REDUCING MISINFORMATION IN QUERY AUTOCOMPLETIONS*

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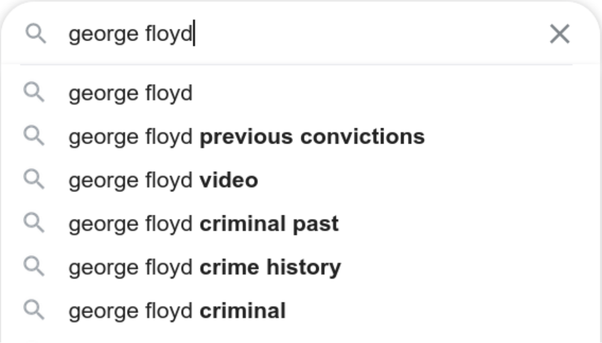
Abstract

Query autocompletions help users of search engines to speed up their searches by recommending completions of partially typed queries in a drop down box. These recommended query autocompletions are usually based on large logs of queries that were previously entered by the search engine's users. Therefore, misinformation entered – either accidentally or purposely to manipulate the search engine – might end up in the search engine's recommendations, potentially harming organizations, individuals, and groups of people. This paper proposes an alternative approach for generating query autocompletions by extracting anchor texts from a large web crawl, without the need to use query logs. Our evaluation shows that even though query log autocompletions perform better for shorter queries, anchor text autocompletions outperform query log autocompletions for queries of 2 words or more.

INTRODUCTION

The brutal killing end of May 2020 by Minneapolis police officers of George Floyd, who was already handcuffed, laying face down, and did not seem to resist arrest, became an immediate target of disinformation on the platforms run by Google and Facebook. Figure 1 shows Google's autocompletions for George Floyd early June 2020. Although it is hard to proof the deliberate manipulation of Google's autocompletions in this particular case, we show below that autocompletions based on previous user interactions have been shown to contain defamatory, racist, sexist and homophobic information, and there is increasing evidence that autocompletions are an easy target for spreading fake news and propaganda.



george floyd

george floyd
george floyd **previous convictions**
george floyd **video**
george floyd **criminal past**
george floyd **crime history**
george floyd **criminal**

Figure 1: Example autocompletions

Search engines suggest completions of partially typed queries to help users speed up their searches, for instance by showing the suggested completions in a drop down box. These *query autocompletions* enable the user to search faster, searching for long queries with relatively few key strokes. Jakobsson [12] showed that for a library information system, users are able to identify items using as little as 4.3 characters on average. Query autocompletions are now widely used, either with a drop down box or as instant results [4]. While Jakobsson [12] used the titles of documents as completions of user queries, web search engines today generally use large logs of queries submitted previously by their users. Using previous queries seems a common-sense choice: The best way to predict a query? Use previous queries! Several scientific studies use the AOL query log provided by Pass et al. [21] to show that query autocompletion algorithms using query logs are effective [3, 8, 19, 24, 28]. However, query autocompletion algorithms that are based on query logs are problematic in two important ways:

1. They return offensive and damaging results;
2. They suffer from a destructive feedback loop.

We discuss these two problems in the following sections.

Offensive queries and misinformation in query autocompletions

Query autocompletion based on actual user queries may return offensive results, and there are several examples where offensive autocompletions hurt organizations or individuals. For instance in 2010, a French appeals court ordered Google to remove the word "arnaque", which translates roughly as "scam", from appearing in Google's autocompletions for the CNFDI, the Centre National Privé de Formation a Distance [17]. Google's defense argued that its tool is based on an algorithm applied to actual search queries: It was users that searched for "cnfdi arnaque" that caused the algorithm to select offensive suggestions. The court however ruled that Google is responsible for the suggestions that it generates, and that Google should remove misinformation that is based on user-generated input of its search engine. Google lost a similar lawsuit in Italy, where queries for an unnamed plaintiff's name were presented with autocomplete suggestions including "truffatore" ("con man") and "truffa" ("fraud") [18]. In another similar law suite, German's former first lady Bettina Wulff sued Google for defamation when queries for her name completed with terms like "escort" and "prostitute" [15]. In yet another lawsuit in Japan, Google was ordered to disable autocomplete results for an unidentified man who could not find a job because a search for his name linked him with crimes he was not involved with [5].

Google has since updated its autocompletion results by filtering offensive completions for person names, no matter who the person is [29]. But controversies over query

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autocompletions remain. A study by Baker and Potts [2] highlights that autocompletions produce suggested terms which can be viewed as racist, sexist or homophobic. Baker and Pots analyzed the results of over 2,500 query prefixes and concluded that completion algorithms inadvertently help to perpetuate negative stereotypes of certain identity groups. A study by Ray and Ayalon [23] suggests that Google plays an important role in the spread of age and gender stereotypes via its autocomplete algorithm. And despite Google intention to filter autocompletions for person names,

There is increasing evidence that autocompletions play an important role in spreading fake news and propaganda. Query suggestions actively direct users to fake content on the web, even when they are not looking for it [22]. Examples include completions like "Did the holocaust happen", which if selected, returned as its top result a link to the neo-Nazi site stormfront.org [7]. Bad publicity will usually persuade Google to remove such autocompletions. In 2016, Google announced it removed "are Jews evil" from its autocompletions, but many similar offensive completions were still suggested two years later [14]. Removing such completions is important, because they led people to search for offensive results that otherwise would not have. Stephens-Davidowitz [26] showed that in the 12 months following Google's removal of "are Jews evil", approximately 10% fewer such questions were asked compared to the 12 months before the removal.

The examples show that query autocompletions can be harmful if they are based on searches by previous users. Harmful completions are suggested when ordinary users seek to expose or confirm rumors and conspiracy theories. Furthermore, there are indications that harmful query suggestions increasingly result from computational propaganda, i.e., organizations use bots to game search engines and social networks [25]. It is not hard to manipulate search autocompletions, as shown by Want et al. [27], who revealed hundreds of thousands of manipulated terms that are promoted through major search engines.

A destructive feedback loop

Misinformation and morally unacceptable query completions are not only introduced by the searches of previous users, they are also mutually reinforced by the search engine and its users. When a query autocompletion algorithm suggests morally unacceptable queries, users are likely to select those, even if the users are only confused or stunned by the suggestion. But how does the search engine ever learn it was wrong? It might not ever. As soon as the system determined that some queries are recommended; they are more of them selected by users, which in turn makes the queries end up in the training data that the search engine uses to train it's future query autocompletion algorithms. Such a destructive feedback loop is one of the features of a *Weapon of Math Destruction*, a term coined by O'Neil [20] to describe harmful statistical models.

O'Neil sums up three elements of a Weapon of Math Destruction: Damage, Opacity, and Scale. Indeed, the *damage* caused by query autocompletion algorithms is extensively discussed in the previous section. Query autocompletion algorithms are *opaque* because they are based on the proprietary, previous searches known only by the search engine. If run by a search engine that has a big market share, the query completion algorithm also *scales* to a large number of users. Query autocompletions of a search engine with a majority market share in a country might substantially alter the opinion of the country's citizens, for instance, a substantial number of people will start to doubt whether the holocaust really happened.

Structure of the paper

This paper is structured as follows. In Section , we describe a simple but powerful approach that trains query autocompletions using the content that is indexed by the search engine by extracting anchor texts from a large web crawl. Section compares these content-based query autocompletions to collaborative query autocompletions based on query logs. Section concludes the paper.

CONTENT-BASED AUTOCOMPLETIONS

It is instructive to view a query autocompletion algorithm as a recommender system, that is, the search engine recommends queries based on some input. Recommender systems are usually classified into two categories based on how recommendations are made [1]:

1. Collaborative recommendations, and
2. Content-based recommendations.

Collaborative query autocompletions are based on similarities between users: "People that typed this prefix often searched for: ...". Content-based query autocompletions are based on similarities with the content: "Web pages that contain this prefix are often about: ...".

Until now, we only discussed collaborative query autocompletion algorithms. What would a content-based query autocompletion algorithm look like? Bhatia et al. [6] proposed a system that generates autocompletions by using all N-grams of order 1, 2 and 3 (that is single words, word pairs, and word triples) from the documents. They tested their content-based autocompletions on newspaper data and on data from ubuntuforums.org. Instead of N-gram models from all text, Kraft and Zien [13] built models for query reformulation solely from the anchor texts, the clickable texts from hyperlinks in web pages. Interestingly, Dang and Croft [10] argue that anchor text can be an effective substitute for query logs. They studied the use of anchor texts for a range of query reformulation techniques, including query-based stemming and query reformulation, treating the anchor texts as if it were a query log.

Inspired by research of Bhatia et al. [6], Kraft and Zien [13], and Dang and Croft [10], we obtain query autocompletions from the anchor texts of web pages, and test how well these autocompletions predict full queries from a large query log of a web search engine, given a query prefix.

COLLABORATIVE VS. CONTENT-BASED AUTOCOMPLETIONS

In this section, we answer the question: Are query suggestions from anchor texts any good compared to query suggestions from query logs? To evaluate this, we used the query log of Pass et al. [21], which contains 20 million queries submitted by about 650,000 users to the AOL search engine between March and May in 2006. Following the recent query autocompletion experiments by Cai et al. [8], we used queries submitted before 8 May 2006 as training queries and queries submitted afterwards as test queries. We removed queries containing URL substrings (‘http:’, ‘https:’, ‘www.’, ‘.com’, ‘.net’, ‘.org’, and ‘.edu’) from both the training and the test queries. We did not further filter the data (Cai et al. [8] only kept queries appearing in both partitions). Because we are not interested in personalization, we put 99% of the users in the training data, and the remaining 1% of the users in the test data. This leaves more than 3.3 million unique training queries and 952 queries for testing the system. For every test query, we used 10 different prefixes as input to: 1 to 5 characters, and 1 to 5 words. If the query has less than 5 characters or less than 5 words, we take the full query as input. For each prefix we measured the mean reciprocal rank (MRR) of the position for which our approaches return the full test query. The MRR is calculated as one divided by the position of the correct result, so it will be 1 if the correct result is returned first, 0.5 if it is returned second, etc. We also measured the average number of results returned for each prefix. The results of autocompletions using the 3.3 million unique queries from the training data are presented in Table 1.

Table 1: Quality of autocompletions using query logs

Prefix	**MRR**	**Returned**
1 char	0.026	10.00
2 char	0.072	10.00
3 char	0.135	9.99
4 char	0.181	9.71
5 char	0.227	9.28
1 word	0.271	8.15
2 word	0.354	4.40
3 word	0.365	3.30
4 word	0.365	3.06
5 word	0.366	3.04

Table 1 shows that after typing 3 characters the MRR is 0.135, so the correct suggestion is on average available in the top 8 results (1/8 = 0.125). After typing 1 word, the MRR is 0.271, i.e., on average the correct suggestion is available in the top 4 results.

For anchor text completions we ideally would need a large web crawl from 2006 (the year of the query log). In absence of such a crawl, we used data from ClueWeb09, a web crawl of more than 1 billion pages crawled in January and February 2009 by Callan and Hoy [9] at Carnegie Mellon University. Anchor texts for the English pages in this collection (about 0.5 billion pages) are readily available [11], so we do not actually need to process the ClueWeb09 web pages themselves. Anchor texts with separators (‘.’, ‘?’,‘!’, ‘|’, ‘-’ or ‘;’) followed by a space were split in multiple strings. Text in braces ‘()’, ‘{}’, ‘[]’ was removed from the strings. We processed the anchor texts by retaining only suggestions that occur at least 15 times. This resulted in 46 million unique suggestions. Performance of the ClueWeb09 anchor text suggestions is presented in Table 2.

Table 2: Quality of autocompletions using anchor texts

Prefix	**MRR**	**Returned**
1 char	0.006	10.00
2 char	0.025	10.00
3 char	0.066	10.00
4 char	0.123	9.92
5 char	0.180	9.71
1 word	0.251	8.62
2 word	0.415	5.42
3 word	0.440	3.95
4 word	0.443	3.67
5 word	0.443	3.64

Table 2 shows that for queries of 2 words or more (the average query length in the test data is 2.6), anchor text autocompletions perform better than query log autocompletions, up till an MRR of 0.443 (0.366 for query logs). Query log autocompletions perform better for shorter queries: Anchor text autocompletions need about one character more than query log autocompletions to achieve a similar MRR for the first 5 characters. The source code for running the experiment is available from `https://github.com/searsia/searsiasuggest`.

CONCLUSION

Query autocompletions based on anchor text from web pages perform remarkably well. For queries of more than one word, they outperform autocompletions that are based on over two months of query log data. Simply extracting all anchor texts is really only a first attempt to get well-performing autocompletions from web content. Ideas to improve suggestions are: Using linguistic knowledge to get suggestions from all web page text (for instance using the Stanford CoreNLP tools [16]), using web knowledge like PageRank scores and Spam scores[1] to improve the quality of suggestions, and reranking of suggestions by their “queryness” using machine learning.

Future work should follow a user-centered evaluation, using ethical instruments of analysis, to better measure the usefulness of autocompletions. This includes measuring if the approach is able to suggest a query that is better than the user’s intended query, measuring the actual amount of

[1] PageRank scores and Spam scores are also available for ClueWeb09 [9].

misinformation in autcompletions (links can also be manipulated, using so-called Google bombing), as well as their timeliness (updating from hyperlinks might be slower than updating from queries).

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