

Towards Query Logs for Privacy Studies: On Deriving Search Queries from Questions

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Abstract. Translating verbose information needs into crisp search queries is a phenomenon that is ubiquitous but hardly understood. Insights into this process could be valuable in several applications, including synthesizing large privacy-friendly query logs from public Web sources which are readily available to the academic research community. In this work, we take a step towards understanding query formulation by tapping into the rich potential of community question answering (CQA) forums. Specifically, we sample natural language (NL) questions spanning diverse themes from the Stack Exchange platform, and conduct a large-scale conversion experiment where crowdworkers submit search queries they would use when looking for equivalent information. We provide a careful analysis of this data, accounting for possible sources of bias during conversion, along with insights into user-specific linguistic patterns and search behaviors. We release a dataset of 7,000 question-query pairs from this study to facilitate further research on query understanding.

1 Introduction

Motivation. Detailed query histories often contain a precise picture of a person's life, including sensitive and personally identifiable information. As sanitization of such logs is an unsolved research problem, commercial Web search engines that possess large datasets of this kind at their disposal refrain from disseminating them to the wider research community. These concerns were made obvious especially after the 2006 AOL log scandal³. Ironically, however, studies examining privacy in search often require detailed search logs with user profiles [10,9,1,13,45,46,40,21]. Even beyond privacy, collections with rich interaction profiles of users are also an asset in personalization [7,37,39] and simulation studies [20,3,8] in information retrieval.

While there exist a number of public IR collections, none of them contain data necessary for such studies. Notable among these, the TREC Sessions Track 2014 data [12] has 148 users, 4.5k queries and about 17k relevance judgments. There are roughly ten sessions per user, where each session is usually a set of reformulations. Such collections are rather small for driving research in user-centric

³ https://en.wikipedia.org/wiki/AOL_search_data_leak, Accessed 06 Jun 2019.

privacy. The 2014 Yandex collection released as part of a workshop on log-based personalization [34] is useful for evaluating personalization algorithms [37,11]. However, to protect the privacy of Yandex users, every query term is replaced by a meaningless numeric ID. This anonymization strategy makes semantic interpretation impossible and may be a reason why this resource did not receive widespread adoption in privacy studies. Interpretability of log contents is important to understand privacy threats [9,10,21,13,40].

Motivated by the lack of publicly available query logs with rich user profiles, Biega et al. [10] synthesized a query log from the Stack Exchange⁴ platform – a collection of CQA subforums on a multitude of topics. Each subforum is focused on a specific topic, like linguistics, parenting, and beer brewing. Queries in the synthetic log were derived from users’ information needs posed as NL questions. A collection like this has three advantages. First, it enables creation of rich user profiles by stitching queries derived from questions asked by the same user across different topical forums. Second, since it was derived from public resources created by users under the Stack Exchange terms of service (allowing for reuse of data for research purposes), it escapes the ethical pitfalls intrinsic to dissemination of private user data. Third, CQA forums contain questions and assessments of relevance in the form of accepted answers *from the same user*, which is vital for the correct interpretation of query intent [15,4]. The proposed derivation approach in [10], however, was rather heuristic: the top- l TF-IDF weighted question words were extracted to form a keyword query, where the query length l was uniformly sampled from a range of one to five words.

Contributions. Such a query log derivation methodology from CQA forums has the potential to produce sizeable IR collections, a fact recognized by recent analogous efforts from Wikipedia [33]. However, to harness CQA resources better, it is necessary to: (i) better understand how humans formulate keyword queries given a verbose information need in natural language, and, (ii) derive other elements like candidate documents and relevance judgments from CQA forums for completeness of derived benchmarks. This paper focuses on these problems and makes the following contributions:

- We conduct a large-scale user study where crowdworkers convert questions to queries;
- We provide insights from the collected data that can drive strategies for automatic conversion at scale;
- We release 7,000 question-query pairs that can be used for training and evaluating such conversion methods at <https://www.mpi-inf.mpg.de/departments/databases-and-information-systems/research/impact/mediator-accounts/>;
- We propose a methodology for deriving other collection elements like documents and relevance labels from CQA forums and analyze the utility of such a resource.

⁴ <https://stackexchange.com/sites>, Accessed 06 Jun 2019.

2 User study: Setup and Pilot

We conduct a large-scale user study to understand how humans create keyword queries for information needs expressed as natural language questions. We use questions from the Stack Exchange forum and ask workers on Amazon Mechanical Turk (AMT) to create queries specifying the same information needs as the questions. Notably, crowdsourcing has recently been successfully applied to similar creative tasks of short text generation [14], where workers paraphrased search result snippets.

2.1 Question sampling

Filtering subforums. We used the Stack Exchange dump from March 2018⁵ with data for more than 150 different subforums. We are interested in questions written in *English text* and thus exclude forums primarily dealing with programming, mathematics, and other languages like French and Japanese. Moreover, we want to avoid highly-specialized forums as the average AMT user may not have any background knowledge to generate queries for such niche domains. To this end, we exclude all subforums with less than 100 questions, as a proxy for expression of a critical mass of interest. We found that 75 subforums satisfy our requirements for subsequent question sampling.

Filtering questions. As a proxy for questions being understandable by users, we choose only those that have an answer accepted by the question author, and with at least five other answers provided.

Sampling questions. Under these constraints, we first sample 50 subforums from the 75 acceptable ones to have high diversity in question topics. Next, we draw 100 questions from each of these thematic groups, producing a sample of 5000 questions, which is used as the data in the user study.

2.2 Study Design

AMT crowdworkers in the study were first presented with a short tutorial explaining the task as well as a number of examples visualizing the task. After familiarizing themselves with the instructions, they proceeded to converting questions to search queries in the main part of the study, followed by a survey on demographic information.

AMT Setup We recruited a total of 100 workers who had Master qualifications and an approval rate of over 95% to ensure quality of annotations. We paid \$6 per assignment in the pilot study (30 questions per assignment), and \$9 per assignment in the main study (50 questions per assignment.) The workers were given three hours to complete the assignments, while the actual average time taken per question turned out to be 116 seconds.

⁵ <https://bit.ly/2JI8ubn>, Accessed 06 Jun 2019.

Instructions

When we need to look for some information or answer a question (that is, satisfy an information need), we often turn to a search engine to find the answers. Search systems such as Google or Bing return results in response to web search queries that succinctly express our information needs.

In this HIT, we ask you to do the following for 50 examples:

1. read a descriptive **question** that was asked by a person looking for certain information,
2. and then, provide a **search query** you would use if you were to look for the **same information** as the author of the question, but **using a search engine** (such as Google).

To formulate the query, you can either select words from the provided body of text, or use your own words if necessary. Seven solved examples that guide you through representative scenarios are provided for your convenience.

Example 1:

[travel] How do I cancel a Schengen tourist visa? I currently have a valid Schengen tourist visa that expires next year, issued by the French Consulate in Saudi Arabia. I am going to a 60-day study abroad program in Italy and they require a student visa. I went to the Italian Consulate in Boston and they asked me to go to the French Consulate and cancel my visa. However, the French Consulate said that I needed to contact the French Embassy in Saudi to cancel the visa. How can I cancel my tourist visa if I am currently in the United States? My Italian student visa application is due tomorrow morning.

An acceptable query is shown here:
cancel tourist visa french consulate usa

The words have been marked in color only for illustrating where they were chosen from. You only have to provide the query text; no explanation or coloring is necessary.

[travel] How do I cancel a Schengen tourist visa? I currently have a valid Schengen tourist visa that expires next year, issued by the French Consulate in Saudi Arabia. I am going to a 60-day study abroad program in Italy and they require a student visa. I went to the Italian Consulate in Boston and they asked me to go to the French Consulate and cancel my visa. However, the French Consulate said that I needed to contact the French Embassy in Saudi to cancel the visa. How can I cancel my tourist visa if I am currently in the United States? My Italian student visa application is due tomorrow morning.

Fig. 1: Instructions from the pilot study.

Instructions and Task We kept the task guidelines simple to avoid biasing participants towards certain answers. We do mention the workers are free to select words from the text of the question or use their own words. Fig. 1 shows a screenshot with the instructions from the pilot study. The instructions give a very high-level overview of the procedure of searching for information using search engines to introduce the context.

We provided several examples as a part of the instructions to better illustrate the task. Examples were meant to cover the various ways of arriving at a correct solution: selecting words from the question, using own words, changing grammatical forms, constructing queries of various length, etc. These cases were not made explicit, but communicated by highlighting words in the text and the query, as shown in Fig. 1.

As a main task, participants were shown a number of questions expressing certain information needs and asked to formulate search queries they would use to search for the same information as the author of the question was searching for. The questions were presented in the following form:

[Forum Name] Title Body

Each question was a concatenation of the Stack Exchange post title and body, and prefixed with the forum name the post comes from to give it the right context. The main task was further accompanied by an optional demographic survey to help us understand if various demographic features influence how people formulate queries.

2.3 Pilot study

We tested the setup in a pilot study with five HITs and 30 questions each. The average query length was 5.65 words with a standard deviation of 2.40. Out of 150 questions, the forum name was included in the corresponding query 33 times. In nine of such cases, the forum name was not present in the title or body of the question, which suggests the presence of the forum name is important in determining the context of the question. Most query words were chosen from the title, although title words are often repeated in the body of the question. Workers used their own words or words modified from the question 47 times. These results suggest that participants generally understood the instructions. The five workers took 22, 75, 92, 88, and 100 minutes to complete the tasks. The demographic survey revealed that the fastest person with 22 minutes worked in the IT industry.

3 User study: Controls and Main

3.1 Control study for title position bias

A vital component of any crowdsourced study is to check if participants are looking for quick workarounds for assigned tasks that would make it hard for requesters to reject payments, and to control for confounding biases. In the current study for converting questions to queries, the source of potential bias stems from the fact that a question is not just a sequence of words but a semi-structured concept: it has (i) a subforum name to which the question belongs, (ii) a title, and (iii) a body. Web users might be aware that question titles in CQA forums often summarize the question. Thus, if the structure is apparent to the annotator, she might use words only from the title without meticulously going through the full question content, which may often be a few hundred words.

To mitigate such a possibility, we present the titles in the same font as the body, and do not separate them with newlines. Regardless of this uniformity of presentation, users may still be able to easily figure out that the first sentence is indeed the question title. To quantify the effect of this *position bias* of the title, we used ten HITs (500 questions) as a *control experiment* where, unknown to the Turkers, the title was appended as the *last sentence* in the question. These same 500 questions were also annotated in the usual setup in the main part of the study for comparison.

We compare the results of the main and the control studies by measuring the fraction of times users chose words from the first and the last sentences. Results are shown in Table 1. Fractions were normalized by the length of the question title, as raw counts could mislead the analysis (longer question titles automatically contribute larger *numbers* of words to the queries). Thus, if two words were chosen from an eight-word-long title to appear in the query, we would compute the reported fraction as 0.25 (25%).

We make the following observations: (i) in both the main study and the control, users choose words from the title very often ($\simeq 97\%$ and $\simeq 84\%$, respectively), showing similar task interpretation. Note that such high percentages are

Property	Main study	Control study
Times question title word chosen for query	96.6%	83.8%
Question title words in query	37.7%	26.1%
Question first sentence words in query	37.7%	12.2%
Question last sentence words in query	9.0%	26.1%

Table 1: Measurements from the position bias control study.

acceptable, as question titles typically do try to summarize intent. Nevertheless, examining the entire body for complete understanding of the asker’s intent is central to our task. (ii) Relatively similar percentages of query words originate from the titles in both cases (37.7% vs. 26.1%). (iii) If Turkers were trying to do the task just after skimming the first sentence (which they would perceive as the title), the percentage of words from the first sentence in the control would have been far higher than a paltry 12.2%, and the last sentence would contribute much lower than a promising 26.1%.

Words in the title, being topical to the question, are often repeated in the body text in CQA forums. To test this word selection owing to presence elsewhere in the question (like body text or subforum name), we also measured the fraction of words chosen by Turkers in the control study that occurred *exclusively* in the last sentence. This was found to be 4.1%: we posit that if Turkers were simply looking to make quick money, or biased by imagining the first line to be the title, this fraction would have been close to zero. We thus conclude that Turkers completed their HITs with due understanding and sincerity: words from titles were chosen frequently because of their *relevance*, and not because of their relative positions in the question. As a result of this study, we chose to keep titles in their original first positions for the remainder of the main study, as putting it at the end degrades the overall coherence and readability of the question.

3.2 Control study for user agreement

While the main focus of the study was to construct a sizable collection of question-query pairs, we were also interested in learning how robust query formulation is to individual differences. To this end, we issued a batch of 10 tasks with 50 questions to be completed by three workers each. The validity of the comparison comes from the experimental design where query construction is conditioned on a specific information need.

We compute the average Jaccard similarity coefficient between all pairs of queries (q_1, q_2) corresponding to the same question: $Jaccard(q_1, q_2) = \frac{|q_1^W \cap q_2^W|}{|q_1^W \cup q_2^W|}$, where q_1^W and q_2^W are the sets of words of the compared queries. We find the average overlap to be 0.325, and to come mostly for the most informative content words in the question.

Property	Value
Title	“Write a Web search query”
Description	“Given a post, formulate a single query.”
Keywords	Question answering, Queries, Web forums
Questions in a HIT	50
Total HITs	100
Reward	\$9 per HIT
Time allotted	3 hours per HIT
Time required	1.6 hours per HIT on average
Restrictions	Workers must be Masters, One Turker one HIT

Table 2: Summary of the AMT main study.

3.3 Main study

Data Collection The main study was conducted with insights obtained from the pilot and the control studies. In total, we asked 100 AMT users to convert 5000 questions to queries. Users who participated in control studies were not allowed to take part again, to avoid *familiarity biases* arising from such overlap. Basic properties of this stage are presented in Table 2. Guidelines were kept the same as in the pilot study. The number of questions in one HIT were increased from 30 to 50, to cover user-specific querying traits better. In line with this change, the reward per HIT was increased from \$6 to \$9. The Turkers took about 1.6 hours per HIT, which comes down to 116 seconds per question. Since Stack Exchange questions can be quite long, we believe that such a mean task completion time is reasonable. The mean query length turned out to be 6.15 words, which is longer than the average Web search query (about three to four words [28,43]). We believe that this is likely because Stack Exchange questions express more complex information needs.

Data Analysis We looked into three aspects of *question-query pairs* when trying to discriminate between words that are *selected* for querying, and those that are not.

Position. We measured relative positions of query and non-query words in the question, and found that a major chunk ($\simeq 60\%$) of query words originate from the first 10% of the question. The next 10% of the question contributes an additional 17% of words to the query; the remaining 80% of the question, in a gently diminishing manner, produce the rest 13% of the query. This is a typical top-heavy distribution, suggesting humans conceptualize the core *content* of the information need first and gradually add specifications or conditions of *intent* towards the end [28,29,30]. Notably, even the last 10% of the question contains 2.78% of the query, suggesting that we cannot disregard tail ends of questions.

Finally, note that the title is positioned at the beginning of the question (Sec. 3.1), and alone accounts for 57% of the query. Title words, however, do repeat in the body, and further inspection reveals that 12% of the query mass is

comprised of words that appear exclusively in the title. In Stack Exchange, title are often constructed as summaries of the questions.

We also allowed users to use their *own words* in the queries. Our analysis reveals that a substantial 17% of query words fell into this category. Such aspects of this data pose interesting research challenges for query generative models.

Part-of-speech (POS). Words play roles of varying importance in sentences, with a high-level distinction between *content words* (carrying the *core* information in a sentence) and *function words* (specifying *relationships* between content words). Search engine users have a mental model of what current search engines can handle: most people believe that function words (prepositions, conjunctions, etc.) are of little importance in query formulation, and tend to drop them when issuing queries. These intuitions are indeed substantiated by our measurements: content words (nouns, verbs, adjectives and adverbs) account for a total of 79% (47%, 15%, 13%, and 4% respectively) of query words, while function words constitute only 21% of the query. In this work, we use the 12 Universal POS tags (UTS)⁶ proposed by Petrov et al. [26]. Our findings partially concur with POS analysis of Yahoo! search queries from a decade back [6] where nouns and adjectives were observed to be the two most dominant tags; verbs featured in the seventh position with 2.4%. We believe that the differences can be attributed to the changing nature of search, where more complex information needs demand more content words to be present in the queries. These insights from POS analysis of queries can be applied to several tasks, like query segmentation [31,18].

Frequency. A verbose information need may be characterized by certain recurring units, which prompted us to measure the normalized frequency TF_{norm} of a term t in a question Q , as $TF_{norm}(t, Q) = TF(t, Q)/len(Q)$, where $len(Q)$ is the question length in words. Query words were found to have a mean TF_{norm} of 0.032, significantly higher than that of non-query words (0.018).

3.4 Demographics

Workers in the study were asked to fill a demographic survey at the end of the task. We made these questions optional so as not to incentivize fake answers if the workers feel uncomfortable giving an answer. We asked about gender, age, country of origin, highest educational degree earned, profession, income, and the frequency of using search engines as the number of search queries issued per day (such activity could be correlated with search expertise, and the expertise may manifest itself subtly in the style of the generated queries).

From the 100 subjects in our study, 50 were female and 50 were male. Nearly all lived in the United States except for three who lived in India. We found a weak correlation between the query length and age (query length generally increased with the age of participants), and found that men formed slightly longer queries on average (6.56 words for men versus 6.15 words for women).

⁶ <https://github.com/slavpetrov/universal-pos-tags>, Accessed 06 Jun 2019.

3.5 Released Data

We release a dataset of 7,000 natural language questions paired with corresponding search queries (5,000 from the main study and 2,000 from the control studies). The average query length is over six words, reflecting a degree of complexity in the underlying information needs, and in turn, interesting research challenges for methods aiming at automated conversion strategies for synthetic query log derivation. Key features of this collection include: (i) question topics spanning 50 different subforums of Stack Exchange, and (ii) question-query pairs grouped by 100 annotator IDs, making the released testbed suitable for analyzing user-specific query formulation, and cross-domain experiments.

4 Potential of Derived IR Collections

The insights from our user study could be used to drive automatic conversion methods for synthetic query logs. The collection derived by Biega et al. [10] contains just a query log with user profiles. However, many more elements of IR collections, including the notion of document relevance, are embedded in the contents and structure of CQA forums. While NL questions represent information needs and can be converted to queries, answers to these questions are analogous to documents that satisfy these needs. Moreover, systems of rating answers such as upvotes or acceptances by the question author, are in fact explicit assessments of relevance. In this section, we aim to analyze the characteristics and potential of such a synthetic IR collection derived from the Stack Exchange forum.

4.1 Deriving a collection from Stack Exchange

Source dataset We extract the collection from the Stack Exchange dump from March 2018. It contains all information publicly available on any of the 152 thematically diverse subforums within Stack Exchange. *Topics* range from the general domain, like fitness, beer brewing, and parenting, to more technical areas, such as astronomy, engineering, or computer programming. We exclude the largest subforum Stack Overflow from the source dataset to avoid the dominance of programming queries in our collection.

Each subforum dump contains, among other content, all posted questions, answers, and comments, as well as information about accepted answers, upvotes and downvotes. User *profiles* can be constructed by joining questions and answers with the same *globalID* attribute across subforums. Such users profiles, often unavailable in other published IR collections, can potentially be an asset for personalization algorithms.

Questions to queries The results of our user study suggest that the term frequency features are indeed a reasonable indicator of whether a term should be included in a query. We thus follow the general methodology of Biega et al. [10] for converting queries to questions where we choose a random number of

question terms with the highest TF-IDF. However, we modify the distribution from which the query lengths are sampled to resemble the distribution estimated from the 2006 AOL log [25]. The term frequency (TF) is measured within the question, and the inverse document frequency (IDF) is calculated from the set of all questions and answers. We retain users with at least 100 queries.

Duplicate queries. A key difference between query logs and questions from strongly moderated forums like Stack Exchange is the lack of duplicate information needs. While a search engine log has many instances of repeated queries, in a CQA forum a question is often closed, merged or deleted if a similar question has been asked before. Thus, to simulate duplicate queries, we use another feature of Stack Exchange: *marking a question as a favorite*. When a user marks another user’s question as a “favorite”, they start following the question and get notified about its updates. We interpret this as a signal of the user expressing the same information need. We thus duplicate a question in the histories of all users who marked it as her favorite, *before* the query extraction process.

Answers to documents Answers in Stack Exchange and other CQA forums like Quora are often several paragraphs long, and can naturally be treated as documents for an IR collection.

Acceptance and votes to *qrels* Most popular online CQA forums now have two features that express relevance: (i) answer acceptance, and (ii) upvotes and downvotes. Acceptance is marked by the user who asked the question when an answer satisfies her information need, and hence can be considered a gold relevance judgment [4] (up to one per question). Upvotes and downvotes are generally given by people who understand the discussion, and hence can be considered silver annotations (domain experts in [4]). Gold and silver judgments are more useful than bronze judgments, which are obtained from annotators who neither issued the query, nor are experts on the topic.

For the purpose of this analysis, we use a three-point graded relevance. We assume the answer accepted by the question author to be *completely relevant* (2), the other answers posted as a response to the question as *partially relevant* (1), and any other answer as *non-relevant* (0). While the assumption about the non-relevance is imperfect, the concern is alleviated by the fact that Stack Exchange is a highly moderated forum with questions often closed or marked as duplicates by the moderators. It is also worth noting that answers from the same subforum but for a different question are likely to have high word-level overlap with the original question, which might be a reasonable approach to generating quality negative training examples for IR models. Using upvotes and downvotes to deduce further levels of relevance is a topic of future work.

4.2 Empirical analysis of the collection

In this subsection, we examine the characteristics of a collection derived using the methodology described in Sec. 4.1 to shed light on its usefulness.

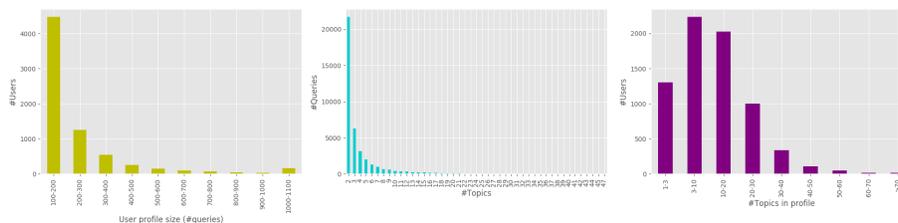


Fig. 2: Distributions describing key features of the presented resource.

No. of users	7,104
No. of queries (distinct)	1,931,336 (1,036,953)
No. of documents	5,262,125
No. of topics (forums)	152
Mean (SD) query length in words	2.45 (1.74)
Mean (SD) document length in words	126.26 (149.22)
Mean (SD) user profile size in queries	271.87 (1392.59)
Mean (SD) topics in user profile	12.99 (10.88)

Table 3: Aggregate statistics for the derived collection.

Corpus statistics Table 3 and Fig. 2 present basic statistics over the elements of the collection. There are about $7K$ user profiles, together issuing approximately $2M$ queries. The distribution of user profile sizes is shown in Fig. 2 (a).

The associated document collection size is about $5M$, created from all answer posts. $1.5M$ of these are an accepted answer to one of the queries, and hence are *completely relevant* for those queries. The rest of the documents ($\approx 3.5M$) are *partially relevant* for those queries to which they were posted as answers. The average document consists of about 126 words, with a standard deviation of about 149 words.

User profiles display rich topical variety, with the average number of distinct subforum contributions from a user being about 13, with a standard deviation of about 10. The user-subforum distribution is shown in Fig. 2 (c). While this diversity in forum contributions suggests that there is a scope for topical personalization, another important aspect to personalization is topical ambiguity. Fig. 2 (b) shows the distribution of the number of queries (y -axis) which are textually equal, but were derived from a number of different topics (x -axis). We removed the bar for queries derived from a single topic only (there were around $1M$ such queries). Table 4 presents representative queries from the collection together with excerpts from the accepted answer document (gold relevance).

Performance in retrieval We perform basic retrieval experiments to gain insights into the retrieval difficulty of the collection. First, we index the documents with Indri [36], using the standard stopwords list (<https://www.ranks>).

Topic	Query with excerpt from accepted answer
Fitness	<i>Query: knee sleeve strengthen</i> <i>Answer:</i> I have osteochondritis desicans (sp?) in my left knee. Basically a nerve is pinched when my support muscles tire and sometimes the pain is bad enough that my knee buckles... But what really helped was lots of squats and bar bell training (deadlift, front squat, back squat, various Olympic lifts)...
Beer	<i>Query: cider pasteurized orchard</i> <i>Answer:</i> I haven't ever been able to tell the difference between a pasteurized or non as a juice base in the final product... THAT stuff still can make a good final beverage, but it turns out quite a bit different than the fresh-pressed stuff. In particular, the store juice tends to be much more tart...
Parenting	<i>Query: snack children sleep</i> <i>Answer:</i> Does a late evening snack improve the odds that a child will sleep well?... But it seems more likely that bedtime snack has become a ritual needed that helps relax a child...
Programming	<i>Query: gpg gpl licensed code</i> <i>Answer:</i> The GPL says you are to free to run, distribute, modify and study the library for any purpose. It does not restrict commercial usage of software...]
Engineering	<i>Query: torsional fem derivation constant</i> <i>Answer:</i> You can find an implementation of a finite element used in computation of arbitrary shape section torsional constant here...

Table 4: Examples from the derived collection.

nl/stopwords) and the Porter Stemmer [27]. We then retrieve the top-100 documents for each of the $2M$ queries in the query log, using Dirichlet smoothing [44].

Effectiveness is assessed using: (i) *Mean Average Precision (MAP)* [23] is computed considering the documents which originally were the answers to corresponding questions as relevant; and (ii) *Mean Reciprocal Rank (MRR)* [38] is computed using the answer accepted by the asker as relevant. All measures are averaged over queries for each user, and then macro-averaged over users.

Table 5 presents the performance of two retrieval baselines. The *Indri* method, representing the raw Indri retrieval, leaves a lot of room for improvement. There are two main reasons for this. First, when long questions are reduced to very short queries, often a large pool of documents match the query, possibly leaving the relevant documents beyond the top-100 results. Second, since the document

Method	MAP	MRR
Indri	0.076	0.053
Indri + q2a	0.398	0.211

Table 5: Basic retrieval performance.

collection consists of posts of type *answer*, the vocabulary of the questions need not match the document literally. To better understand this vocabulary mismatch issue in the collection, we perform retrieval with Indri over a collection where the questions are appended to the answers to form the documents. The *Indri+q2a* row in Table 5 quantifies to what extent this influences performance.

Summary. Results suggest that the derived collection leaves ample room for improvement for more advanced methods.

5 Related work

Collections for privacy studies. Research on privacy-preserving search has been perennially plagued by a scarcity of corpora with interaction and profile information. Consequentially, quite a few works on privacy remain theoretical or proposals without empirical validation [32]. Otherwise, it is a common practice to resort to using the 2006 AOL logs [25] despite the controversial circumstances of its release [9,35]. Volunteers have shared their search profiles in exceptional cases [41], but this may lead to a feeling of regret later on.

CQA datasets. The idea of tapping into CQA for curated resource creation has been around for a while. For example, there exists a small collection of crowd-sourced queries based on questions from Yahoo! Answers [17]. However, to the best of our knowledge, no large scale query collections with detailed user histories and relevance judgments have been extracted from CQA datasets. Harnessing CQA resources is an active topic now, and datasets like duplicate questions (<https://bit.ly/2upwz0x>) and question-code pairs [42] have recently been extracted. However, these resources are not suitable for directions discussed here.

Reducing queries. With regard to methodology, our work is related to *verbose query reduction* [16,19,2]. A number of such techniques have been evaluated in the context of CQA forums [19]. Kumaran and Carvalho [22] looked at query reduction based on query quality predictors, including IDF-based scores. We note, however, that these techniques aim at producing short queries that maximize retrieval effectiveness, while our goal is to produce queries that resemble those issued by real users. Since we also release the original NL questions along with the queries, the community is encouraged to explore other query reduction techniques [5,24] which can contribute to an improved version of our resource.

6 Conclusion

In this paper, we conducted a user study to provide a better understanding of how humans formulate queries from information needs described by natural language questions. Gaining insights into this process forms an important foundation for automatic conversion methods, which would allow us to create IR collections from the publicly available CQA resources. Such collections with rich user profiles, unavailable to academic researchers otherwise, would be a great asset driving research on user-centric privacy.

Beyond query log synthesis, our paper proposed a methodology for deriving other IR collection elements from the data and structure of CQA forums, including documents and gold relevance judgments. We further empirically analyzed a collection derived from Stack Exchange, showing its potential as a difficult retrieval benchmark. We release a dataset of 7,000 crowdsourced question-query pairs as well as the derived collection to foster further research in automatic derivation of large-scale privacy-friendly IR collections from CQA forums.

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