TripClick: The Log Files of a Large Health Web Search Engine

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1 INTRODUCTION

User interactions with information systems are a valuable resource for retrieval system training, refinement and evaluation. These interactions, in the form of click logs, contain submitted queries alongside clicked documents from the result page. To be effective, these collections are sizable, and can be exploited for search engine effectiveness improvement [3, 5, 34], as well as studying user behavior [23], and information needs [11].

In the health domain, information needs are often diagnostic, therapeutic or educational in nature. Common queries reflect patient characteristics such as demographics, general disposition or symptoms [8, 15, 27, 32, 33] and aim at obtaining a differential diagnosis [6, 17], suggested treatments [8], or tests that might help narrow down the range of candidate diagnoses. In comparison with general-purpose search engines, the user base of health search engines is almost exclusively composed of domain experts (healthcare professionals) and behavioral traces may differ significantly from those observed on the popular web.

This work develops and shares TripClick, a large-scale dataset of the click logs provided by https://www.tripdatabase.com, a health web search engine for retrieving clinical research evidences, used almost exclusively by health professionals. The dataset consists of 5.2 million clicks collected between 2013 and 2020, and is publicly available for research purposes. Each log entry contains an identifier for the ongoing search session, the submitted query, the list of retrieved documents, and information on the clicked document. TripClick is one of the very few datasets providing the necessary data richness and scale to train deep learning-based IR models with a high number of parameters. To the best of our knowledge, this is the first effort to release a large-scale click log dataset in the health domain. It can serve various information processing scenarios, such as retrieval evaluation, query analysis, and user behavior studies. In particular, covering the search activities throughout the year 2020, the TripClick dataset provides an interesting resource capturing the COVID-19 pandemic.

Based on the click logs, we create and provide a health IR benchmark. The benchmark consists of a collection of documents, a set of queries, and the query-document relevance information, extracted from user interactions. Regarding the documents collection, since the vast majority of the retrieved and clicked documents in the
dataset are medical articles originating from the MEDLINE catalog.⁹ We create the IR benchmark using the subset of the click logs containing the documents in MEDLINE. This results in a 1.5 million medical articles’ abstracts, 692,000 unique queries, and 4 million pairs of interactions between these queries and documents. We create and provide two estimations of query-document relevance using two click-through models [1]. The first one, referred to as RAW, follows a simple approach by considering every clicked document relevant to its corresponding query. The second uses the Document Click-Through Rate (DCTR) [4], which estimates query-document relevance as the rate of clicking the document over all retrieved results of a specific query.

The TripClick benchmark provides three groups of queries for evaluation of IR models. The groups are created according to specific query frequency ranges. Concretely, the HEAD group consists of most frequent queries which appear more than 44 times, non-frequent ones with frequencies between 6 and 44 times are grouped in TORSO, and TAIL encompasses rare queries appearing less than 6 times. To facilitate research on neural IR models, we create a large training set in pairwise learning-to-rank format [18]. Each item in the training data consists of a query, one of its relevant documents, and a randomly selected non-relevant document.

Using this data, we study the performance of several recent neural IR models as well as strong classical baselines. Evaluation is carried out using standard IR evaluation metrics, namely Mean Reciprocal Rank (MRR), Recall at cut-off 10, and Normalized Discounted Cumulative Gain (NDCG) at cut-off 10. The results show significant improvements of neural architectures over classical models as well as strong classical benchmarks.

The contribution of this work is three-fold:

- Creating a novel health IR benchmark, suited for deep learning-based IR models.
- Conducting evaluation experiments on various classical and neural IR models on the collection.

The click logs dataset, the benchmark, and all related resource as well as the code used to create the benchmark are available on https://tripdatabase.github.io/tripclick.

The remainder of this paper is structured as follows: Related resources are reviewed in Section 2. Section 3 describes the dataset of click logs, followed by explaining the process of creating the TripClick IR benchmark in Section 4. We lay out our experiment setup and report and discuss the results in Section 5.

2 RELATED RESOURCES

In this section, we review some of the existing resources related to TripClick, in particular large-scale search log datasets in the web domain, as well as some common health IR collections. The statistics of these resources as well as our novel TripClick dataset are summarized in Table 1.

Table 1: Number of queries and number of query-document interactions (Q-D) of various IR collections in the web and health domain.

| Collection                        | Queries | Q-D |
|-----------------------------------|---------|-----|
| Sogou-QCL [37]                    | 537K    | 12.2M |
| MS MARCO Passage Retrieval [21]   | 1.0M    | 532K |
| MS MARCO Document Retrieval [21]  | 367K    | 384K |
| ORCAS [2]                         | 10.4M   | 18.8M |
| TripClick Logs Dataset            | 1.6M    | 5.2M |
| TREC Precision Medicine 2019 [26] | 40      | 13K  |
| CLEF Consumer Health Search 2018 [13] | 50    | 26K  |

Figure 1: Sample click log entry.

Large-scale click log datasets in the English Web domain have first been released by AOL [23] and MSN [36], containing thousands of search queries. Later on, Yandex² provided a dataset with 35 million anonymized search sessions [29]. Recently, Sogou³ has made available a dataset of 537,000 queries in Chinese, accompanied with 12.2 million user interactions (Sogou-QCL) [37]. Another recent IR collection in the web domain, MS MARCO [21], provides a large set of informational question-style queries from Bing’s search logs. These queries are accompanied by human-annotated relevant/non-relevant passages and documents. More recently, the ORCAS collection [2] releases a large dataset of the click logs related to MS MARCO.

In the health domain, several standard IR benchmarks have been developed over the years, especially through evaluation campaigns such as the Text Retrieval Conference (TREC) and Conference and Labs of the Evaluation Forum (CLEF). Examples of some IR tasks are CLEF eHealth Consumer Health Search [13] and TREC Precision Medicine [26]. The related collections consists of some dozens of queries, where each query is accompanied by a set of human-annotated relevance judgements on documents. TripClick complements the previous efforts in creating standard health IR collections, by providing a novel dataset of health queries and query-document relevance signals, several orders of magnitude larger in size.

¹https://pubmed.ncbi.nlm.nih.gov
²https://www.yandex.com
³https://www.sogou.com

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¹https://pubmed.ncbi.nlm.nih.gov
3 TRIPCLICK LOGS DATASET

The TripClick logs dataset consists of the user interactions of the Trip search engine collected between January 2013 and October 2020. A sample click log entry is shown in Figure 1. Each entry consists of date and time of search (in Unix time, in milliseconds), search session identifier, submitted query (Keyword's field), document identifiers of the top 20 retrieved documents, and the metadata of the clicked document. For the clicked document, the provided data contains its unique identifier and URL. If the clicked document is a scientific publication, its title, DOI, and clinical areas are also stored. We should emphasize that the privacy of individual users is preserved in the clicked search logs by cautiously removing any Personally Identifiable Information (PII).

The statistics of the TripClick logs dataset are reported in Table 2. It consists of approximately 5.2 million click log entries, appeared in around 1.6 million search sessions (~3.3 interactions per session).

The click logs contain around 1.6 million unique queries. These unique queries appear in the logs at varying frequencies. Figure 2 shows the log-scaled query frequency histogram. The histogram fairly follows an exponential trend – there are many rare queries (issued only a few times to the search engine), while there are few highly frequent ones. Examples of a frequent and a rare query are “asthma pregnancy”, and “antimicrobial activity of medicinal plants”, respectively.

As reported in Table 2, the log files contain approximately 2.3 million documents. Together with the dataset of click logs, we provide the corresponding titles and URLs of all documents. Examining the origin of clicked documents, we observe that approximately 80% of the documents point to articles in the MEDLINE catalog, around 11% to entries in https://clinicaltrials.gov, and the rest to various publicly available resources on the web.

Finally, looking at the query contents, Figure 3 reports the number of times a query related to the COVID-19 virus is submitted to the search engine in the period of 2018-2020. The data for 2018 and 2019 are presented as annual sums, while for the year 2020, numbers are reported per month. While there are only few COVID-19-related queries before the February of 2020, the information need rapidly gains popularity with a peak in April. The provided data is potentially a useful resource for studying the COVID-19 pandemic, as well as the reaction and evolution of search engines regarding the sudden emergence of previously unknown/uncommon diseases.

4 TRIPCLICK HEALTH IR BENCHMARK

To create the TripClick benchmark, we use a subset of click log entries that refer to those documents that are indexed in the MEDLINE catalog. This choice was made because the majority of the click logs refer to MEDLINE articles (~80%). Additionally, from a practical point of view, considering that the MEDLINE articles remain constant over time, the contents of the corresponding documents can be conveniently determined from the present MEDLINE catalog, despite the fact that each document in the logs is accessed at some historic timestamp. MEDLINE articles are similarly used in several other health IR benchmarks [24–26]. This subset encompasses around 4 million log entries. The statistics of the TripClick benchmark are reported in Table 3. The process of creating the benchmark is explained in the following.

We create the collection of documents that appear in the subset of click logs, resulting in approximately 1.5 million unique documents. For each document, we fetch the corresponding article from the MEDLINE catalog. Similar to the TREC Precision Medicine

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Table 2: Statistics of the TripClick logs dataset.

| Statistic                              | Value  |
|----------------------------------------|--------|
| Number of click log entries            | 5,272,064 |
| Number of sessions                     | 1,602,648 |
| Average number of query-document interactions per session | 3.3 |
| Number of unique queries               | 1,647,749 |
| Number of documents (clicked or retrieved) | 2,347,977 |

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Figure 2: Query frequency histogram. The vertical axis is presented in log scale.

Figure 3: Number of submitted queries related to the COVID-19 pandemic. The entries 2018 and 2019 compound all occurrences in those years.

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4 We count those queries containing the keywords corona, covid, covid-19, and covid19
track [24–26], we use the title and abstract of the articles as documents of the TripClick benchmark.

We then extract the queries from the subset of click logs, resulting in around 692,000 unique queries. As shown in Figure 2, many queries appear rarely while some few queries are submitted very often. In creating the TripClick benchmark, we are interested in studying the performance of various IR models on queries in different frequency ranges, namely the sets of infrequent, modestly-frequent, and highly-frequent queries. To this end, we split the queries into three groups, namely HEAD, TORSO, and TAIL, such that the queries in this sets cover 20%, 30%, and 50% of the search engine traffic (according to the subset of click logs). This, in fact, results in assigning the queries with frequencies lower than 6 to TAIL, the ones between 6 and 44 to TORSO, and all the rest with frequencies higher than 44 to HEAD. The number of queries in each group is reported in the upper section of Table 3. While the numbers of unique queries in HEAD and TORSO are much smaller than those in TAIL, the former together still cover half of the search engine’s traffic since their queries repeat much more often than the ones of TAIL.

Next, we create two sets of query-to-document relevance signals, each created using a click-through model. The first relevance set, referred to as RAW, follows a simple approach by considering every clicked document as relevant to its corresponding query. The second set uses the Document Click-Through Rate (DCTR) [1, 4]. Creating two sets using different click-through models provides insight about the effect of each click-through model on the final evaluation results, achieved using the corresponding relevance signals.

To calculate the two sets of relevance scores, we first collect all retrieval information related to each query, consisting of the retrieved documents and the clicked ones. In the RAW set, for a given query, a relevance score of 1 is assigned to each of its clicked documents. For completeness, we also include a set of non-relevant documents (relevance score of 0) for each query, consisting of the documents in the ranked list of the query that appear in higher positions than the clicked one. This in fact follows the common assumption in click-through models, that the user has checked the documents in the retrieved ranked list from top till the clicked document, and has not found the top non-clicked ones relevant [1]. We should note that adding these non-relevant scores typically does not affect the evaluation results, as relevance scores of 0 are commonly ignored.

Regarding the DCTR set, the relevance score of a document for a given query is defined as the number of times that the document is clicked divided by the number of times the document is retrieved in the result lists of the query. These scores have a numeric range from 0 to 1. To be able to use these scores for retrieval evaluation, we need to discretize them to relevance grades. To this end, we follow a similar approach to the one in Xiong et al. [34]. In particular, we project the DCTR scores to 4 relevance grades (0 to 3), where 0 is non-relevant and 3 is highly relevant. The DCTR scores are discretized to these grades by selecting thresholds such that the relevance grades follow a similar distribution as TREC Web Track 2009-2012 query-relevance data. The selected thresholds are 0.0, 0.04, 0.3, and 1, resulting in a distribution of 71.4%, 19.7%, 6.0%, and 2.9% of scores for grades 0 to 3, respectively. We should note that similar to Xiong et al. [34], the DCTR model is only calculated for HEAD queries. This is due to the fact that the DCTR method provides meaningful relevance signals from click logs only if the queries are sufficiently frequent. The statistics of the numbers of relevance data points as well as their averages per query, for each group are reported in the center section of Table 2.

The provided documents, queries, and relevance signals are well suited for training neural IR models or as an evaluation benchmark. To enable consistent and reproducible training and evaluation in future studies, we construct pre-defined validation and test sets as well as pair-wise training data. In particular, for each group (HEAD, TORSO, and TAIL), we create validation and test sets by randomly selecting 1,175 queries from the pool of the queries in the corresponding group. To create the training data, we use the remaining queries of the three groups (~685,000), and their non-zero RAW relevance data points (~1.1 million). We follow the pair-wise learning to rank method [18], where each data entry is a triple, consisting of a query, a relevant, and a non-relevant document. Similar to

| Table 3: Statistics of TripClick IR benchmark. |
|-----------------------------------------------|
| Number of query-document interactions | 4,054,593 |
| Number of documents | 1,523,878 |
| Number of queries (all/HEAD/TORSO/TAIL) | 692,699 / 5,879 / 108,314 / 578,506 |
| Average query length | 4.4 ± 2.4 |
| Average document length | 259.0 ± 81.7 |
| Number of relevance data points in RAW (all/HEAD/TORSO/TAIL) | 2,870,826 / 246,754 / 994,529 / 1,629,543 |
| Average relevance data points per query in RAW (HEAD/TORSO/TAIL) | 41.9 / 9.1 / 2.8 |
| Number of relevance data points in DCTR (HEAD) | 263,175 |
| Average relevance data points per query in DCTR (HEAD) | 46.2 |
| Number of non-zero RAW relevance data points used to create training set | 685,649 |
| Number of items in training set | 1,105,811 |
| Number of queries in validation sets (HEAD/TORSO/TAIL) | 1,175 / 1,175 / 1,175 |
| Number of queries in test sets (HEAD/TORSO/TAIL) | 1,175 / 1,175 / 1,175 |
Nguyen et al. [21], for each relevant query-document pair, we create 20 training triples, where the query and relevant document are taken from the given estimated relevance, and the non-relevant document is randomly sampled from the top 1,000 results of a BM25 model. This results in training data with more than 23 million data items, as reported in the lower section of Table 2. We would like to point out that, considering the relatively high number of relevance signals per query especially in the HEAD and TORSO group, training data can also be created for list-wise learning-to-rank approaches.

5 RETRIEVAL EXPERIMENTS ON TRIPCLICK BENCHMARK

In this section, we demonstrate the usefulness of the proposed dataset for model training and benchmarking, by reporting the performance of various IR models on the TripClick benchmark collection. We first explain our experimental setup, followed by presenting and discussing the evaluation results.

5.1 Experiment Setup

IR Models. We conduct studies using several classical IR models as well as recent neural ones. As strong classical IR baselines, we use BM25 [28] as a widely used exact matching model, and the RM3 Pseudo Relevance Feedback (PRF) model [16, 19] as a strong query expansion baseline. In addition, we study the effectiveness of five recent neural IR models, namely Position Aware Convolutional Recurrent Relevance Matching (PACRR) [12], Match Pyramid (MP) [22], Kernel-based Neural Ranking Model (KNRM) [34], Convolutional KNRM (ConvKNRM) [5], and Transformer-Kernel (TK) [10]. These neural models are selected due to their strong performance on retrieval tasks as well as their diversity in terms of model architectures.

Evaluation. Performance evaluation is carried out in terms of Mean Reciprocal Ranks [31] (MRR), Recall at a cutoff of 10, and Normalized Discounted Cumulative Gain (NDCG) at a cutoff of 10. Statistical significance tests are conducted using a two-sided paired t-test and significance is reported for \( p < 0.05 \). The evaluation is performed using treceval.5

Hyper-parameters and Training. For classical IR models, we use the default hyper-parameters of the Anserini toolkit [35]. For neural IR models, we use pre-trained word2vec Skipgram [20] embeddings with 400 dimensions, trained on biomedical texts from the MEDLINE dataset.6 In a preprocessing step, all documents are casefolded by projecting all characters to lower case. We remove numbers and punctuation (except periods), and apply tokenization using AllenNLP WordTokenize [7]. The vocabulary set is created by filtering those terms with collection frequencies lower than 5, resulting in 215,819 unique terms. To train the neural models, we use the code provided by Hofstätter et al. [9]. We use the Adam optimizer [14] with learning rate 0.001, a maximum of 3 epochs, and early stopping. We use a batch size of 64. The maximum length of queries and documents is set to 20 and 300 tokens, respectively. For KNRM, ConvKNRM, and TK, we set the number of kernels to 11 in the range of \(-1\) to \(+1\) with a step size of 0.2, and standard deviation of 0.1. The dimension of the convolutional vectors in ConvKNRM is set to 400. The TK model consists of 2 layers of Transformers [30] with 2 heads and intermediate vector size of 512. In MP, the number of convolution layers is set to 5, each with kernel size 3×3 and 16 convolutional channels. The pre-trained word embeddings are updated during training. The threshold for selecting the top \( n \) retrieved documents for re-ranking is chosen by tuning the \( n \) parameter on a range from 1 to 100, based on the NDCG results of the validation set.

5.2 Evaluation Results

The evaluation results on the test sets of HEAD, TORSO, and TAIL using RAW relevance information are shown in Table 4. Table 5 reports the evaluation results on the HEAD queries using the DCTR relevance information.7 The best results for each evaluation metric

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5https://github.com/ustmigov/treceval
6http://nlp.cs.aueb.gr/software.html
7Please note that DCTR results are only meaningful for HEAD (see Section 4).
are shown in bold. Significant improvements over the other models are indicated with the superscript script letters inside the parentheses in front of the models. For brevity, we assign the same sign of significance to the two classical baselines (superscript letter a), indicating significant improvements over both models.

In general, the neural models significantly outperform the classical ones, where the TK model in particular shows the best overall performance by significantly outperforming the classical IR models across all groups and evaluation metrics. We observe similar patterns between the results of DCTR and RAW on the HEAD set. The overall achieved improvements with neural models are more prominent for groups containing more frequent queries, namely the improvements of the queries in HEAD are higher than the ones in TORSO, and subsequently in TAIL.

The evaluation results on the TripClick benchmark and specifically the improvements of the various neural models relative to each other are similar to the behavior observed on the MS MARCO collection in previous studies [9, 10]. This is in particular the case for the results of HEAD (according to both RAW and DCTR) and TORSO groups. These results highlight the value of the provided benchmark and training data for research on neural and deep learning-based IR models in general, and in the health domain in specific.

6 CONCLUSION

This work provides a novel click-log dataset covering the 7 years of user interactions of a health search engine. The dataset consists of approximately 5.2 million user interactions. Based on the dataset, we create TripClick, a novel large-scale health IR benchmark with approximately 700,000 queries and 2.8 million query-document relevance signals. We use TripClick to train several neural IR models and evaluate their performances on well-defined held-out sets of queries. The evaluation results in terms of NDCG, MRR, and Recall demonstrate the adequacy of TripClick for training large, highly parametric IR models and show significant improvements of neural models over classical ones, particularly for queries that appear frequently in the log dataset. The log dataset as well as the created benchmark and training data are made available to the community to foster reproducible academic research on neural IR models, particularly in the health domain.

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