Driving the Herd: Search Engines as Content Influencers

Gregory Goren* ggoren@ebay.com eBay Research

Moshe Tennenholtz moshet@ie.technion.ac.il Technion

ABSTRACT

In competitive search settings such as the Web, many documents' authors (publishers) opt to have their documents highly ranked for some queries. To this end, they modify the documents - specifically, their content - in response to induced rankings. Thus, the search engine affects the content in the corpus via its ranking decisions. We present a first study of the ability of search engines to drive pre-defined, targeted, content effects in the corpus using simple techniques. The first is based on the herding phenomenon a celebrated result from the economics literature - and the second is based on biasing the relevance ranking function. The types of content effects we study are either topical or touch on specific document properties - length and inclusion of query terms. Analysis of ranking competitions we organized between incentivized publishers shows that the types of content effects we target can indeed be attained by applying our suggested techniques. These findings have important implications with regard to the role of search engines in shaping the corpus.

CCS CONCEPTS

• **Information systems** → **Information retrieval**; Search engine architectures and scalability; **Adversarial retrieval**;

KEYWORDS

adversarial retrieval; herding; competitive retrieval

1 INTRODUCTION

Search engines are mediators [29]: they connect, using a query and a ranking function, users that have information needs with content in the corpus. It is therefore not a surprise that search engines have been traditionally perceived as "passive observers" of the eco system they operate in. That is, they search the corpus on behalf of users but do not actively affect the corpus or document authors. This is indeed the reality in search settings such as library archives and enterprise collections.

CIKM '21, November 1-5, 2021, Virtual Event, QLD, Australia

https://doi.org/10.1145/nnnnnnnnnnn

Oren Kurland kurland@technion.ac.il Technion

Fiana Raiber fiana@yahooinc.com Yahoo Research

In large-scale adversarial search settings such as the Web, search engines are far from being passive observers. To begin with, authors of Web pages — henceforth referred to as publishers — are affected by induced rankings. Specifically, users pay most attention to top-retrieved documents [16] which has direct effect on publishers' exposure [5, 9, 26, 32, 36].

Rankings in adversarial (competitive) retrieval settings such as the Web have additional effects on publishers. Specifically, many publishers often change the content of their documents to have them highly ranked in response to queries of interest — a practice named search engine optimization (SEO). Thus, the ranking incentives of publishers, together with the search engine's ranking function, affect the content in the corpus. For example, it was shown, using game theoretical analysis, that applying common relevance ranking functions¹ in competitive retrieval settings results in decreased topical coverage in the corpus [3]. One reason is that a common strategy of publishers is to mimic competing documents that are ranked higher [23], thereby potentially reducing topical diversity.

Despite their far reaching — societal and other — implications, the effects of rankings induced by search engines on content in the corpus have attracted very little research attention [3, 23]. Indeed, the large body of prior work on studying content changes in the Web was performed regardless of ranking effects (e.g., [20, 21, 25]).

We present the first study, to the best of our knowledge, of the potential ability of search engines to shape the content of documents in a corpus in *specific pre-defined* ways via the rankings they induce. To demonstrate this ability, we explore a few types of content effects on the corpus and techniques that a search engine can apply to drive these effects. One of these techniques is essentially an example in the relevance ranking domain of the celebrated *herding model* from the economics literature [2, 6, 28].

Some of the content effects we study are topical. That is, the search engine affects the coverage of topics in documents, and to the extreme, the availability of content pertaining to selected information needs. Other types of content effects touch on specific document properties — length and inclusion of query terms.

To empirically evaluate the content effects and the techniques for driving them, and inspired by recent work on publishers' SEO strategies [23], we organized content-ranking competitions between students². These competitions were approved by international and institutional ethics committees. The students produced and changed

^{*}Work done while at the Technion.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

^{© 2021} Copyright held by the owner/author(s). Publication rights licensed to ACM. ACM ISBN 978-xxx-xxxx-x/YY/MM...\$15.00

¹Specifically, functions based on the probability ranking principle (PRP) [24]: documents are ranked by their relevance probability. This holds for most relevance ranking functions.

²The dataset is available at https://github.com/herdingcikm/herding_data.

documents throughout time in response to induced rankings so as to promote them in future rankings. The empirical findings that emerged from the competitions' analysis are quite striking: search engines have an incredible power to drive pre-defined targeted content effects in the corpus; specifically, using the suggested techniques and with respect to the content-effect types we studied.

It is well known that rankings induced by search engines affect the corpus content since publishers are often incentivized to have their documents highly ranked. However, this is a general observation with no concrete realization — specifically, in terms of connecting the search engine ranking decisions with their corpus effects. We present a novel concrete realization: pre-defined, specific, content effects in the corpus can be relatively easily driven by applying simple techniques.

It is also important to point out that there is no reason for search engines to intentionally drive content effects. However, their ability to do so due to the herding phenomenon has two direct consequences. First, biases of the ranking function - e.g., due to biases in training data - together with the herding phenomenon can lead to unwarranted content effects on the corpus. A case in point, using the cosine measure to rank documents in the vector space model is known to lead to a bias in favor of short documents [27]. Now, we show in our experiments that positioning very short documents at the highest ranks of the retrieved document lists leads, due to the herding phenomenon, to a document length decrease effect in a competitive retrieval setting. Second, the ability of a search engine to drive specific content effects can potentially be abused by publishers who are interested in driving such effects. Recent progress in language generation methods facilitates opportunities for such an abuse. We discuss this issue in Section 5. Hence, whenever we write that the search engine can apply the techniques to drive content effects we mean that it has the *ability* to do so. The operational activation of this ability is either due to inherent biases of ranking functions or abuse by publishers.

In summary, we demonstrate the relative ease by which search engines in competitive search settings can drive pre-defined, targeted, content effects in the corpus due to ranking incentives of publishers. This concrete realization of the effects of ranking decisions on corpus content has important implications which we discuss. The ranking-competitions dataset we created can facilitate further research on ranking effects in competitive settings.

2 RELATED WORK

Work on adversarial retrieval has mainly focused on different types of spamming and methods to address them [1, 10, 15]. In contrast, we study the ability of search engines to affect corpus content.

Deception and spread of misinformation in content-based platforms, specifically in social networks, was the subject of many studies (e.g., [7, 14]). Our focus is different: the connection between search engines' ranking decisions and content effects on the corpus.

The Facebook experiment [17] showed that the sentiment of content promoted in users' feeds affected the sentiment of posts the users wrote. The search setting we address is different, and our focus is on other types of content effects.

There are many studies of the interactions between search engines and their users [30], including those of the effects of the engines on users' behavior via the advertisements they promote [34, 35]. In contrast, we study the effects of search engines on the corpus via the rankings they induce.

There is work on ranking fairness with respect to publishers' representation in top-retrieved results (e.g., [5, 26, 32, 36]). Our focus is on the effects of rankings on documents in the corpus.

Herding of publishers, which is an economic/game-theoretic phenomenon, can already be observed when publishers compete on their relative ranking with respect to a single query [23]. This phenomenon occurs due to uncertainty about the ranking function. Some recent work on search engines and recommendation systems deals with other game theoretic effects, resembling the ones that appear in facility location games [3, 4]. As in the single-query setting that we address in this paper, it was shown that due to competition, publishers will be inclined to write on similar topics [3, 4]. This finding is reminiscent of the phenomenon that facilities of competitors are located in similar locations in equilibrium. Interestingly, the finding holds for a set of queries even if publishers have full information of the ranking/recommendation function.

Raifer et al. [23] showed that publishers in ranking competitions tend to mimic content in documents highly ranked in the past for the same query. This is evidence for the general herding effect. We study the herding effect from the perspective of leading to specific content effects and the ability to actively drive them.

3 CONTENT EFFECTS

Our goal is to study the ability of a search engine to drive predefined types of content effects in a corpus upon which search is performed. This ability relies on the fundamental characteristics of any competitive search setting (e.g., the Web): some publishers (authors) of documents are incentivized to have their documents highly ranked for queries of interest. Hence, they respond to rankings induced for the queries by modifying their documents — a practice often referred to as search engine optimization (SEO) [15]. We focus on "white-hat SEO" *content* modifications [15]; i.e., legitimate modifications of document content that are *not* considered spamming, and more generally, that do not degrade document quality. Yet, such modifications can certainly have negative effects on the search eco system as we discuss below.

Our treatment of content effects is on a per-query basis. That is, we study how the search engine can affect, via the rankings it induces for a given query, the content of documents whose publishers opt to promote for this query. Obviously, publishers can strive to promote their documents, simultaneously, for several queries. We leave the study of driving content effects via induced rankings for a set of queries for future work.

In Section 3.1 we discuss the types of content effects we explore. These are examples and do not constitute a complete set of all potential effects. Section 3.2 presents techniques for driving these effects. We use q and d to denote a query and a document, respectively.

3.1 Types of Content Effect

The first type of content effect is with respect to topics discussed in documents. Suppose that query q represents the topic (information need) T. We set as a goal for the search engine to affect the treatment of T in documents whose authors are interested in rank promotion

for *q*. A concrete example we study here is trying to bias the content in these documents towards a specific aspect, or sub-topic, T^{sub} of *T*. Accordingly, we term this type of content effect **Sub-Topic**.

For example, consider TREC topic #167 from the ClueWeb09 collection. The description of the information need (topic), T, is: "Find information on Barbados history". Two of the sub-topics, T_1^{sub} and T_2^{sub} , for this topic are described as: "What does the Barbados flag look like?" and "Suggest tourist activities in Barbados", respectively. The topic title, "barbados", serves for the query q. The question we explore below is how the search engine can drive publishers interested in rank promotion for q to focus on one of the two sub-topics.

While documents written on T_1^{sub} and T_2^{sub} are relevant to T, the sub-topic focus just described results in potential loss of valuable information in the corpus. Namely, if one assumes that, a-priori, both sub-topics are discussed in documents in the corpus, then the topical coverage in the corpus is reduced. The direct consequence is hurting, in the long run, the effectiveness of any search intended for finding information about the sub-topic which the publishers drift away from; i.e., the one not driven by the search engine.

The Sub-Topic effect results in different coverage of sub-topics of T, but does not necessarily reduce the overall amount of information in the corpus that pertains to T. We thereby take a step forward and study the ability of the search engine to inflict more harm in terms of topical coverage in the corpus; specifically, to drive the reduction of the amount of content relevant to T.³ To this end, we introduce the **Not-Relevant** content-type effect: driving publishers with rank-promotion incentive for q to write documents not relevant to T. These documents can naturally still include q's terms and exhibit other properties that result in having them highly ranked for q, but their content cannot satisfy the information need about T.

The types of content effects we consider next touch on two fundamental building blocks of classical retrieval methods which rank documents by surface-level similarity to the query [13]; namely, term frequency and document length. The Doc-Length effect simply refers to the impact on document length. The Query-Terms effect refers to the extent of occurrences of terms from the query, q, in a document whose publisher wants to rank-promote for q. Our goal here is to study whether the search engine can drive publishers to reduce the number of query-term occurrences in documents. This type of a change stands in clear contrast to the common wisdom of publishers about relevance ranking functions; i.e., that they reward documents containing many occurrences of query terms. Indeed, a common SEO technique is keyword stuffing: adding query terms to documents [15]. Thus, the goal is to study whether a search engine can actually drive a content effect which contradicts the common belief of publishers about relevance ranking functions.

3.2 Approaches for Driving Content Effects

We next describe approaches that a search engine can employ to drive content effects; specifically, the four types discussed above.

3.2.1 Herding. The first approach we consider is inspired by recent work on analyzing the strategies employed by publishers who have

rank-promotion incentives [23]. An important result of a game theoretical analysis of the "ranking competition" between publishers was as follows: a publisher who opts to promote her document in rankings induced for query q should mimic documents that were highly ranked for q in the past [23]. Empirical analysis of ranking competitions provided support for this finding [23]. The simple intuitive rationale behind this "mimicking" strategy is that given that the ranking function is not known to publishers, the rankings they observe — of their documents and others — are essentially the only (implicit) signal about the ranking function.

Interestingly, the mimicking strategy just described is a specific example of the celebrated herding model from an exciting branch of the economics literature [2, 6, 28]. The literature refers to a paradigm known as the wisdom of the crowd; it suggests that a population can aggregate knowledge from individuals to collectively learn new things. A well established negative result from that literature is that whenever agents have full observability of selected actions of others, a herd may form on an inferior alternative. This phenomenon is often referred to as an information cascade: an information cascade occurs when an initial set of agents is ill-informed. As a result, these agents take some inferior action. Subsequent agents are then convinced that the aforementioned action is optimal and so dismiss their own private information and follow the herd by taking the inferior action as well. In our setting, publishers are the agents who are ill-informed about the ranking function and who follow the herd by mimicking documents highly ranked. The inferior alternatives they herd on can be, for example, focusing on specific sub-topics or not producing relevant information as in the content-type effects described in Section 3.1.

Following the observations about the mimicking strategy [23] and the herding phenomenon [2, 6, 28], we apply the following simple approach, denoted **Herding**, for driving content effects. For query q, we manually create a document d that manifests the type of content effect the search engine opts to drive. Then, d is positioned at the highest rank of any ranking induced for q, regardless of its actual retrieval score. That is, the approach is agnostic to the ranking function employed by the search engine. We note that using several manually created documents per query and determining their positions is a study left for future work.

For the Sub-Topic effect, the document d is written so that it is relevant to the sub-topic T^{sub} the search engine wants the publishers to focus on; hence, the document is also relevant to the topic T that q represents. We take care that d is not relevant to other (given) sub-topics of T so as to further highlight the potential topic drift that the search engine drives.

For the Not-Relevant effect, we create a document which contains q's terms, but is not relevant to the topic T that q represents. Such non-relevant documents are often highly ranked by retrieval methods based on document-query surface-level similarities.

For Doc-Length we create a short relevant document, and for Query-Terms we create a relevant document which does not contain any of the query terms. (This is mainly done by using abbreviations and language that avoids using the query terms.)

It is important to make the following observations about the Herding approach. First, if d is kept as is at the first rank along time, then publishers will figure out that straightforward mimicking of d

³We write "reduction" and not "elimination" as we operate within the scope of a single query and other queries might target the same topic. Furthermore, there could be publishers with no rank incentives who are not affected by induced rankings.

does not necessarily lead to improved ranking, and more generally, that external intervention takes place. This is because d is not necessarily assigned a (very) high retrieval score, which will also be the case for documents mimicking it. To address this issue, one should engineer d – using the full knowledge of the ranking function – so that it not only manifests the desired content effect, but it is also assigned a very high retrieval score. Furthermore, d can be changed along time, and so does the rank at which it is positioned, to avoid suspicions of the publishers. We leave the exploration of these directions for future work and focus on the fundamental Herding principle. To that end, in the experiments with iterative ranking competitions reported in Section 4.2, we demonstrate the impact of the approach when used for very few iterations (i.e., short time span). This short span effect is along the lines of the herding literature mentioned above [2, 6, 28] which deals with a single decision made by agents, rather than a repeated one.

3.2.2 Biasing the Ranking Function. In the Herding approach, publishers have an explicit example — the highest ranked document d— to follow towards the desired content effect. The next approach, termed **Biasing**, is based on providing the publishers with an implicit signal about the desired effect by biasing the relevance ranking function. For example, documents can be rewarded also based on the extent to which they manifest the desired content effect. Hence, changes that publishers introduce to documents and which are aligned with this effect will result in improved ranking.

A basic approach to biasing a ranking function is biasing the training data used to learn the function. It is easy to bias the training data for the four content-effect types discussed in Section 3.1: one can reward, via boosting of relevance grades, the documents that manifest the effect. For the Sub-Topic effect, the relevance grades of documents relevant to the sub-topic the engine wants to focus on should be increased. For the Not-Relevant effect, non-relevant documents (but with high surface-level query similarity) should be assigned high relevance grades. For the Doc-Length and Query-Terms effects, the relevance grades of short relevant documents and those of relevant documents which include very few occurrences of the query terms, respectively, should be increased.

As a proof of concept, we present an alternative unsupervised approach to biasing the ranking function for the Sub-Topic effect. Specifically, since our focus is on content effects, we devise a ranking function that is solely based on content. The retrieval scores assigned to documents by this function can be incorporated in feature-based learning-to-rank approaches so as to bias them [19].

Let q be a query representing topic T, and suppose that the goal is to have publishers focus on sub-topic T_i^{sub} of T. We assume a set of documents $S_{T_i^{sub}}$ which were judged as relevant to T_i^{sub} .⁴ Then, we construct a unigram relevance language model from $S_{T_i^{sub}}$ [18]:

$$p(w|R) \stackrel{def}{=} \frac{1}{|S_{T_i^{sub}}|} \sum_{d' \in S_{T_i^{sub}}} p(w|d'), \tag{1}$$

where p(w|R) is the probability assigned to term *w* by the relevance model *R* and p(w|d') is the probability assigned to *w* by a (Dirichlet)



Table 1: Summary of the ranking competitions.

-					
	Competition	Effect	Approach	Ranking Function	# Competitions
Part I	Control STH STP	None Sub-Topic	None Herding	LambdaMART LambdaMART	30 60
rt II	NRH DI H	Not-Relevant	Herding	LambdaMART	30 30
Pa	QTH	Query-Terms	Herding	LambdaMART	30

smoothed language model induced from d'.⁵ To rank document d using R, we use the negative cross entropy:

$$Score(d;q) \stackrel{def}{=} -CE(p(\cdot|R) \mid| p(\cdot|d)) = \sum_{w} p(w|R) \log p(w|d).$$
(2)

Increased values of the cross entropy correspond to decreased language-model similarity. Hence, a document *d* whose induced language model is similar to the relevance model induced for sub-topic T_i^{sub} will be rewarded. This will presumably incentivize publishers to emphasize T_i^{sub} in documents they want to promote for query *q*. We point out that the specific choice of a relevance model to

We point out that the specific choice of a relevance model to represent sub-topic T_i^{sub} entails an implicit herding/mimicking effect. That is, changing document *d* to increase its retrieval score means that its induced language model becomes more similar to *R*. Now, *R*, as defined in Equation 1, is an arithmetic centroid in the simplex of the language models induced from the documents in $S_{T_i^{sub}}$ which represent T_i^{sub} . Hence, to promote their documents in a ranking induced for *q*, publishers should essentially make them become more similar to a pseudo document that represents T_i^{sub} . An additional perspective can be gained by plugging Equation 1 in Equation 2 and re-arranging the summations:

$$Score(d;q) \stackrel{def}{=} -\frac{1}{|\mathcal{S}_{T_{i}^{sub}}|} \sum_{d' \in \mathcal{S}_{T_{i}^{sub}}} CE(p(w|d') \mid\mid p(w|d)).$$
(3)

That is, the retrieval score of *d* is the average negative cross entropy between language models induced from documents *d'* in $S_{T_i^{sub}}$ and *d*'s induced language model. Thus, promoting *d* in a ranking means making it more similar to these representatives of T_i^{sub} which the publisher is not aware of. This is in contrast to the explicit Herding effect from Section 3.2.1 where publishers observe the document most highly ranked which was "planted" there by the search engine.

We note that regardless of the ranking function being biased, publishers are somewhat likely to mimic the documents most highly ranked for the query in the past [23]. With the proposed relevance-model-based biasing, these documents were highly ranked due to high similarity to the sub-topic representative documents ($S_{T_i^{sub}}$), as discussed above. Thus, we get a double mimicking/herding effect: making a document similar to those highly ranked in the past makes the document become more similar to documents representing the sub-topic of interest.

⁵Uniform weighting of documents for constructing a relevance model from true relevant documents is superior to other weighting approaches [18, 22]. We use relevance model #1 (RM1) and do not interpolate it with the original query model (RM3) as our experiments showed that the resultant effect is stronger for RM1.

Table 2: Example of documents created for topic #167, which is represented by the query "barbados". T: " Find information on Barbados history." T_1^{sub} : "What does the Barbados flag look like?". T_2^{sub} : "Suggest tourist activities in Barbados."

Effect	Document
Initial Document	"The island of Barbados is located at 13.4N and 54.4W and is situated in the western area of the North Atlantic Ocean and 100 kilometers east of the Windward Islands and the Caribbean Sea. The island is seen by most scientists as geologically unique as it was formed as a result of an amalgamation of two land masses over a period of many years. The peaceful Arawaks and the more ferocious Caribs were the first inhabitants of Barbados"
Sub-Topic (T_1^{sub})	"Barbados flag consists of a triband of two bands of ultramarine, which are said to stand for the ocean surrounding the country and the sky, separated by a golden middle band, which represents the sand. A black trident head, commonly called the broken trident, is centered in the golden band, and the fact that the staff is missing is significant. The trident symbol was taken from Barbados colonial badge, where the trident of Poseidon is shown with Britannia holding it"
Sub-Topic (T_2^{sub})	"Barbados is one of the most popular destinations for vacation in the Caribbean, due to its beautiful scenery and high standard of living. There are many excursions for travelers to this island nation to take advantage of, no matter what their travel interests may be. One place tourists will want to go in Barbados is Harrisons Cave"
Not-Relevant	"Barbados is known for two pirates of the Caribbean - Sam Lord and Stede Bonnet. Stede Bonnet - Known as the pirate gentleman, Stede Bonnet became one of the pirates of the Caribbean in a most unusual way! A retired British army major and well off plantation owner in Barbados, the middle aged Major Stede Bonnet suddenly turned to piracy in early 1717 and actually purchased his own pirate ship, an unheard of act among the pirates of the Caribbean!"
Doc-Length	"The limestone rock has created the island of Barbados, and the land area of the isle measures 166.4 square miles (431 km2). It is 21 miles (34 kilometers) in length and 14 miles (23 kilometers)."
Query-Terms	"The island of Bimshire is located at 13.4N and 54.4W and is situated in the western area of the North Atlantic Ocean and 100 kilometres east of the Windward Islands and the Caribbean Sea. The island is seen by most scientists as geologically unique as it was formed as a result of an amalgamation of two land masses over a period of many years. The peaceful Arawaks and the more ferocious Caribs were the first inhabitants of Bimshire"

4 EMPIRICAL EXPLORATION

4.1 Experimental Setting

To empirically evaluate the content effects presented in Section 3.1 and the techniques proposed in Section 3.2 to drive them, we organized content-based ranking competitions between students in the spirit of those recently used to analyze publishers' strategies [23]. The competitions were approved by an international and an institutional ethics committees. The students who decided to participate signed consent forms and could have opted out at any point.

The competitions are divided to two parts as summarized in Table 1. Each competition in each part is a repeated ranking match for a given query that spans five iterations. A match is described below. In the first part, we applied the Herding and Biasing approaches to drive the Sub-Topic effect; these competitions are referred to as **STH** and **STB**, respectively. During this part we held additional **Control** competitions that did not involve any external intervention. In the second part, we applied the Herding approach to drive the Not-Relevant, Doc-Length, and Query-Terms effects. These three types of competitions are denoted **NRH**, **DLH** and **QTH**.

One hundred students in an information retrieval course participated in the competitions in two different semesters. Fifty students participated in each semester. The two-parts structure of the competitions was identical in both semesters. The quantitative findings for the two semesters were very similar. We report the overall quantitative findings over the two semesters.⁶ We used 30 out of the 31 queries used by Raifer et al. [23]⁷. These queries were originally selected from the TREC 2009-2012 topic titles [23]; the topics were selected as they had a commercial intent which was likely to stir up a competition between the students [23].

In each of the two parts of the competitions, a student was assigned to three queries — each in a different competition — which differ between the two parts. In both parts, each student participated in at least two different types of competitions. (There are six types of competitions described in Table 1.) For each of the Sub-Topic-effect types of competitions (STH and STB), two independent competitions were held per query. Each competition focused on one of the two sub-topics considered for the query which were selected from those of TREC. This resulted in 60 competitions for the Sub-Topic effect. For all other types of competitions, a single competition was held per query resulting in 30 competitions. All in all, we ran 240 competitions of 5 iterations, each focused on a single query.

Before each competition started, we provided the students with a query and an initial relevant document. (Details about the initial documents are provided below.) In each iteration (match), students were presented with the content and the ranking of the documents submitted in the previous iteration by all the participants in the same competition. The students were incentivized by *bonuses* to course grades to modify their documents so as to potentially promote them in the ranking induced in the next iteration. (Students could have received the perfect grade in the course without participating in the competitions.) The documents were plain text of up to 150 terms.

Two students participated in each competition.⁸ To maintain lively and dynamic competitions, we artificially added to each pair of students three additional players so that the students will see rankings induced over five documents.⁹ Each such "player" impersonated one of the students that participated in the competition reported in Raifer et al. [23]¹⁰ with the following exception. If the student remained passive in one of the iterations and did not modify her document in the competition held in [23], we randomly selected a document from those submitted by other students for the same query in the corresponding iteration.

The students' identities were anonymized throughout the competitions. Hence, they did not know who their opponents were, and were not aware of the fact that only one of their opponents was a real student. The analysis presented in Section 4.2 is based solely on

⁶Note that each competition in each semester was held separately from the others. The students did not know against whom they were competing as we describe below. ⁷Query (topic) #002 was randomly chosen to not be used.

⁸Each pair of students competed against each other in at most one competition.

⁹ In the herding experiments described below, only two players were added as the biased document driving the herding was positioned at the first rank of the ranking. Hence, there were five documents in each match. Further details are provided below. ¹⁰ All the documents are available at https://github.com/asrcdataset/asrc.

the documents created by the students who actually participated in the competition, and not those created by the additional "players".

Documents. We used the same initial example document in all the different competitions held for a query q. We required the initial document to be relevant — according to TREC's topic description — to the topic T that q represents and non-relevant to the two selected sub-topics, T_1^{sub} and T_2^{sub} . If a previously published initial document [23] did not meet these relevance requirements, and could therefore not be used for our competitions, we created a new document using text snippets that were retrieved for the queries by a commercial search engine.

For the Herding experiments, we created documents - to be shown at the highest rank - that manifested the four types of content effects that we wanted to drive as follows. For the STH competitions, we created two biased documents for each query: one of the documents focused on sub-topic T_1^{sub} and the other on sub-topic T_2^{sub} . Hence, we have 60 STH competitions in total (30 queries \times two competitions per query). In these competitions we positioned the biased documents at the top of the presented rankings to drive the Sub-Topic effect. The ranking over the documents participating in a competition was induced using the LambdaMART ranking function described below. In contrast, in the corresponding 60 STB competitions, to drive the same effect, we used a sub-topic biased relevance model to rank the documents participating in the competition; the relevance model was induced using Equation 1 for one of the sub-topics using documents relevant to this sub-topic. We also verified that the biased document focusing on T_1^{sub} was ranked higher than the biased document focusing on T_2^{sub} by a biased relevance model induced for sub-topic T_1^{sub} , and vice versa. In addition, in the first iteration before revealing the ranking of documents to the students, we verified that each biased document would have been ranked first in the STB competition when using the corresponding relevance model. For the NRH competitions, we created non-relevant documents that contained query terms. For DLH we created short relevant documents and for QTH relevant documents that did not contain query terms. Each document that was created for a competition was evaluated by three annotators. Table 2 shows examples of documents created for the competitions.

Ranking Functions. We used Category B of the ClueWeb09 collection with topics 1-200 from TREC 2009-2012 to devise the ranking functions. Topic titles were used as queries. We applied Krovetz stemming to all documents and queries, and removed stopwords on the INQUERY list from queries only. The experiments were performed using the Indri toolkit (www.lemurproject.org/indri).

For all the competitions except for STB, we followed the approach used in [23] to learn a ranking function. Specifically, we used a learning-to-rank approach, where each query-document pair was represented by a vector of 26 content-based features. Most of the features are based on those used in Microsoft's learning-to-rank datasets¹¹. The model was trained using the top 1000 documents in a ranking produced using a language-model-based approach (LM): the negative cross entropy between the unsmoothed unigram query language model and the Dirichlet-smoothed (with $\mu = 1000$)

document language models. Similarly to Raifer et al. [23], we deliberately did not filter out spam documents, i.e., those assigned a low score by Waterloo's spam classifier [11]. Instead, we used Waterloo's score as a feature. Because these scores are not available for the documents used in our competitions, we did the following. Five annotators in Figure Eight (www.figure-eight.com) labeled each document as valid, keyword stuffed or spam. Then, to simulate Waterloo's classification scores, we used 20*v*, where *v* is the number of annotators that marked the document as valid. Since $0 \le v \le 5$, the scores we get are in [0, 100], as is the case for the original Waterloo's spam scores, and applied using the human-created scores.

We used LambdaMART [31] via the RankLib library (https:// sourceforge.net/p/lemur/wiki/RankLib) to learn the model. We randomly split the queries into four folds. Three folds were used to train the model and the remaining fold to set hyper-parameter values; NDCG@5 served as the optimization metric. The number of trees and leaves in LambdaMART were set to 250 and 50, respectively, following experiments with values in {250, 500} and {5, 10, 25, 50}.

The relevance model (RM1) for the STB competitions (Equation 1) was constructed from five randomly sampled relevant documents per sub-topic. To set the number of expansion terms, we created relevance judgments as follows. The five documents from which the relevance model was constructed were considered "relevant". Five documents that were relevant to the topic, but not to the sub-topic in question and were assigned the highest LM score (see above) were considered "non-relevant". The number of expansion terms was set to 100 to optimize the NDCG@5 of a ranking over the ten "judged" documents, following experiments with values in {10, 25, 50, 100}.

All the documents created by students throughout the competitions were judged for relevance with respect to a query's topic by five annotators in Figure Eight. In addition, documents created in the Sub-Topic-effect competitions were also judged for relevance with respect to the two selected sub-topics. For the STB and STH competitions, queries #144 and #164 were removed from the final analysis due to lack of available sub-topics.

The statistical significance of the difference between two *sets* of 30 competitions (each held for a different query) with respect to a measure/effect is determined using a paired permutation (randomization) test with p = 0.05; 100000 permutations were randomly sampled. Pairing is done with respect to queries and iterations. The value of the measure/effect per query and iteration is the average value for the two documents of the two participating students. Bonferroni correction was applied for multiple comparisons.

4.2 Experimental Results

4.2.1 The Sub-Topic Effect. To drive the Sub-Topic effect we used the Herding and Biasing approaches in the STH and STB competitions, respectively. For a given query, we selected two sub-topics and held a competition with respect to each. Only one sub-topic was "active" in a given competition; i.e., the sub-topic was the focus of the highest ranked document in STH (which was biased) or of the biased relevance model (Equation 1) used for document ranking in STB. The second selected sub-topic in this competition was "passive"; i.e., no "driving" with respect to this sub-topic was performed.

¹¹ https://tinyurl.com/rmslr

A and **P** denote the active and passive sub-topics. Thus, for each topic, there was one competition where one sub-topic was active and the other one passive and one competition in which the reverse holds. Accordingly, we have equal representation for each of the two sub-topics of a topic as active and passive in the competitions.

To measure the extent of documents becoming focused on a sub-topic, we can measure the relative similarity of their induced language models to the sub-topic biased relevance models.¹² However, the sub-topic biased relevance models also encode information about the topic as a whole. To distill the information specific to the sub-topic with respect to the entire topic, and use that information to measure similarities to sub-topics, we utilized a two component mixture model described in Appendix A to induce a distilled sub-topic model. Then, similarity of a document to a sub-topic is measured based on the negative cross entropy between the distilled sub-topic model and the document language model. In addition, we analyze the cosine similarity between the TF-IDF vectors representing a student's document and the biased (planted) documents in the STH competitions. The different similarity scores are averaged over documents per match and over queries per iteration. We present for reference the results for the Control competitions where the similarity scores to both sub-topics were averaged.

We see in Figure 1 that most similarities increase along the iterations regardless of the distilled models or biased documents used. Even in the Control competitions, which did not involve any external intervention, a general moderate upward trend is observed. The average language-model-based similarity of a document to a distilled active sub-topic is almost always higher than that for the distilled passive sub-topic (STB-A vs. STB-P and STH-A vs. STH-P in the top figure); the gap between these two similarities almost always increases along the iterations and is, on average, statistically significant for the STB competitions. The languagemodel-based similarity for STB-P is also higher (in a statistically significant manner) than the average similarity to both sub-topics in the Control group.¹³ These findings suggest that the topics of the documents created by students gradually shifted towards the active sub-topic to a larger extent compared to the passive sub-topic in both approaches for driving the Sub-Topic effect (Herding and Biasing). In comparing STB-A with STH-A, we see that the former posts higher similarities which means that the Biasing approach is more aggressive in driving the Sub-Topic content effect than the Herding approach.

We also see in Figure 1 (bottom) that in the STH competitions, documents written by students are much more similar to the biased document which focuses on the active sub-topic and which is shown at the top of the ranking than they are to the document biased to the passive sub-topic which they were not shown (STH-A vs. STH-P). The differences are statistically significant. These findings further attest to a herding effect.



Figure 1: The Sub-Topic effect. Top figure: the average language model similarity (negative cross entropy) between a document and a distilled sub-topic model in the STH and STB competitions. {STH,STB}-{A,P} refers to the similarity in the STH/STB competitions to the distilled model induced for the active (A) or passive (P) sub-topic. Bottom figure: average cosine similarity with the documents biased for the active (STH-A) and passive (STH-P) sub-topics in the STH competitions. Both figures: in the Control competitions, the average similarity is computed for both sub-topics (A and P). In terms of -CE, STB-A is statistically significantly different from STB-P and Control. In terms of Cosine, STH-A is statistically significantly different from Control and STH-P.



Figure 2: The average number of relevant labels assigned to documents with respect to a query's topic (top) and the two sub-topics (bottom). STB is statistically significantly different from both Control and STH. STH-A is statistically significantly different from STH-P and STB-P.

To summarize, both the Herding and Biasing approaches were effective in driving the Sub-Topic effect with the latter being somewhat more effective.

¹²In both STH and STB, the documents became more similar to the active sub-topic than to the passive sub-topic in terms of language models. These results are omitted as they exhibited similar patterns, although to a somewhat less emphasized extent, than those presented below.

¹³In the Control groups there is no herding or biasing of the ranking function. Hence, similarities are computed for both sub-topics and are then averaged.



Figure 3: The Not-Relevant effect: average number of relevant labels per document and iteration. NRH is statistically significantly different from DLH, QTH and Control.

Relevance. As noted in Section 4.1, all the documents created by students for a query were annotated by five annotators for relevance with respect to the query's topic and the two sub-topics. Figure 2 presents the average number of relevant labels (per topic and sub-topic) assigned to a document.

We see in Figure 2 (top) that in the STH competitions, the relevance of documents to the query's topic (top figure) substantially decreased until iteration three and then rised a bit, but to a level quite lower than that at the first iteration. In contrast, in the STB competitions, the relevance level at iteration five was almost as that as at the first iteration, albeit fluctuations along the iterations.

Figure 2 (bottom) shows that the relevance to both sub-topics, in both STH and STB, overall increased from iteration one to iteration five. This is in line with the sub-topic-based similarity findings presented above. The most prominent increase is for STH-A whose results are statistically significantly higher than those for STH-P. In contrast, the difference between STB-A and STB-P is not statistically significant. Thus, while both the Herding and Biasing approaches drove the Sub-Topic effect, the former also helped more in increasing relevance for the target (active) sub-topic.

4.2.2 The Not-Relevant Effect. The Not-Relevant effect was driven in the NRH competitions using the Herding approach. Non-relevant documents were positioned at the top of the presented rankings. Figure 3 presents the average number of relevant labels assigned to the students' documents in each iteration. For reference, we show the results for the (i) Control competitions, in which no external interventions were performed, and (ii) the DLH and QTH competitions, in which two other content effects were driven using the Herding approach. In the Control, DLH and QTH competitions we observe fluctuations in the average number of relevant labels assigned to documents; but, the number for the first iteration is not very different than that for the last iteration. Recall that the students had no incentive to produce relevant documents, but rather documents that are highly ranked.

Strikingly, we see in Figure 3 that for NRH there is a sharp decline in the number of relevant labels which results in a statistically significant difference with all other three competitions. This finding shows that using a rather simple Herding approach, a search engine can lead to a substantial reduction of the amount of relevant content for a specific topic in the corpus.

4.2.3 The Doc-Length Effect. Thus far, we showed that search engines can affect the coverage of topics in a corpus. We now turn to



Figure 4: The Doc-Length effect. DLH is statistically significantly different from NRH, QTH and Control.



Figure 5: The Query-Terms effect. We present for each iteration the average percentage of query terms appearing in a document (QueryCover) and the average percentage of terms in a document that are query terms (FracQuery). QTH is statistically significantly different from NRG, DLH and Control for both QueryCover and FracQuery.

study the ability of search engines to drive surface-level changes in the corpus. We examine the DLH competitions in which short relevant documents were positioned at the top of the rankings to drive the Doc-Length effect.

Figure 4 shows for each iteration the average length of students' documents across the queries. We see that in the DLH competitions, the document length sharply decreased during the first four iterations. On average, the document length in these competitions was statistically significantly lower than that in the other three competitions which attests to a clear herding effect. The mild increase of document lengths in the fifth iteration of the DLH competitions can potentially be explained as follows: students started noticing that further shortening the documents does not help them to promote them for two reasons: (i) the top most document throughout the iterations was the biased one we planted, and (ii) the ranking function we employed does not necessarily reward short documents.

We also see in Figure 4 a gradual decrease of document length in the QTH, Control and NRH competitions, with the latter exhibiting the largest decrease of the three. The finding about NRH can be explained by the fact that the non-relevant documents we planted to drive the Not-Relevant effect via herding, were on average shorter than the initial relevant documents provided to the students as examples (118.6 terms vs. 133.1 terms). Hence, there was a double herding effect in the NRH competitions: documents were made shorter and less relevant. Still, the length decrease is statistically significantly smaller than that for DLH where the planted documents were of an average length 30.3 terms. For QTH and Control the planted documents were of similar length to that of the example relevant documents, which could potentially help to explain the very mild length decrease in these competitions.

To summarize, the shorter the documents we posted at the top of the ranking, the shorter the documents created by the students were. This finding attests to a clear herding effect.

4.2.4 The Query-Terms Effect. To drive the Query-Terms effect in the QTH competitions, relevant documents that do not contain query terms were positioned first in the rankings presented to students. In Figure 5 we show the percentage of query terms that appear in a document (QueryCover) and the percentage of terms in a document that are query terms (FracQuery). The values are averages over documents and queries per iteration.

Figure 5 shows that in the QTH competitions, there is a substantial downward trend for both QueryCover and FracQuery along the first few iterations and then some increase in the last iteration or two. The initial decrease together with the – statistically significantly different – upward trend observed for NRH, DLH and Control, attests to an herding effect in the QTH competitions. This finding is quite striking: while the participating students knew about the importance of query-terms occurrence in documents as a relevance signal in virtually all retrieval methods, they inferred that the biased document was ranked first due to not having query terms; hence, they reduced query term occurrences in their documents.

The increase of values in the last iteration or two in the QTH competitions can be explained as follows. The ranking function used in all the herding-based competitions rewards query terms occurrence as the features it uses are based on textual documentquery similarities. In fact, QueryCover is one of the features used in the learning-to-tank model. (Refer back to Section 4.1 for details.) This explains, for example, the upward trend for the NRH, DLH and Control competitions. Now, presumably, students that removed query terms from their documents in the first few iterations of the QTH competitions following the planted document, did not manage to promote their documents in rankings. On the contrary, some of these documents were demoted.

5 DISCUSSION

Heretofore, we have focused on the ability of search engines to drive pre-defined, targeted, content effects. There is obviously no reason for search engines to employ such practices. However, this ability can potentially be abused by publishers as we discuss next.

Say that a publisher is interested in promoting a content effect in the corpus. She can then write a document that manifests the effect and try to optimize it with respect to the ranking function. If successful in having her document ranked first, the publisher can potentially affect the content other publishers produce due to the herding phenomenon. In the experiments we reported in Section 4, documents we planted at the first rank which manifested specific content effects were manually selected and modified to this end. However, we argue that with the progress in language generation capabilities based on pre-trained language models (e.g., BERT [12], XLNet [33], GPT3 [8], etc.), this challenge will become easier along time. For example, "high quality" fake news were generated using advanced language generation techniques [37].

6 CONCLUSIONS AND FUTURE WORK

We presented a first study of simple techniques that search engines can employ to drive pre-defined targeted content effects in the corpus via the rankings they induce. The first is based on the *herding* phenomenon from the economics literature, and the second is based on biasing the ranking function. We explored topical effects and several document-property effects. Analysis of content-based ranking competitions we organized demonstrated the ability of a search engine to drive these effects using the suggested techniques. The concern is not that search engines will actually deploy such techniques, but rather that documents' authors will use the engines as platforms to applying such techniques.

For future work we plan to study herding effects, both theoretically and empirically, when publishers optimize their documents for multiple queries; i.e., going beyond the single-query setting addressed here and by Raifer et al. [23].

Acknowledgments. We thank the reviewers for their comments. The work by Moshe Tennenholtz and Gregory Goren was supported by funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement 740435).

A DISTILLING SUB-TOPIC MODELS

To distill a unigram language model, $\theta_{T_s^{sub}}$, that represents the unique information in a sub-topic T_s^{sub} with respect to the more general topic *T*, we use a mixture model (cf., [38]):

$$\log \mathcal{L} \stackrel{def}{=} \sum_{d_i \in T_s^{sub}} \sum_{w \in d_i} tf(w; d_i) \log((1-\lambda)p(w|\theta_{T_s^{sub}}) + \lambda p(w|T));$$

 \mathcal{L} is the likelihood function; $d_i \in T_s^{sub}$ are all documents (in TREC's qrels files) marked as relevant to T_s^{sub} ; w is a term; $tf(w; d_i)$ is the number of times w appears in d_i ; λ is a free parameter; p(w|T) is the probability assigned to term w by a maximum likelihood estimate induced from all documents marked as relevant to T (in TREC's qrels files). We use the EM algorithm to infer $\theta_{T_s^{sub}} - \text{i.e.}$, set $p(w|\theta_{T^{sub}})$ for each term w.

To compute the cross-entropy-based similarities between a distilled sub-topic model $\theta_{T_s^{sub}}$ and a document language model (see Section 4.2.1), we clip (and normalize) $\theta_{T_s^{sub}}$ (cf. [38]) to use the α terms to which it assigns the highest probability. The procedure that was used to set the number of expansion terms in the relevance model (see Section 4.1) was also used to set α (\in {10, 25, 50, 100}) and λ (\in {10, 25, 50, 100}).

REFERENCES

- AIR 2005-2009. AIRWeb International Workshop on Adversarial Information Retrieval on the Web.
- [2] Banerjee. 1992. A simple model of herd behavior. The Quarterly Journal of Economics 107 (1992), 797–817.
- [3] Ran Ben-Basat, Moshe Tennenholtz, and Oren Kurland. 2017. A Game Theoretic Analysis of the Adversarial Retrieval Setting. J. Artif. Intell. Res. 60 (2017), 1127– 1164.
- [4] Omer Ben-Porat and Moshe Tennenholtz. 2018. A Game-Theoretic Approach to Recommendation Systems with Strategic Content Providers. In Proceedings of NeurIPS. 1118–1128.
- [5] Asia J. Biega, Krishna P. Gummadi, and Gerhard Weikum. 2018. Equity of Attention: Amortizing Individual Fairness in Rankings. In Proceedings of SIGIR. 405–414.
- [6] S. Bikhchandani, D. Hirshleifer, and I. Welch. 1992. A theory of fads, fashion, custom and cultural change as information cascade. *The Journal of Political Economy* 100 (1992), 992–1026.
- [7] Nadya Bliss, Elizabeth Bradley, Joshua Garland, Filippo Menczer, Scott W. Ruston, Kate Starbird, and Chris Wiggins. 2020. An Agenda for Disinformation Research. *CoRR* abs/2012.08572 (2020).
- [8] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language Models are Few-Shot Learners. arXiv:2005.14165
- [9] Carlos Castillo. 2018. Fairness and Transparency in Ranking. SIGIR Forum 52, 2 (2018), 64–71.
- [10] Carlos Castillo and Brian D. Davison. 2010. Adversarial Web Search. Foundations and Trends in Information Retrieval 4, 5 (2010), 377–486.
- [11] Gordon V. Cormack, Mark D. Smucker, and Charles L. A. Clarke. 2011. Efficient and effective spam filtering and re-ranking for large web datasets. *Informaltiom Retrieval Journal* 14, 5 (2011), 441–465.
- [12] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *CoRR* abs/1810.04805 (2018).
- [13] Hui Fang and ChengXiang Zhai. 2005. An exploration of axiomatic approaches to information retrieval. In *Proceedings of SIGIR*. 480–487.
- [14] Jamie Guillory and Jeffrey T. Hancock. 2012. The Effect of Linkedin on Deception in Resumes. *Cyberpsychology Behav. Soc. Netw.* 15, 3 (2012), 135–140.
- [15] Zoltán Gyöngyi and Hector Garcia-Molina. 2005. Web Spam Taxonomy. In Proceedings of AIRWeb 2005. 39–47.
- [16] Thorsten Joachims, Laura Granka, Bing Pan, Helene Hembrooke, and Geri Gay. 2005. Accurately interpreting clickthrough data as implicit feedback. In Proceedings of SIGIR. 154–161.
- [17] Adam D. I. Kramer, Jamie Elizabeth Guillory, and Jeffrey T. Hancock. 2014. Experimental evidence of massive-scale emotional contagion through social networks. *In Proceedings of the National Academy of Sciences of the United States of America* 111 24 (2014), 8788–90.
- [18] Victor Lavrenko and W. Bruce Croft. 2003. Relevance Models in Information Retrieval. In Language modeling for information retrieval. Kluwer academic publishers, Chapter 2, 11–56.

- [19] Tie-Yan Liu. 2011. Learning to Rank for Information Retrieval. Springer. I–XVII, 1–285 pages.
- [20] Kira Radinsky and Paul N. Bennett. 2013. Predicting content change on the web. In Proceedings of WSDM. 415–424.
- [21] Kira Radinsky, Fernando Diaz, Susan T. Dumais, Milad Shokouhi, Anlei Dong, and Yi Chang. 2013. Temporal web dynamics and its application to information retrieval. In *Proceedings of WSDM*. 781–782.
- [22] Fiana Raiber and Oren Kurland. 2010. On identifying representative relevant documents. In *Proceedings of CIKM*. 99–108.
- [23] Nimrod Raifer, Fiana Raiber, Moshe Tennenholtz, and Oren Kurland. 2017. Information Retrieval Meets Game Theory: The Ranking Competition Between Documents' Authors. In Proceedings of SIGIR. 465–474.
- [24] Stephen E. Robertson. 1977. The Probability Ranking Principle in IR. Journal of Documentation 33 (1977), 294–304.
- [25] Aécio S. R. Santos, Bruno Pasini, and Juliana Freire. 2016. A First Study on Temporal Dynamics of Topics on the Web. In Proceedings of WWW. 849–854.
- [26] Ashudeep Singh and Thorsten Joachims. 2018. Fairness of Exposure in Rankings. In Proceedings of SIGKDD. 2219–2228.
- [27] Amit Singhal, Chris Buckley, and Mandar Mitra. 1996. Pivoted Document Length Normalization. In Proceedings of SIGIR. 21–29.
- [28] L. Smith and P. Sorensen. 2000. Pathalogical outcomes of observational learning. Econometrica 68 (2000), 371–398.
- [29] Moshe Tennenholtz and Oren Kurland. 2019. Rethinking search engines and recommendation systems: a game theoretic perspective. *Commun. ACM* 62, 12 (2019), 66–75.
- [30] Ryen W. White. 2016. Interactions with Search Systems. Cambridge University Press.
- [31] Qiang Wu, Christopher J. C. Burges, Krysta Marie Svore, and Jianfeng Gao. 2010. Adapting boosting for information retrieval measures. *Information Retrieval* 13, 3 (2010), 254–270.
- [32] Ke Yang and Julia Stoyanovich. 2017. Measuring Fairness in Ranked Outputs. In Proceedings of the 29th International Conference on Scientific and Statistical Database Management, Chicago, IL, USA, June 27-29, 2017. 22:1–22:6.
- [33] Zhilin Yang, Zihang Dai, Yiming Yang, Jaime G. Carbonell, Ruslan Salakhutdinov, and Quoc V. Le. 2019. XLNet: Generalized Autoregressive Pretraining for Language Understanding. In *Proceedings of NeurIPS*. 5754–5764.
- [34] Elad Yom-Tov, Anat Brunstein-Klomek, Or Mandel, Arie Hadas, and Silvana Fennig. 2018. Inducing Behavioral Change in Seekers of Pro-Anorexia Content Using Internet Advertisements: Randomized Controlled Trial. *JMIR Ment Health* 5, 1 (22 Feb 2018), e6.
- [35] Elad Yom-Tov, Peter Muennig, and Abdulrahman M El-Sayed. 2016. Web-Based Antismoking Advertising to Promote Smoking Cessation: A Randomized Controlled Trial. J Med Internet Res 18, 11 (21 Nov 2016), e306.
- [36] Meike Zehlike, Francesco Bonchi, Carlos Castillo, Sara Hajian, Mohamed Megahed, and Ricardo A. Baeza-Yates. 2017. FA*IR: A Fair Top-k Ranking Algorithm. In Proceedings of CIKM. 1569–1578.
- [37] Rowan Zellers, Ari Holtzman, Hannah Rashkin, Yonatan Bisk, Ali Farhadi, Franziska Roesner, and Yejin Choi. 2019. Defending Against Neural Fake News. In Proceedings of NeurIPS. 9051–9062.
- [38] Chengxiang Zhai and John D. Lafferty. 2001. A Study of Smoothing Methods for Language Models Applied to Ad Hoc Information Retrieval. In *Proceedings of* SIGIR. 334–342.