indeed, the more query terms it contains, the less likely its replacement is to promote the document in a ranking.

The next three features with the highest weights are SimTargetTop(T), SimTargetPrevTop(W) and SimTargetTop(W). These are measures of the (lexical and semantic) similarity of a candidate replacing passage to the documents most highly ranked in the current

Table 3: Feature weights of the passage-pair ranker.

Feature	Weight
QueryTermTarget	0.189
SimTargetTop(TF.IDF)	0.134
SimTargetPrevTop(W2V)	0.138
SimTargetTop(W2V)	0.085
SimSrcPrevTop(W2V)	0.084
SimTargetPrecPsg(W2V)	0.034
SimSrcPrecPsg(W2V)	0.024
SimSrcTarget(W2V)	0.015
SimTargetFollowPsg(W2V)	0.015
SimSrcTop(W2V)	-0.013
SimSrcFollowPsg(W2V)	-0.015
SimSrcPrevTop(TF.IDF)	-0.020
SimTargetPrevTop(TF.IDF)	-0.022
SimSrcTop(TF.IDF)	-0.025
QryTermSrc	-0.073

(SimTargetTop(T), SimTargetTop(W)) and previous (SimTargetPrevTop(W)) rankings. This finding provides further support to the merits of mimicking documents most highly ranked in the past.

Other features with positive weights include the semantic similarity of the candidate replacing passage with the passage to be replaced (SimSrcTarget(W)) and its preceding passage in the document (SimTargetPrecPsg(W)). These features quantify the potential change of local coherence as a result of the passage replacement.

## 6 CONCLUSIONS

We presented a novel method of modifying a document so as to promote it in rankings induced by a non-disclosed ranking function for a given query. The only information about the function is past rankings it induced for the query. Our method is designed to maintain the content quality of the document it modifies.

Our method replaces a passage of the document with another passage — a challenge we address as a learning-to-rank task over passage pairs with a dual-objective: rank promotion and contentquality (coherence) maintenance.

Our method served as a bot in content-based ranking competitions between students. The bot produced documents that were of high quality, and better promoted in rankings than the students' documents. The bot's modifications did not hurt relevance in contrast to the modifications introduced by students. Additional offline evaluation further demonstrated the merits of our bot. *Ethical considerations.* Worries about potential abuse of our method for black hat SEO can be alleviated: the method is tuned for maintaining content quality. Furthermore, as the ranking competitions show, the method's potential negative effects on the search echo system are not significant, and can be smaller than those introduced by human authors who try to promote documents. Dropping the constraint of quality maintenance in our method will result in the produced documents being of low quality. But in this case, simple quality estimates used in Web search methods [6] can be used to easily disqualify these documents or penalize them in rankings.

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## A APPENDIX

We next provide some additional technical details about the experimental setting.

## A.1 Document Ranking Function

For document ranking, we used the same learning-to-rank approach, and features, used by Raifer et al. [38] in their fundamental ranker. Specifically, the state-of-the-art LambdaMART learning-to-rank (LTR) approach [42]<sup>15</sup> was used with 25 content-based features. (Recall that we focus on content-based modifications.) These features were either used in Microsoft's learning-to-rank datasets<sup>16</sup>, or are query-independent document quality measures — specifically, stopword-based measures and the entropy of the term distribution in a document — demonstrated to be effective for Web retrieval [6].

To train the ranking function, we used the ClueWeb09 Category B collection and its 200 topic-title queries (TREC 2009-2012). We used the query likelihood retrieval approach [39] with Dirichlet smoothed document language models; the smoothing parameter was set to 1000 [46]. Documents assigned a score below 50 by Waterloo's spam classifier were removed from rankings. The resultant top-1000 documents were used for training. We used default values of the free parameters in the implementation except for the number of leaves and trees which were selected from {5, 10, 25, 50} and {250, 500}, respectively, using five-fold cross validation performed over queries: four folds were used for training and one for validation of these two parameters; NDCG@5 was the optimization criterion. We select the parameter values that result in the best NDCG@5 over all 200 queries when these were used as part of the validation folds.

## A.2 Learning-To-Rank Passage Pairs

Our approach is based on ranking for a given document  $d_{cur}$ , which we want to rank-promote, passage pairs  $(g_{src}, g_{target})$ , where  $g_{src}$ is a passage in  $d_{cur}$  and  $g_{target}$  is a passage in a document among the most highly ranked in the current ranking,  $\pi_{cur}$ . (Refer back to Section 4 for details.) We use a learning-to-rank method to learn a passage-pair ranker and to apply it. To train our approach, we used all 31 queries and all the documents submitted for these queries in round 6 of Raifer et al.'s competition [38]<sup>17</sup>, except for those which were not marked as of high quality by at least 3 out of 5 crowd-sourcing annotators [38]. To induce document ranking, we used the ranking function from Appendix A.1 which was also used in the ranking competitions. Recall that our approach has no knowledge of the document ranking function.

We let our approach modify a document,  $d_{cur}$ , which is either the lowest ranked or the second highest ranked for a query. Thus, we have a mix of low ranked and high ranked documents which we let our approach train with. As a result, for each query we consider two identical current rankings,  $\pi_{cur}$ , over the given documents. In each of these two rankings, a single document — ranked second or last — is designated as  $d_{cur}$ . And, we induce two new rankings,  $\pi_{next}$ , where  $d_{cur}$  was modified by our approach to  $d_{next}$ . The rest of the documents are not modified; i.e., we train our approach by assuming that other documents do not change<sup>18</sup>. Our training dataset contains 57 documents which serve for  $d_{cur}$  and 3399 passage pairs ( $g_{src}, g_{target}$ ). For each document there are, on average, 59.6 such pairs (standard deviation: 42.32) to be ranked.

Some of the features on which our approach relies, namely SimSrcPrevTop(T), SimTargetPrevTop(T), SimSrcPrevTop(W) and SimTargetPrevTop(W), utilize information about the past p rankings. For training, we let our approach observe all current and past rankings (i.e., p = 6) where these were induced using our ranking function over the documents in each of the first five rounds of Raifer et al.'s competition [38]. Recall from Section 5.1 that we also do not bound p when we apply the bot in the online evaluation.

As noted in Section 4, any feature-based learning-to-rank approach can serve for our passage-pair ranking function. Since we do not have large amounts of training data, we used a linear RankSVM [24]<sup>19</sup>; all free parameters were set to default values of the implementation, except for *C* which was set using cross validation. Specifically, we used 5 fold cross validation over all 57 documents<sup>20</sup> which serve as  $d_{cur}$ , where 4 folds were used to train RankSVM and one fold (validation) was used to set *C*'s value ( $\in \{0.001, 0.01, 0.1\}$ ) by optimizing for NDCG@5. NDCG is computed for the ranking of passage pairs with their assigned *l* labels; these lables are also used for training; see Section 5.1 for details. As each document is part of a single validation fold, we set *C* to the value that optimized NDCG@5 over all documents when these were part of a validation fold. We then trained the approach with this *C* value using all documents and used it as a bot in the online and offline evaluations.

As described in Section 4, our approach utilizes, as features, Word2Vec-based similarities. We train a query-based Word2Vec model [11], so as to rely on the query context, using the gensim package (https://radimrehurek.com/gensim/models/word2vec. html). Specifically, for a query q, the model was trained on the top-10000 documents retrieved from ClueWeb09 Category B for qusing the query likelihood retrieval model [39]; spam removal was not applied here. Default parameter values of the gensim package

 $<sup>^{15}</sup>$  We used the RankLib implementation: www.lemurproject.org/ranklib.ph.  $^{16}$  https://tinyurl.com/rmslr

<sup>&</sup>lt;sup>17</sup>In round 5 of Raifer et al.'s competition, the incentive system has changed [38]. Hence, we selected a round which is after the change.

<sup>&</sup>lt;sup>18</sup>The alternative would have been to have other documents modified simultaneously to  $d_{cur}$ . However, this would have introduced much noise to the learning phase as the ranking of  $d_{next}$  could have changed with respect to that of  $d_{cur}$  not necessarily due to the modification of  $d_{cur}$ , but rather due to those of others.

<sup>19</sup>https://www.cs.cornell.edu/people/tj/svm\_light/svm\_rank.html

<sup>&</sup>lt;sup>20</sup>Recall that ranking of passage pairs is with respect to a specific document  $d_{cur}$ .

Conference'17, July 2017, Washington, DC, USA

Gregory Goren, Oren Kurland, Moshe Tennenholtz, and Fiana Raiber

were used, except for the threshold of number of occurrences per word which was set to 0, the window size which was set to 8, and the vector size which was set to 300.

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