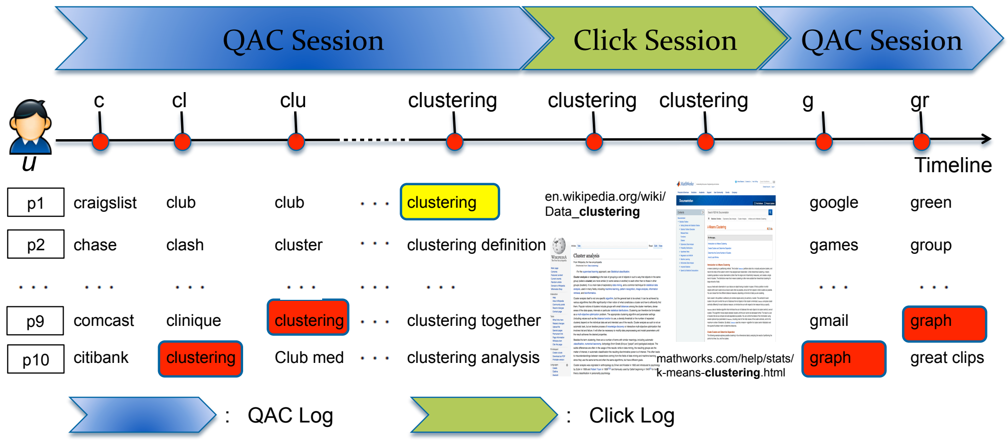

Figure 1: A Toy Example of how QAC and Click Logs Align in the Timeline. Yellow tag highlights the query a user finally clicks, red tag highlights the user's intended query he/she doesn't click.

Our goal is to effectively utilize the contextual data to model users' behaviors from both logs. The key idea is to cluster users' behaviors on QAC and click logs into several patterns, separately, and investigate the correlation between users' behavior patterns on QAC and click logs. We believe such correlation does exist, as users' search behaviors are usually consistent, which originate from users' personal search habits, preferences, interests, or instant circumstance. It is reasonable that a group of users may share similar behavior patterns. In addition, a user's QAC (or click) behavior pattern will be most likely correlated with a certain click (or QAC) behavior pattern. For instance, if a QAC log shows that a user types a query very fast, it is very likely that the user is familiar with the query. Then, in the following click log, the longer time the user landed on the SERP page may indicate the more relevant results presented to the user. One possible reason is that user likely will click the relevant results and check the detailed information which usually takes longer time. However, if there were no relevant results presented in the SERP page, the user might reformulate/reissue a new query shortly which will start a new QAC session similar to previous query. Based on the learned correlation, given an inferred behavior pattern of a user on one type of log, we can leverage such information to accurately infer the user's following behavior pattern on the other type of log.

To capture such correlation, we propose a novel probabilistic model based on Latent Dirichlet allocation (LDA). Based on the likelihood of the co-occurrences of adjacent QAC behavior patterns and click behavior patterns, the model explores the conditional distribution of consequential behavior patterns given a certain behavior pattern of the other type. A mean-field variational inference algorithm is developed to estimate the membership of behavior patterns for two types of logs in each session. We evaluate the proposed model on real-world logs collected from a commercial search engine. We design experiments to evaluate the effectiveness of the learned behavior patterns on with the application of query auto-completion on QAC logs, and the prediction of web document clicking on click logs as well as the relevance ranking of web documents. Experimental results show that the proposed model achieves remarkable improvement on both applications over state-of-the-art approaches.

In a nutshell, our major contributions include: (1) This is the first study to explore two types of logs, QAC and click logs, simultaneously to model search behaviors. We utilize users' recent history on one type of log as the context for the other type of log. This new source of context data is demonstrated to mutually enhance behavior modeling on both types of logs. (2) We proposed a novel probabilistic model to capture the correlation between users' behavior patterns on QAC and click logs. The model is designed to study the conditional distribution of one type of behavior patterns given a certain preceding behavior pattern of the other type.

2. PROBLEM DEFINITION

In this section, we first introduce the concept of high-resolution QAC log, and analyze the relationship between QAC and click logs of a search engine. Then, we come up with methods for modeling users' behaviors on both logs simultaneously as the contextual data for each other.

2.1 A High-Resolution QAC Log

Traditionally, the search query log only includes the submitted query and its associated search results, while it does not contain the sequential keystrokes (prefixes) user typed in the search box, as well as their corresponding QAC suggestions. In order to better analyze and understand real users' behaviors, a high-resolution QAC log is introduced and analyzed in [20], which records users' interactions with a QAC engine at each keystroke and associated system respond in an entire QAC process. For each submitted query, there is only one record in a traditional search query log. However, in the high-resolution QAC log, each submitted query is associated with a **QAC session**, which is defined to begin with the first keystroke a user typed in the search box towards the final submitted query. The information recorded for each QAC session includes every keystroke a user entered, the timestamp and top-10 suggested queries corresponding to each keystroke, the anonymous user ID, and the final clicked query.

Let us take a toy example to briefly introduce how a user interacts with a QAC engine and makes the final click in an entire QAC session. As shown in the left part of Figure 1, the **QAC session** for the query "clustering" contains 10 keystrokes and each keystroke has a suggested query list of length 10[1]. A QAC session ends at the last keystroke when the user clicks a suggestion or hits enter/search to submit a fully typed query. Notice that although a user's actual click happens on a slot in the column of the last keystroke, the user intended query may appear in many slots in any columns. In this work, we leverage such a QAC log data to get better understanding of user's sequential behavior, which can provide useful information for predicting the user's following behavior.

[1]We experiment with real-world QAC logs where $D = 10$.

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