Identifying and Labeling Search Tasks via Query-based Hawkes Processes

Liangda Li[†], Hongbo Deng[‡], Anlei Dong[‡], Yi Chang[‡], and Hongyuan Zha[¶†]

[†]College of Computing
Georgia Institute of Technology
Atlanta, GA 30032

[‡]Yahoo Labs
701 First Avenue
Sunnyvale, CA 94089

[¶]Software Engineering Institute
East China Normal University
Shanghai, China 200062

ldli@cc.gatech.edu, {hbdeng, anlei, yichang}@yahoo-inc.com, zha@cc.gatech.edu

ABSTRACT

We consider a search task as a set of queries that serve the same user information need. Analyzing search tasks from user query streams plays an important role in building a set of modern tools to improve search engine performance. In this paper, we propose a probabilistic method for identifying and labeling search tasks based on the following intuitive observations: queries that are issued temporally close by users in many sequences of queries are likely to belong to the same search task, meanwhile, different users having the same information needs tend to submit topically coherent search queries. To capture the above intuitions, we directly model query temporal patterns using a special class of point processes called Hawkes processes, and combine topic models with Hawkes processes for simultaneously identifying and labeling search tasks. Essentially, Hawkes processes utilize their self-exciting properties to identify search tasks if influence exists among a sequence of queries for individual users, while the topic model exploits query co-occurrence across different users to discover the latent information needed for labeling search tasks. More importantly, there is mutual reinforcement between Hawkes processes and the topic model in the unified model that enhances the performance of both. We evaluate our method based on both synthetic data and real-world query log data. In addition, we also apply our model to query clustering and search task identification. By comparing with state-of-the-art methods, the results demonstrate that the improvement in our proposed approach is consistent and promising.

Categories and Subject Descriptors:
H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval; I.2.6 [**Artificial Intelligence**]: Learning; J.4 [**Computer Applications**]: Social and Behavioral Sciences

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1. INTRODUCTION

Nowadays, search engines have become the most important and indispensable Web portal, whereby people pursue a wide range of searches in order to satisfy a variety of *information needs*. To better understand users' information needs and search behaviors, one important research direction is to detect and split users' temporal sequences of queries into disjoint *query sessions*, which are often defined as a sequence of queries issued within a fixed period of time, ranging from 5 to 120 minutes. However, a user's single session may contain queries with multiple intents, or consist of seeking information on single or multiple topics [28]. Going beyond a search session, a *search task* [23, 17, 30], which is defined as a set of queries serving for the same *information need*, has been recognized as a more suitable atomic unit than a single query or session, not only for better modeling user search intent but also for improving other downstream search engines' applications, such as query suggestion [9, 17] and personalized search [33]. Additionally, analyzing the formation of search tasks also deepens our understanding of the simultaneous temporal diffusion of multiple memes, i.e., intents or ideas, in social networks [34]. Therefore, how to effectively identify and label search tasks becomes an interesting and challenging problem.

Recently, there have been attempts to extract in-session tasks [28, 23, 17], and cross-session tasks [18, 19, 1, 30] from sequences of queries. They build clustering or classification methods to identify tasks based on time splitting, lexicon similarity, and query reformulation patterns. Even though the temporal submission patterns in query sequences carry valuable information for mining search tasks, those existing methods only use them for either simply splitting sequences of queries into temporally-demarcated sessions [18, 19, 23], or transforming them as features among queries [19, 17, 30]. We believe that by directly modeling temporal information as part of extracting search tasks in a richer way, we can substantially improve search task mining. Another key drawback of those existing methods is that most of them focus only on the query sequences of individual users instead of considering the whole query log. Only very recently, there has been an attempt which tries to take advantage of the collective intelligence of many users for discovering tasks [24]. It is obvious that different users may have the same information need, and share the same search task, thus modeling query sequences across different users will be very valuable for capturing semantically similar search tasks in a global context.

Generally, two consecutive queries issued by a user are more likely to belong to the same search task than two non-contiguous queries, but that is not necessary always the case. For example, as shown in Figure 1, the consecutive queries "autotrader" and "Yahoo autos" issued by user u_a belong to the same search task, while the consecutive queries "Yahoo autos" and "wells fargo" belong to two separate search tasks. Another complicated case is that two non-contiguous queries may belong to the same or different tasks

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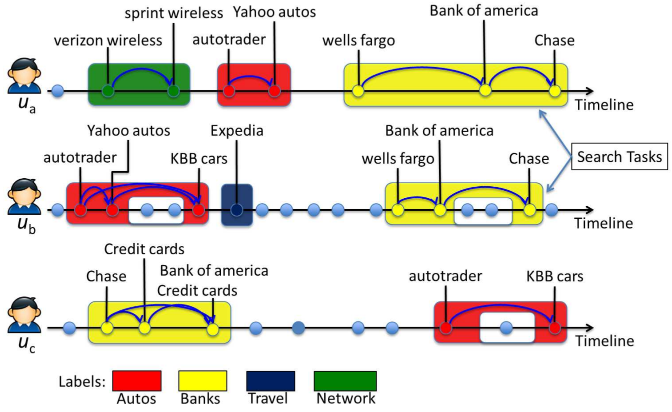


Figure 1: An Illustration of Relationship between Consecutive Queries and Search Tasks. Every circle represents a query issued by a user at time t_n. The blue arrow line indicates an influence exists between queries. A set of queries linked by blue lines denotes a search task, and some topically coherent search tasks across three users are labeled by different colors.

as well, e.g., "verizon wireless" and "autotrader" issued by user u_a belong to two different search tasks, but "Yahoo autos" and "KBB cars" issued by users u_b belong to the same search task. These examples show that in reality we cannot simply rely on the time splitting or an individual user behavior for identifying search tasks. It makes more sense to take into account the explicit temporal information of query sequences exhibited by many different users in the whole query logs. *The basic intuition is that if two consecutive or temporally-close queries are issued many times by the same user or many others users, it is more likely these two queries are semantically related to each other, i.e., belong to the same search task.* As we can see, the consecutive queries "wells fargo" and "Bank of america" are issued by both u_a and u_b (and possible many other users), while the consecutive queries "Yahoo autos" and "wells fargo" are only issued by user u_a. Therefore, according to the above intuition, "wells fargo" and "bank of america" are more likely to belong to the same search task compared with "Yahoo auto" and "wells fargo". Similarly, for non-contiguous queries, "autotrader" and "KBB cars" are issued temporally very close by both u_b and u_c, which indicates they have higher chance of belonging to the same search task. Moreover, different users may engage in different search patterns, e.g., user u_b searches more frequently than user u_a, which indicates how likely the search tasks may change within a certain time period for different users, and then they should be treated differently based on their search activities. All in all, we choose to identify search tasks by leveraging the temporally weighted query co-occurrence — this not only guarantees sound performance by making full use of both textual and temporal information of the entire query sequences, but also enables the labeling of the identified search tasks since semantically related queries are clustered together through query links determined by co-occurrence.

To model temporally close query co-occurrences, we turn to Latent Dirichlet Allocation (LDA) [7], one powerful graphical model that exploits co-occurrence patterns of queries in query sequences. Existing temporal LDA models [16, 32] learned distinguished topic distributions from temporal fragments of data, while ignored query co-occurrence across different fragments, thus failed to make full use of the temporal information. Recently, some spatial-LDA models [31] encouraged queries that are very close in space to share similar topic distributions, i.e., weighing the reliability of query co-occurrence based on spatial closeness. However, there exists no uniform standards for measuring such closeness across different instances, especially in temporal data. Our research, on the other hand, considers making full use of temporal information by weighing the reliability of each co-occurrence of a pair of queries based on how likely an *influence* exists between this pair of queries. Here we define query *influence* as:

- The occurrence of one query raises the probability that the other query will be issued in the near future.

Influence, rather than closeness, enables us to distinguish temporally close query co-occurrence from temporally regular query co-occurrence for each user based on his own propensity of query submission. For instance, in Figure 1, the absolute temporal distance between "KBB cars" and "Expedia" is smaller than that between "verizon wireless" and "sprint wireless", however, *influence* exists between the latter pair of queries rather than the former one, since user u_b's query submission propensity is much larger than that of user u_a. To model such personal propensity and *influence*, in this paper, we utilize Hawkes processes [14], a special class of point processes, whose intensity functions characterize how likely an event will happen at each timestamp. The intensity function of Hawkes includes a base intensity, along with a positive influence of the past events on the current one. Such a positive influence is originated from the *self-exciting* property that the occurrence of one event in the past increases the probability of events happening in the future. We find that Hawkes's *self-exciting* property coincides with the concept of *influence* in our situation, and its base intensity captures the personal propensity. Thus we employ Hawkes processes to fully utilize temporal information in query sequences for identifying the existence of query *influence*.

From the perspective of Hawkes processes, *influence* generally exists between temporally-close queries. However, for an observed query sequence, not all temporally-close query-pairs have the actual *influence* in between, since in some cases the occurrence of the later queries may result from the base intensity rather than *self-exciting* property. Furthermore, existing Hawkes models [20, 35] find it intractable to obtain an optimal solution of *influence* existence based on temporal information only. Last but the most important, it is unable to directly identify search tasks by either generating topics based on query co-occurrence using LDA, or estimating all *influence* candidates by Hawkes. To address the above issues, we concentrate on the *influence* existence between semantically related queries, whose estimation can be simplified by the joint efforts of LDA and Hawkes and enable a direct identification of search tasks.

According to the above intuition, a search task can be viewed as a sequence of semantically related queries linked by *influence*. A query that does not satisfy user's *information need* will *self-excite* the submission of another semantically related query in the near future. On the other hand, a query rarely excites the submission of another semantically unrelated query even if their timestamps are very close. Thus we believe that those semantic *influence* are the *influence* that actually take effect, and our paper solves search task identification directly by identifying those *influence*. To limit the solution space of such *influence*, we cast both *influence* existence and query-topic membership into latent variables, and identify the existence probability of pairwise *influence* with the similarity of the memberships of associated two queries. This identification works as a bridge between LDA and Hawkes processes, as LDA assigns high *influence*-qualified co-occurred queries to the same topic, while query co-occurrence frequency narrows the solution space of *influence*. In this way, LDA and Hawkes mutually benefit each other in identifying search tasks using both temporal and textual information. To this end, we propose a probabilistic model that incorporates this equalization to combine the LDA model with Hawkes processes, and develop a mean-field variational inference algorithm to estimate the *influence* by optimizing the data likelihood. We evaluate our method on synthetic data, and also apply it to mine search tasks in both AOL and Yahoo query log data. Experimental results show that the proposed method can achieve significantly better performance than existing state-of-the-art methods.

In a nutshell, our major contributions include: (1) We cast search task identification into the problem of identify semantic *influence* in observed query sequences, and propose a probabilistic model by combining LDA model with Hawkes processes to address the problem. Most importantly, there is mutual reinforcement between Hawkes processes and the topic model in the unified model that enhances the performance of both. (2) We employ Hawkes processes to directly model temporal information as part of search task identification, which has never been explicitly exploited in the existing works.

The rest of the paper is organized as follows. We first introduce Hawkes processes, and the proposed model by combining LDA with Hawkes processes in Section 2. In Section 3, we develop a fast mean-field variational inference algorithm for the resulting optimization problem. We then describe and report the experimental results in Section 4. Finally, we introduce the related work in Section 5, and present our conclusions and future work in Section 6.

2. PROBLEM DEFINITION

Let us consider a typical scenario where M users issue M corresponding query sequences, and we mark the query sequence of user m as $T_m = \{t_{m,n}, n = 1, \ldots, N_m\}$, where $t_{m,n}$ is the time-stamp of the n-th query. We denote the word set of the n-th query of user m as $W_{m,n} = \{w_{m,n,1}, \ldots, w_{m,n,c_{m,n}}\}$. Existing works generally identify search task by sequentially solve two subproblems: 1) using queries' textual information to cluster queries in observed query sequences, and 2) using obtained clusters together with temporal information to partition query sequences into search tasks. In this section, we show how these two subproblems can be simultaneously addressed by combining Hawkes processes with the LDA model, and how temporal and textual information can be combined to address the above two subproblems in a mutually-beneficial way. We also show how our model can be used to automatically label search tasks along with search task identification.

2.1 Query Co-occurrence and LDA

We address the query clustering problem using graphical models like LDA [7], which has been proven to be effective in topic discovery by clustering words that co-occur in the same document into topics. Let us first introduce how to use LDA to cluster queries based on their textual information only. One straightforward idea is to treat each user's query sequence as a document, and cluster queries that co-occur in the same query sequence into topics, since queries issued by the same user are generally more likely to share the same *information need* than queries issued by different users. Since we focus on query co-occurrence instead of word co-occurrence, we enforce that words in one query belong to the same topic. Our LDA model assumes K topics lie in the given query sequences, and each user m is associated with a randomly drawn vector π_m, where $\pi_{m,k}$ denotes the probability that a query issued by user m belongs to topic k. For the n-th query in the query sequence of user m, a K-dimensional binary vector $Y_{m,n} = [y_{m,n,1}, \ldots, y_{m,n,K}]^T$ is used to denote the query's topic membership. One challenge we encounter in the inference of topic membership Y is that, without temporal information of queries, it is difficult to judge whether two non-contiguous co-occurred queries should belong to the same topic or not. The reason is that the reliability of the co-occurrence of queries heavily depends on their temporal distances. A pair of queries that co-occurs many times may be completely unrelated if the temporal gap between them is always large.

Since the co-occurrence of queries with large temporal gap can be harmful, we make use of temporal information to decide which query co-occurrence should be taken into account by LDA, i.e., how a document in LDA model should be constructed. One simple way of utilizing temporal information is to define a document as consecutive queries in a fixed time window (or time session), which enables us to focus on temporally close query co-occurrence. Temporally close queries that issued many times by the same user or many other users are more likely to be semantically related to each other, i.e., belong to the same search task. However, a time window based LDA model may suffer from the following drawbacks: 1) Usually no optimal solution exists for cutting the entire query sequence into different time-sessions. If we allow different time-sessions to overlap, redundant query co-occurrence will be taken into account; otherwise, pairs of queries with very small temporal gap can be partitioned into different tasks, which may cause information loss. 2) Using time windows will ignore or misunderstand users' own temporal patterns in searching.

To address the above drawbacks, we can weigh each query co-occurrence based on how likely an *influence* exists between this pair of queries, i.e., the degree to which the occurrence of one query raises the probability that the other query will be issued in the near future. That is to say, one document is a subsequence of queries linked through *influence*. This *influence*, rather than time window, enables us to distinguish temporally close query co-occurrence from temporally regular query co-occurrence for each user based on his/her own propensity of query submission. To model such personal propensity and *influence*, we will utilize Hawkes processes to capture the temporal information in different query sequences.

2.2 Hawkes Process

One powerful tool in statistics for modeling event (query) sequence data is temporal point processes, which are widely used to describe data that are localized at a finite set of time points $\{t_1, \ldots, t_N\}$ [27]. In a temporal point process, $N(t)$ counts the number of events that has occurred up to and including time t, and the conditional intensity function $\lambda(t|\mathcal{H}_t)$ denotes the expected infinitesimal rate at which events occur at timestamp t depending on $\mathcal{H}_t$, the history of events preceding t. For clarity, hereafter we use $*$ to imply the dependence on $\mathcal{H}_t$, i.e., $\lambda(t|\mathcal{H}_t)$ will be denoted $\lambda^*(t)$.

The Hawkes process is a class of self- or mutually-exciting point process models [14]. A univariate Hawkes process $\{N(t)\}$ is defined by its intensity function

$$\lambda^*(t) = \mu(t) + \int_{-\infty}^{t} \kappa(t-s)dN(s),$$

where $\mu > 0$ is a base intensity, κ is a kernel function capturing the positive influence of past events on the current value of the intensity process, which is the process's *self-exciting* property that the occurrence of one event in the past will trigger events happening in the future. Such *self-exciting* property can either exists between every pair of events as assumed in a normal univariate Hawkes process, or only exists between limited pair of events. For instance, any query but the last one in a search task can imply an increased probability of future queries issued in the same search task, since the user's *information need* in this search task hasn't been satisfied. Meanwhile, queries from different search tasks may rarely affect each other.

Since our definition of *influence* coincides with the *self-exciting* property of Hawkes process, we propose to identify the *influence* among queries by building one separate Hawkes process on each user's query sequence. In the query sequence of user m, we use $R_{m,n,n'}$ to denote whether *influence* exists between the n-th and n'-th query. If *influence* exists, we believe that the occurrence of n-th query has a time-decay effect on increasing the intensity at the timestamp of the occurrence of the n'-th query. Thus based on *influence* R_m, we model the query sequence issued by user m with a univariate Hawkes process, whose intensity can be written as:

$$\lambda_m(t) = \mu_m + \sum_{t_{m,l}<t} R_{m,l,n}\beta_m\kappa(t - t_{m,l}). \tag{1}$$

Here the baseline intensity μ_m captures how often user m issues a query spontaneously[1] (i.e., not triggered by any other queries), while β_m models the degree of *influence* between sequential queries issued by user m, and $\kappa(t - t_{m,l})$[2] captures the time-decay effect only.

Influence R can be estimated together with μ and β by maximizing the likelihood of the proposed Hawkes model on observed query sequence $\{T_m = \{t_{m,n}\}\}$. The estimation of R is actually to identify query-pairs in which the occurrence of the later query most likely violates the normal query-submission propensity, and gets triggered by the earlier one. In other words, if *influence* exists between two queries, the corresponding temporal gap can be significantly less than the average temporal gap of pairs of queries in the same query sequence (issued by the same user). Since the definition of *influence* suggests that queries linked by significant *influence* naturally form search tasks, a thresholding of $R_{m,l,n}\beta_m\kappa(t-t_{m,l})$ with a small constant automatically results in search task partition. The estimation of R consequently partitions observed query sequences into search tasks.

2.3 LDA-Hawkes

Estimated by Hawkes processes, *influence* R captures the unique temporal pattern of each user's query sequence. We use R to weight the query co-occurrence, which bridges the LDA model and Hawkes process through:

$$R_{m,n,n'} = Y_{m,n}^T * Y_{m,n'}, \tag{2}$$

that is to say, *influence* exists between these two queries if and only if the two queries share the same topic. Since queries in the same search task are linked by *influence*, all queries in the same search task share the same topic, which labels this search task as well.

Through our defined bridge between *influence* R and query-topic membership Y, the Hawkes process and the LDA model mutually benefit each other in identifying and labeling search tasks. On the one hand, provided *influence* among queries, we obtain 0-1 weighted query co-occurrence of each candidate query-pair in observed query sequences, and generate topics accordingly. For instance, in Figure 2, although 8 pairs of queries (9 possible combinations with 8 unique query-pairs) co-occur in query sequences, only the co-occurrences of query-pairs “bank of america”–“wells fargo” and “Expedia”–“american airline” have positive weights. These weighted query co-occurrences contain personal temporal information, thus are expected to lead to improved topics compared with existing LDA-based methods [16, 32, 31] that used no weight scheme or only unifom standard weight scheme.

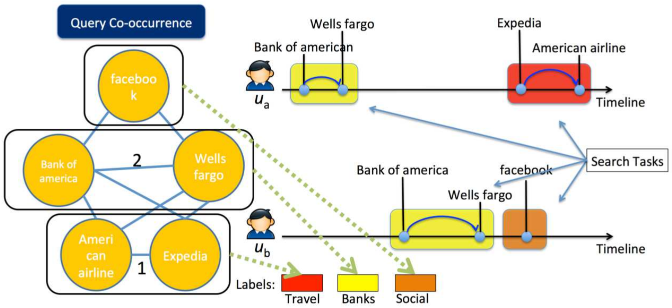


Figure 2: A Toy Example of our LDA-Hawkes model. Blue line denotes the influence among queries. Green dash line shows the label each query belongs to.

On the other hand, the estimation of *influence* R only based on temporal data $\{T_m\}$ can be intractable, since the exploration of the whole space of R is known to very costly ($2^{\sum_m N_m}$ possible solutions). LDA-Hawkes further makes use of textual data to limit the output space of R to the most probable subspace, since topics learned by the LDA part in turn justify the *influence* existence between each pair of queries. Two queries rarely co-occur can be clustered into different topics by the LDA part, based on such query-topic membership no *influence* exists between these two queries. For example, in the query sequence of user u_b shown in Figure 2, the temporal gap between query-pair “bank of america”–“wells fargo” is larger than the temporal gap between query-pair “wells fargo”–“facebook”. However, the pair of queries “bank of america”–“wells fargo” also co-occurs in the query sequence of user u_a, while “wells fargo”–“facebook” does not, which in turn emphasizes that *influence* should exist between “bank of america” and “wells fargo” rather than between “wells fargo” and “facebook”. To sum up, combined through *influence*, Hawkes process and LDA reciprocally contribute to the search task identification and labeling.

Finally, we present our generative model that combines Hawkes process and LDA as follows:

- For each topic k, draw a V dimensional membership vector $\sigma_k \sim \text{Dirichlet}(\alpha')$.
- For each user m, draw a K dimensional membership vector $\pi_m \sim \text{Dirichlet}(\alpha)$.
- For the content of the n-th query issued by user m,
  - $Y_{m,n} \sim \text{Multinomial}(\pi_m)$;
  - For the i-th word in the n-th query issued by user m,
    - $w_{m,n,i} \sim \text{Multinomial}(Y_{m,n}, \sigma)$;
- For the timestamp of the sequence of queries issued by user m,
  - draw personal base intensity μ_m and degree of *influence* β_m;
  - derive R_m from $\{Y_{m,n}\}$ through Eqn (2);
  - $N_m(\cdot) \sim \text{HawkesProcess}(\lambda_m(\cdot))$, where the intensity λ_m is defined as in Eqn (1).

[1] For simplicity, we assume this cascade-birth process is a homogeneous Possion process with $\mu_m(t) = \mu_m$.

[2] Our paper uses the exponential kernel in experiments, i.e., $\kappa(\Delta t) = \omega e^{-\omega\Delta t}$ if $\Delta t \geq 0$ or 0 otherwise. However, the model development and inference is independent of kernel choice and extensions to other kernels such as power-law, Rayleigh, nonparametric kernels are straightforward.

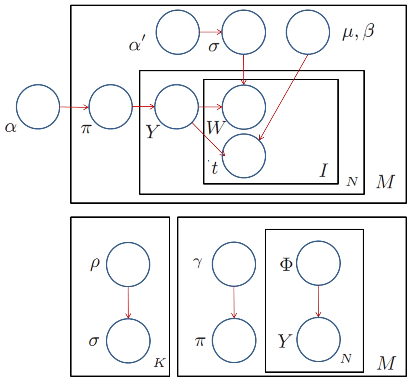


Figure 3: Graphical model representation of LDA-Hawkes and the variational distribution that approximates the likelihood. The upper figure shows the graphical model representation of LDA-Hawkes, while the lower figure shows the variational distribution that approximates the likelihood.

Here V is the size of vocabulary. Note that in our LDA-Hawkes model, queries issued by one user share the same topic distribution, while words in one query belong to the same topic. The topic membership of the n-th query of user m, $Y_{m,n}$, determines not only the words the query owns, but also the timestamp of its occurrence through Hawkes process $\lambda_m(\cdot)$.

Under our LDA-Hawkes model, the joint probability of data $T = \{N_m(\cdot)\} = \{\{t_{m,n}\}_{n=1}^{N_m}\}$, $W = \{\{W_{m,n}\}_{n=1}^{N_m}\}$ and latent variables $\{\pi_{1:M}, Y\}$ can be written as follows:

$$\begin{aligned}&p(T, W, \pi_{1:M}, Y, \sigma|\alpha, \alpha', \mu, \beta)\\ =&\prod_m P(\{t_{m,n}\}_{n=1}^{N_m}|Y_{m,1:N_m}, \mu_m, \beta_m) \prod_m \prod_n \prod_i P(w_{m,n,i}|Y_{m,n}, \sigma)\\ &\prod_m \prod_n P(Y_{m,n}|\pi_m) \prod_m P(\pi_m|\alpha) \prod_k P(\sigma_k|\alpha').\end{aligned}$$

3. INFERENCE

Despite that a tremendous amount of work on inference of topic models have been published, none of them are designed to address topic model combined with point processes. In this section, we derive a mean-field variational Bayesian inference algorithm for our proposed LDA-Hawkes model.

3.1 Variational Inference

Under LDA-Hawkes model, given observations of both temporal information $T = \{N_m(\cdot)\} = \{\{t_{m,n}\}_{n=1}^{N_m}\}$ and textual information $W = \{\{W_{m,n}\}_{n=1}^{N_m}\}$ of query sequences, the log-likelihood for the complete data is given by $\log P(T, W|\mu, \beta, \alpha, \alpha')$. Since this true posterior is hard to infer directly, we turn to variational methods [6], whose main idea is to posit a distribution over the latent variables with variational parameters, and find the settings of the parameters so as to make the distribution close to the true posterior in Kullback-Leibler (KL) divergence. In Figure 3, the lower part shows the variational distribution that approximates the data likelihood. Our paper chooses to introduce a distribution of latent variables q specified as the mean-field fully factorized family as follows:

$$\begin{aligned}&q(\pi_{1:M}, Y, \sigma_{1:K}|\gamma_{1:M}, \Phi, \rho_{1:K})\\ =&\prod_m q_1(\pi_m|\gamma_m) \prod_m \prod_n q_2(y_{m,n}|\phi_{m,n}) \prod_k q_1(\sigma_k|\rho_k)\end{aligned}$$

where q_1 is a Dirichlet, q_2 is a multinomial, and $\{\gamma_{1:M}, \Phi, \rho_{1:K}\}$ are the set of variational parameters. We optimize those free parameters to tight the following lower bound $\mathcal{L}'$ for our likelihood:

$$\begin{aligned}\log p(T, W|\mu, \beta, \alpha, \alpha') \geq& E_q[\log p(T, W, \pi_{1:M}, Y, \sigma|\alpha, \alpha', \mu, \beta)]\\ &- E_q[\log q(\pi_{1:M}, Y, \sigma_{1:K})]. \qquad (3)\end{aligned}$$

Isolating terms containing λ in Eqn (3), we have

$$\mathcal{L}_h = \sum_{m=1}^{M} \sum_n E_q(\log \lambda(t_{m,n})) - \sum_{m=1}^{M} \int_0^T E_q(\lambda(s))ds, \qquad (4)$$

as the partial likelihood on temporal data assuming query-topic distribution is known. On one hand, we have $\sum_{m=1}^{M} \int_0^T E_q(\lambda(s))ds = \sum_{m=1}^{M} b_m + T \sum_{m=1}^{M} \mu_m$. Here

$$b_m = \sum_{n=1}^{N_m} \sum_{l=1}^{n-1} r(\phi_{m,l}, \phi_{m,n})(K(t_{m,n} - t_{m,l}) - K(t_{m,n-1} - t_{m,l})),$$

where $K(t) = \int_0^t \kappa(s)ds$, and we define function $r(\phi_{m,l}, \phi_{m,n}) = \sum_k \phi_{m,l,k}\phi_{m,n,k}$, which can be viewed as the latent variable that approximates *influence* R. On the other hand, in order to update each Hawkes hyper-parameter μ and β independently, we adopt the strategy in [34], and break down the log sum $E_q(\log \lambda(t_{m,n}))$ based on Jensen's inequality as:

$$\begin{aligned}\mathbb{E}_q(\log(\lambda(t_{m,n}))) \geq& \eta_{m,nn} \log(\mu_m) + \sum_{l=1}^{n-1} \eta_{m,ln} \log(\beta_m \kappa(t_{m,n} - t_{m,l}))\\ &- \eta_{m,nn} \log(\eta_{m,nn}) - \sum_{l=1}^{n-1} r(\phi_{m,l}, \phi_{m,n})\eta_{m,ln} \log(\eta_{m,ln}),\end{aligned}$$

where $\{\eta\}$ is a set of branching variables constrained by:

$$\eta_{m,ln} \geq 0,\ \eta_{m,nn} + \sum_{l=1}^{n-1} r(\phi_{m,l}, \phi_{m,n})\eta_{m,ln} = 1.$$

Under a coordinate descent framework, we optimize the lower bound as in Eqn (3) against each variational latent variable[3] and the model hyper-parameter, including both LDA hyper-parameters and Hawkes hyper-parameters. For variational latent variables, we have the following process

- update rules for ϕ's as:

$$\begin{aligned}\phi_{m,n,k} \propto \exp(&\sum_m (\Psi(\gamma_{m,k}) - \Psi(\sum_k \gamma_{m,k}))\\ &+ \sum_i \sum_v w_{m,n,i,v}[\Psi(\rho_{k,v}) - \Psi(\sum_v \rho_{k,v})]\\ &+ \sum_{l=1}^{n-1} f_{l,n} + \sum_{l'=n+1}^{N_m} f_{n,l'}),\end{aligned}$$

where we define $f_{l,n} = \phi_{m,l,k}(\eta_{m,ln} \log(\frac{\beta_m \kappa(t_{m,n} - t_{m,l})}{\eta_{m,ln}}) - \beta_m(K(t_{m,n} - t_{m,l}) - K(t_{m,n-1} - t_{m,l})))$;

- update rules for γ's as:

$$\gamma_{m,k} = \alpha_k + \sum_n \phi_{m,n,k};$$

- update rules for ρ's as:

$$\rho_{k,v} \propto \alpha'_v + \sum_m \sum_n \sum_i \phi_{m,n,k} w_{n,i,v};$$

[3] Here we categorize branching variables η as variational latent variables.

- and update rules for η as:

$$\eta_{m,nn} = \frac{\mu_m}{\mu_m + \sum_{l=1}^{n-1} r(\phi_{m,l}, \phi_{m,n})\beta_m \kappa(t_{m,n} - t_{m,l})},$$

$$\eta_{m,ln} = \frac{\beta_m \kappa(t_{m,n} - t_{m,l})}{\mu_m + \sum_{l=1}^{n-1} r(\phi_{m,l}, \phi_{m,n})\beta_m \kappa(t_{m,n} - t_{m,l})}.$$

3.2 Learning

We use a variational expectation-maximization (EM) algorithm [11] to compute the empirical Bayes estimates of the LDA hyper-parameters α and α' in our LDA-Hawkes model. This variational EM algorithm optimizes the lower bound as in Eqn (3) instead of the real likelihood, it iteratively approximates the posterior by fitting the variational distribution q and optimizes the corresponding bound against the parameters.

In updating α, we use a Newton-Raphson method, since the approximate maximum likelihood estimate of α doesn't have a closed form solution. The Newton-Raphson method is conducted with a gradient and Hessian as follows:

$$\frac{\partial \mathcal{L}'}{\partial \alpha_k} = N(\Psi(\sum_k \alpha_k) - \Psi(\alpha_k)) + \sum_m (\Psi(\gamma_{m,k}) - \Psi(\sum_k \gamma_{m,k})),$$

$$\frac{\partial \mathcal{L}'}{\partial \alpha_{k_1} \alpha_{k_2}} = N(\mathbb{I}_{(k_1=k_2)} \Psi'(\alpha_{k_1}) - \Psi'(\sum_k \alpha_k)).$$

Similar update rules can be derived for α'.

On the other hand, to obtain the approximate maximimum likelihood estimation of Hawkes hyper-parameters, we optimize the lower bound as in Eqn (3) against each Hawkes hyper-parameter, and update μ and β independently with closed-form solutions as follows:

$$\beta_m = \frac{1}{b_m} \sum_{n=1}^{N_m} \sum_{l=1}^{n-1} r(\phi_{m,l}, \phi_{m,n}) \eta_{m,ln}, \quad \mu_m = \frac{1}{T} \sum_{n=1}^{N_m} \eta_{m,nn}.$$

Our variation inference algorithm, named LDA-Hawkes, can be interpreted intuitively in the following way. The label/topic distribution γ in each user's query sequence is determined by both the topic prior and the topic assignment of each query. The word distribution ρ in each topic is determined by both the word prior and the topic assignment of each word. The probability of a query n issued by user m belonging to topic k is jointly determined by: (a) Users' label/topic distributions; (b) how queries are semantically clustered; (c) the influence from labels of queries in the past to the label of the current query; and (d) the influence from the label of the current query to labels of queries in the future.

In our mean-field variation inference algorithm, the computational cost of inferring variational variables is $O((\sum_m N_m)K\bar{C})$, where $\bar{C}$ is the average number of words in a query. The computational cost of the estimation of LDA hyper-parameters is $O(K + V)$. The computational cost of the estimation of Hawkes hyper-parameters is $O(\sum_m N_m^2)$, which can be reduced to $O(\sum_m N_m)$ by controlling the number of *influence* candidate for each query. Most queries have only limited number of *influence* associated, since for each query, most of the rest queries are far from it, and there exist many other queries in between. Thus the total computational cost of our algorithm is $O((\sum_m N_m)K\bar{C} + V)$.

4. EXPERIMENTS

We evaluated our LDA-Hawkes model on both synthetic and real-world data sets, and compared the performance with the following baselines:

- two alternative LDA-based probabilistic models:

  Time-Window(TW): This model assumes queries belong to the same search task only if they lie in a fixed or flexible time window, and uses LDA to cluster queries into topics based on the query co-occurrences within the same time window. We tested time windows of various sizes.

  Word-Related: This model assumes queries belongs to the same search task only if they share at least one word, and uses LDA to cluster queries into topics based on the co-occurrences of queries that sharing at least one word.

- two state-of-the-art query clustering approaches:

  Session-Similarity[36]: This method evaluated query similarity based on both query sessions and query content, and used those similarity scores for query clustering.

  GATE[2]: This is a Greedy Agglomerative Topic Extraction algorithm. It extracted topics based on a pre-defined topic similarity function, which considered both semantic similarity and mission similarity. Here mission similarity refers to the likelihood that two queries appear in the same mission, while missions are sequences of queries extracted from users' query logs through a mission detector.

- and three state-of-the-art search task identification approaches:
  Bestlink-SVM [30]: This method identified search tasks using a semi-supervised clustering model based on the latent structural SVM framework. A set of effective automatic annotation rules were proposed as weak supervision to release the burden of manual annotation.

  QC-HTC/QC-WCC [23]: This series of methods viewed search task identification as the problem of best approximating the manually annotated tasks, and proposed both clustering and heuristic algorithms to solve it. QC-WCC conducted clustering by dropping query-pairs with low weights, while QC-HTC considered the similarity between the first and last queries of two clusters in agglomerative clustering.

  Reg-Classifier[18]: This method designed a diverse set of syntactic, temporal, query log and web search features, and used them in a logistic regression model to detect search tasks.

4.1 Synthetic data

Data Generation. Given parameters $(M, N, K, \alpha, \alpha', \mu, \beta)$, the synthetic data is sampled according to the proposed generative model. We record the sampled values of Y, and calculate the ground-truth *influence* R for evaluating the accuracy of our prediction of *influence* among queries. Notice μ and β are both vectors of size M, where the elements μ_m and β_m are randomly generated in $[0.5\hat{\mu}, 1.5\hat{\mu}]$ and $[0.5\hat{\beta}, 1.5\hat{\beta}]$ respectively before the simulation. Vectors α and α' are of size K and V respectively, where the element α_k and α'_v are generated in $[0.5\hat{\alpha}, 1.5\hat{\alpha}]$ and $[0.5\hat{\alpha'}, 1.5\hat{\alpha'}]$ respectively before the simulation.

Our synthetic data are simulated with two different settings:

- `Small`: $M = 100$, $N = 120$, $K = 10$, $\hat{\mu} = 0.01$, $\hat{\beta} = 0.5$, $\hat{\alpha} = 0.1$, $\hat{\alpha'} = 0.1$. Simulations were run 1,000 times using the pre-generated parameters μ, β;
- `Large`: $M =$ 10,000, $N =$ 10,000, $K = 50$, $\hat{\mu} = 0.01$, $\hat{\beta} = 0.5$, $\hat{\alpha} = 0.1$, $\hat{\alpha'} = 0.1$. Simulations were run 10 times.

To test the robustness of our method, we add two types of noise to the original synthetic data:

`Event Noisy`: We generate additional 10% of total number of queries randomly in the time window of each already sampled query sequence, and add them to the sequence;

Intensity Noisy: Instead of using $\lambda(t)$ to simulate the query occurrence at time t, we use a noisy value $\lambda'(t)$, which is obtained by adding Guassian noise on $\lambda(t)$:

$$\lambda'(t) = \max(0.1e + 1, 0)\lambda(t), \ e \sim \mathcal{N}(0, \sigma). \quad (5)$$

The default value of σ is set to be 1.

Inference and Estimation. Table 1 evaluates both training likelihood, and the accuracy of our proposed variational inference algorithm in parameter estimation and latent variable inference on the synthetic data. We can find that, on the small synthetic data, LDA-Hawkes can recover the Hawkes parameters μ and β very well, which represent users' personal temporal patterns of query submission. Meanwhile, based on the inferred query-topic membership $\hat{Y}$, we predict the *influence* $\hat{R}$ among queries, and compare with the ground-truth *influence* R to evaluate the accuracy of our *influence* prediction through:

$$\text{Proc}_R = \sum_m \frac{1}{N_m(N_m-1)/2} \sum_{n=1}^{N_m} \sum_{n'=n+1}^{N_m} I(R_{n,n'} = \hat{R}_{n,n'}).$$

Results in Table 1 show that LDA-Hawkes can accurately predict *influence*. We also find an interesting phenomenon that the accuracy of our estimated Hawkes parameters and the accuracy of our predicted *influence* are highly correlated, since given different predicted *influence* $\hat{R}$, the optimal parameters μ and β that maximize the likelihood of Hawkes processes on a query sequence can be very different. On the large synthetic data, LDA-Hawkes's performance on parameter estimation becomes worse, while the accuracy of *influence* prediction also decreases. Due to the shapely increased data size, the combination of textual and temporal information becomes more complicated, which makes *influence* prediction more difficult, and further affects the learning of users' personal temporal patterns. On both noisy data sets, LDA-Hawkes's performances in both inference and estimation become worse.

4.2 Real-world Data

We also conducted extensive experiments on two real-world data sets. The first data set is adapted from the query log of AOL search engine [4]. The entire collection consists of 19.4 million search queries from about 650,000 users over a 3-month period. We cleaned the data by removing the duplicated queries which were submitted consecutively within 1 minute. We randomly selected a subset of users who submitted over 1,000 queries during this period, and collected their corresponding search activities, including the anonymized user ID, query string, timestamp, the clicked URL. As a result, we collected 1,786 users with 2.2 million queries, and their activities span from 18 days to 3 months. The second data set is collected from Yahoo search engine, from Jan 2013 to September 2013. Similarly, we cleaned the data and randomly selected a subset of users who submitted over 3,000 queries during this period. As a result, we collected 1,475 users with 1.9 million queries, and their activities span from 54 days to 9 months.

Model Fitness. Table 2 shows the log predictive likelihood on events falling in the final 10% of the total time of query data. To avoid overfitting issues, we adopt a k-fold cross validation strategy, and select the optimal number of topics K. According to Table 2, LDA-Hawkes fits both synthetic and real-world data better than TW and Word-Related. This illustrates that a Hawkes process can better utilize the temporal information in benefiting LDA's learning of textual data than simply considering the co-occurrence of queries within a time session or queries sharing at least one same word. The larger a time-window TW uses, the worse its performance will be. Time-window based LDA models generally perform better than Word-Related. Word-Related performs the worst, which illustrates that using lexicon-similarity only is far from enough for grouping semantically related queries. On both noisy data sets, the performances of all models become worse. However, the decrease of the performance of LDA-Hawkes is smaller than that of TW and Word-Related, which demonstrates the robustness of our proposed model.

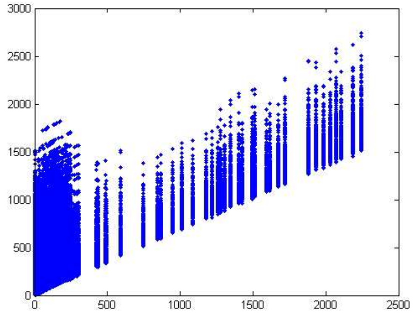


Figure 4: Q-Q plot of the predictive query sequence simulated with inferred Hawkes parameters versus the real query sequence.

In addition, another experiment is conducted to study how well the proposed model can fit the temporal data of query logs. Figure 4 shows the Q-Q plot of the predictive query sequences based on Hawkes parameters inferred from AOL versus the real query sequences in AOL. If the distribution of the timestamps of the predictive query sequences and that of the real query sequences are similar, the points in the Q-Q plot will approximately lie around the diagonal. If these two distributions are linearly related, the points in the Q-Q plot will approximately lie on a line, but not necessarily on the diagonal. From Figure 4, we can find that LDA-Hawkes fits the temporal data of real-world query logs very well.

Query clustering. Along with search task identification, the proposed model simultaneously clusters queries into topics, and automatically labels identified search tasks. According to our definition of search tasks, the performance of their identification depends heavily on the accuracy of per-query topic prediction. Moreover, whether our identified search tasks are labeled appropriately depends on how well our inferred topics match real-world semantic concepts. Thus the performance of identifying and labeling search tasks mainly depends on how we cluster query words into different topics. In this series of experiments, we evaluate the quality of obtained query clusters/topics, which depends on their purity, or semantic coherence. Since no ground truth about the correct composition of a topic is available, we assess purity by the average similarity of each pair of queries within the same topic as:

$$\text{Purity} = \frac{1}{K} \sum_k \frac{\sum_{q_i, q_j \in t_k} \text{Sim}(q_i, q_j)}{N_k(N_k-1)/2} \times 100\%,$$

where N_k is the number of queries in topic k.

We evaluate the query similarity based on their categorical labels from the Open Directory Project (ODP)[4], which has been widely used to measure the semantic relations between queries [5, 12]. The ODP , also known as DMOZ, is a human-edited directory of more than 4 million URLs. These URLs belong to over 590,000 categories organized in a tree-structured taxonomy where more general topics are located at higher levels. Users can issue queries in ODP and use the returned categories to categorize those queries. For instance, the URL {tech.groups.yahoo.com/group/amrc-l/} belongs

[4] http://www.dmoz.org/

Table 1: Inference and Estimation of LDA-Hawkes on Synthetic data

Data set	$\frac{1}{M}\sum_m \lvert\frac{\bar{\mu}_m-\mu_m}{\mu_m}\rvert$	$\frac{1}{M}\sum_m \lvert\frac{\beta_m-\beta_m}{\beta_m}\rvert$	Prec$_R$	log likelihood
Small Synthetic	0.058	0.204	0.9175	-92.38
Small Event Noisy	0.083	0.317	0.8847	-95.02
Small Intensity Noisy	0.101	0.362	0.8675	-96.80
Large Synthetic	0.174	0.381	0.8573	-115.29
Large Event Noisy	0.202	0.413	0.8291	-119.38
Large Intensity Noisy	0.219	0.436	0.8107	-122.25

Table 2: Log Predictive Likelihood on Both Synthetic and Real-world Data

Model/Data set	LDA-Hawkes	TW(5 min)	TW(1 hour)	TW(1 day)	TW(1 week)	Word-Related
Small Synthetic	-110.32	-121.87	-124.08	-137.21	-168.40	-504.83
Small Event Noisy	-122.83	-135.23	-139.37	-152.15	-184.50	-536.21
Small Intensity Noisy	-127.36	-139.21	-146.59	-159.42	-192.23	-543.19
Large Synthetic	-163.84	-177.48	-182.43	-198.20	-239.04	-846.14
Large Event Noisy	-179.34	-193.05	-200.13	-221.49	-263.91	-880.04
Large Intensity Noisy	-184.27	-198.30	-207.23	-228.91	-270.92	-889.36
AOL	-153.12	-165.03	-169.83	-184.27	-221.32	-815.42
Yahoo	-192.36	-217.32	-222.95	-236.03	-275.74	-896.17

to Top/Arts/Animation/Anime/Clubs_and_Organizations, while the URL {http://valleyofazure.tripod.com/} belongs to another directory Top/Arts/Animation/Anime/Characters. Hence, to measure how related these two queries are, we can use a notion of similarity between the corresponding categories provided by ODP. In particular, we measure the similarity between category C_i of query q_i and category C_j of query q_j as the length of their longest common prefix $P(C_i, C_j)$ divided by the length of the longest path between C_i and C_j. More precisely, we define this similarity as:

ODP Similarity

$$\text{Sim}(q_i, q_j) = |P(C_i, C_j)| / \max(|C_i|, |C_j|),$$

where $|C|$ denotes the length of a path. For instance, the similarity between the two queries above is 3/5 since they share the path "Top/Arts/Animation" and the longest one is made of five directories. We evaluate the similarity between two queries by measuring the similarity between the most similar categories of the two queries, among the top 5 answers provided by ODP.

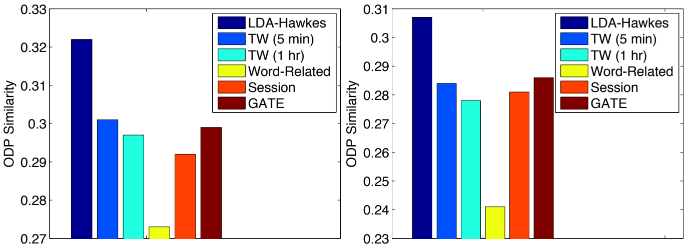
Figure 5 compares the purity of topics detected by LDA-Hawkes, alternative probabilistic models, and state-of-the-art query clustering approaches on AOL and Yahoo data sets. We can find that LDA-Hawkes outperforms all compared approaches. It improves over the second best method by up to 10%. `Gate` and TW(5 min) take the second place, both of them are slightly better than `Session-Similarity` and TW(1 hr), which again demonstrates that a small time window better benefits the LDA model in detecting semantically related queries. Word-Related performs significantly worse than other methods, which shows that considering only the co-occurrence of queries sharing words is very limited. Meanwhile, we find that compared with TW, LDA-Hawkes, `Session-Similarity`, and `Gate` perform relatively better on Yahoo data set, which implies that LDA-Hawkes works for various real-world query logs. Notice that the absolute value of topic purity is not very high, since the ODP categories are fine-grained, the categories of queries from the same search task are very likely to be different, but share paths, i.e., have common prefix.

Search Task Identification. To justify the effectiveness of the proposed model in identifying search tasks in query logs, we employ a public AOL data subset[5] with 554 annotated search tasks. This subset contains 13 users with around 110 queries per user. We also recruit eight editors to annotate 1150 search tasks in a randomly chosen subset from the Yahoo data, which contains 100 users with around 50 queries per user. We measure the performance by a widely used evaluation metric,

F_1 score

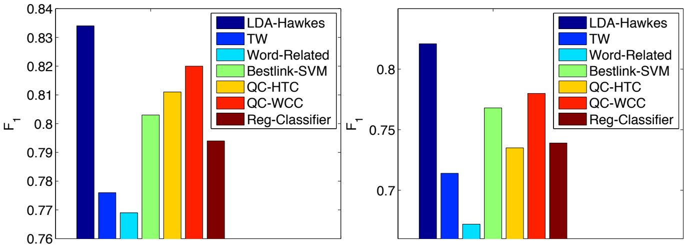
$$F_1 = \frac{2 * p_{pair} * r_{pair}}{p_{pair} + r_{pair}},$$

where p_{pair} denotes the percentage of query-pairs in our predicted search tasks that also appear in the same ground-truth task, while r_{pair} denotes the percentage of query-pairs in the ground-truth tasks that also appear in the same predicted task.



(a) AOL (b) Yahoo

Figure 5: Query Clustering measured by Topic Purity. This metric relies on ODP Similarity to evaluate the pairwise similarity between queries.



(a) AOL (b) Yahoo

Figure 6: Performance Comparison of Search Task Identification measured by F_1 Score.

[5] http://miles.isti.cnr.it/ tolomei/?page_id=36.

Figure 6 compares the proposed model with alternative probabilistic models and state-of-the-art search task identification approaches by F_1 score. Here among TW models with various time-window sizes, we only include the "5 min" sized Time-Window in comparison, since it performs the best in both model fitness and query clustering. From Figure 6, we find that LDA-Hawkes performs the best among all compared approaches, and outperforms the second best approach by over 5%. Furthermore, LDA-Hawkes outperforms baselines in terms of both accuracy and recall. TW and Word-Related perform the worst since their assumptions on query-relationship within the same search task are too strong. Moreover, LDA-Hawkes's advantage over Bestlink-SVM and Reg-Classifier illustrates that employing self-exciting point processes like Hawkes to utilize the temporal information in query logs can be a better choice than incorporating temporal information in features. The advantage over QC-HTC and QC-WCC demonstrates that appropriate usage of temporal information in query logs can even better reflect the semantic relationship between queries, rather than exploiting it in some collaborative knowledge. The advantage of the performance of LDA-Hawkes over other baselines on Yahoo query log is greater than that on AOL. One possible reason is that the average length of search tasks in Yahoo is larger than that in AOL, which results in more influence occurrences, and enables LDA-Hawkes to better learn the temporal patterns of users.

Case Study of Identified Search Tasks. In this part, we try to show a few examples that LDA-Hawkes identify and label search tasks in Yahoo query log, so as to illustrate the validity of our identified search tasks and their labeling. From Figure 7, we can find that both the word co-occurrence and temporal gap play a important role in predicting *influence* among sequential queries. Although chances are very small that queries “aircract carrier” and “aircraft carrier” will co-occur, we predict an *influence* between them, since they are temporally close. On the other hand, query-pair “tibet” and “ryukyu islands”, and query-pair “aircraft carrier” and “battleships us” are not consecutive, however, we predict that *influence* exist between those pairs of queries, as they co-occur in quite a few number of users' query sequences. Thus we may conclude that the existence of *influence* demands both temporal and sematic closeness. Queries linked by *influence* belong to the same search task since the user's *information need* is not satisfied by the former query, which makes the user additionally issue the later semantically related query, whose occurrence violates that user's regular query submission propensity. The figure also shows that LDA-Hawkes is able to assign the same label to different search tasks which are semantically related, despite that the temporal gap between them are very long.

5. RELATED WORK

Search query logs have been extensively studied to improve the search relevance and provide better user experience. There has been a large body of work focused on the problem of identifying search tasks or sessions from sequences of queries. Many of these methods use the idea of a “timeout” cutoff between queries, where two consecutive queries are considered as two different sessions or tasks if the time interval between them exceeds a certain threshold. Often a 30-minute timeout is used to segment sessions [9, 22, 30]. In addition, other timeout thresholds have been proposed, from 1 to 120 minutes [15, 18, 23]. However, the experimental results of these methods indicate that the timeouts, whatever their lengths, are of limited utility in predicting whether two queries belong to the same task, and unsuitable for identifying session boundaries. Beyond that, Wang et al. [30] and Hua et al. [17] treated the time intervals between queries as pairwise features in their models. But no previous work has explicitly exploited the temporal information directly in their models. In our work, we directly integrate the temporal information into our model, rather than highly relying on different timeouts, for identifying search tasks.

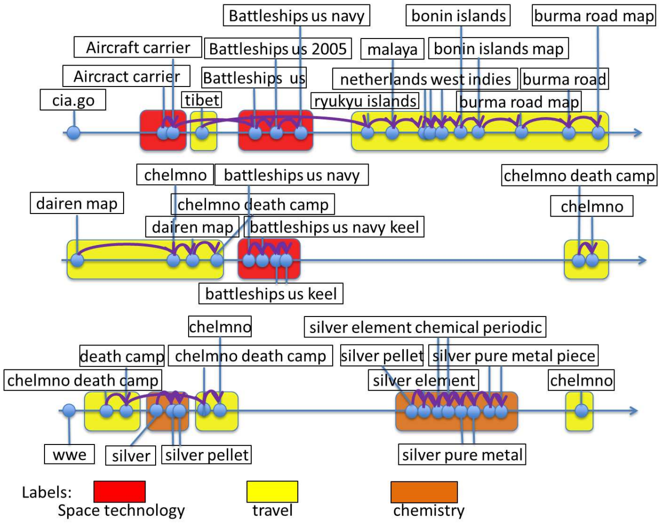


Figure 7: Case Study: Purple arrow line denotes the *influence* identified by the proposed model, rounded rectangle denotes the identified search tasks, rectangle denotes the labels our model assigns to search tasks.

There have been attempts to extract in-session tasks [28, 18, 23], and cross-session tasks [18, 19, 1, 30] from query sequences based on classification and clustering methods. Jones and Klinkner [18] proposed to learn a binary classifier to detect whether two queries belong to the same task or not, which organized and segmented query sequences into hierarchical units. Moreover, Kotov et al. [19] and Agichtein et al. [1] studied the problem of cross-session task extraction via binary same-task classification, and found different types of tasks demonstrate different life spans. Another suitable mechanism for identifying sessions or tasks may rely on *unsupervised learning* approaches, i.e., query clustering algorithms, especially when no labeled training set is available. The intuition for using query clustering is based on the assumption that if two queries belong to the same cluster, then they are topically related. Cao et al. [9] proposed a clustering algorithm for summarizing queries into concepts throughout a click-through bipartite graph built from a search log. Lucchese et al. [23, 24] and Hua et al. [17] exploited the knowledge base for detecting semantically related query pairs that are not similar from a lexical content point of view. In addition, Wang et al. [30] proposed a semi-supervised clustering method for identifying cross-session tasks. Different from these existing methods, our paper assumes that queries belonging to the same search task are linked by influence. Moreover, instead of focusing on the query sequence of each single user, we take into account the query sequences issued by different users simultaneously in a unified framework, such that our model can identify and label coherent search tasks across users.

Our proposed model is closely related to point processes, which have been used to model social networks [8] and natural events [37]. People find self-exciting point processes naturally suitable to model continuous-time events where the occurrence of one event can affect the likelihood of subsequent events in the future. One important self-exciting process is Hawkes process, which is first used to analyze earthquakes [25, 37], and then widely applied to many different areas, such as market modeling [13, 3], crime modeling [29], terrorist [26], conflict [35, 21], and viral videos on the Web [10]. A novel Hawkes model was also proposed to model both temporal and textual information in viral [34]. To solve such models, an EM algorithm is generally adopted to estimate the maximum likelihood of Hawkes process [20].

6. CONCLUSION AND FUTURE WORK

In this paper, we have presented a probabilistic model to integrate the LDA model with Hawkes processes for identifying and labeling search tasks. Basically, Hawkes processes utilize their self-exciting properties to identify search tasks if influence exists among a sequence of queries for individual users, while the LDA model exploits query co-occurrence across different users to discover the latent information needed for labeling search tasks. By leveraging the temporally weighted query co-occurrence, our model not only guarantees sound performance by making full use of both textual and temporal information of the entire query sequences, but also enables the labeling of the identified search tasks since semantically related queries are clustered together through query links determined by co-occurrence. We have applied the proposed LDA-Hawkes model to analyze search tasks on both AOL and Yahoo query logs, and compare with several alternative approaches. Experimental results show that the improvements of our proposed model are consistent, and our LDA-Hawkes model achieves the best performance. In future work, it would be interesting to consider other information, e.g., click-through data, into this framework, and investigate the performance of LDA-Hawkes in other domains.

7. ACKNOWLEDGMENT.

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8. REFERENCES

[1] E. Agichtein, R. W. White, S. T. Dumais, and P. N. Bennett. Search, interrupted: understanding and predicting search task continuation. In *SIGIR*, pages 315–324, 2012.

[2] L. M. Aiello, D. Donato, U. Ozertem, and F. Menczer. Behavior-driven clustering of queries into topics. In *CIKM*, pages 1373–1382, New York, NY, USA, 2011. ACM.

[3] Y. Ait-Sahalia, J. Cacho-Diaz, and R. Laeven. Modeling financial contagion using mutually exciting jump processes. *Tech. rep.*, 2010.

[4] AOL. http://gregsadetsky.com/aol-data/.

[5] R. Baeza-Yates and A. Tiberi. Extracting semantic relations from query logs. KDD, pages 76–85, New York, NY, USA, 2007. ACM.

[6] D. Blei and M. Jordan. Variational inference for dirichlet process mixtures. In *Bayesian Analysis*, volume 1, pages 121–144, 2005.

[7] D. M. Blei, A. Y. Ng, and M. I. Jordan. Latent dirichlet allocation. *J. Mach. Learn. Res.*, 3:993–1022, March 2003.

[8] C. Blundell, K. A. Heller, and J. M. Beck. Modelling reciprocating relationships with hawkes processes. *NIPS*, 2012.

[9] H. Cao, D. Jiang, J. Pei, Q. He, Z. Liao, E. Chen, and H. Li. Context-aware query suggestion by mining click-through and session data. In *KDD*, pages 875–883, 2008.

[10] R. Crane and D. Sornette. Robust dynamic classes revealed by measuring the response function of a social system. *Proceedings of the National Academy of Sciences of the United States of America*, 105(41):15649–15653, 2008.

[11] A. P. Dempster, N. M. Laird, and D. B. Rubin. Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society. Series B (Methodological)*, pages 1–38, 1977.

[12] H. Deng, I. King, and M. R. Lyu. Entropy-biased models for query representation on the click graph. SIGIR, pages 339–346, New York, NY, USA, 2009. ACM.

[13] E. Errais, K. Giesecke, and L. R. Goldberg. Affine point processes and portfolio credit risk. *SIAM J. Fin. Math.*, 1(1):642–665, Sep 2010.

[14] A. G. Hawkes. Spectra of some self-exciting and mutually exciting point processes. *Biometrika*, 58:83–90, 1971.

[15] D. He, A. Göker, and D. J. Harper. Combining evidence for automatic web session identification. *Inf. Process. Manage.*, 38(5):727–742, 2002.

[16] M. D. Hoffman, D. M. Blei, and F. Bach. Online learning for latent dirichlet allocation. In *NIPS*, 2010.

[17] W. Hua, Y. Song, H. Wang, and X. Zhou. Identifying users' topical tasks in web search. In *WSDM*, pages 93–102, 2013.

[18] R. Jones and K. L. Klinkner. Beyond the session timeout: automatic hierarchical segmentation of search topics in query logs. In *CIKM*, pages 699–708, 2008.

[19] A. Kotov, P. N. Bennett, R. W. White, S. T. Dumais, and J. Teevan. Modeling and analysis of cross-session search tasks. In *SIGIR*, pages 5–14, 2011.

[20] E. Lewisa and G. Mohlerb. A nonparametric em algorithm for multiscale hawkes processes. *Journal of Nonpara-metric Statistics*, 1, 2011.

[21] L. Li and H. Zha. Dyadic event attribution in social networks with mixtures of hawkes processes. CIKM, pages 1667–1672, New York, NY, USA, 2013. ACM.

[22] Z. Liao, Y. Song, L.-w. He, and Y. Huang. Evaluating the effectiveness of search task trails. In *Proceedings of the 21st international conference on World Wide Web*, pages 489–498. ACM, 2012.

[23] C. Lucchese, S. Orlando, R. Perego, F. Silvestri, and G. Tolomei. Identifying task-based sessions in search engine query logs. In *WSDM*, pages 277–286, 2011.

[24] C. Lucchese, S. Orlando, R. Perego, F. Silvestri, and G. Tolomei. Discovering tasks from search engine query logs. *ACM Trans. Inf. Syst.*, 31(3):14, 2013.

[25] Y. Ogata. Statistical models for earthquake occurrences and residual analysis for point processes. *Journal of the American Statistical Association.*, 83(401):9–27, 1988.

[26] M. D. Porter and G. White. Self-exciting hurdle models for terrorist activity. *The Annals of Applied Statistics*, 6(1):106–124, 2011.

[27] F. Schoenberg. Introduction to point processes. *Wiley Encyclopedia of Operations Research and Management Science*, pages 616–617, 2010.

[28] A. Spink, S. Koshman, M. Park, C. Field, and B. J. Jansen. Multitasking web search on vivisimo.com. In *ITCC (2)*, pages 486–490, 2005.

[29] A. Stomakhin, M. B. Short, and A. L. Bertozzi. Reconstruction of missing data in social networks based on temporal patterns of interactions. *Inverse Problems.*, 27(11), Nov 2011.

[30] H. Wang, Y. Song, M.-W. Chang, X. He, R. W. White, and W. Chu. Learning to extract cross-session search tasks. In *WWW*, pages 1353–1364, 2013.

[31] X. Wang and E. Grimson. Spatial latent dirichlet allocation. NIPS, pages 1577–1584, 2007.

[32] Y. Wang, E. Agichtein, and M. Benzi. Tm-lda: efficient online modeling of latent topic transitions in social media. In *KDD*, pages 123–131, New York, NY, USA, 2012. ACM.

[33] R. W. White, W. Chu, A. Hassan, X. He, Y. Song, and H. Wang. Enhancing personalized search by mining and modeling task behavior. In *WWW*, pages 1411–1420, 2013.

[34] S. Yang and H. Zha. Mixture of mutually exciting processes for viral diffusion. In *ICML*, volume 28, pages 1–9, 2013.

[35] A. Z.-Mangion, M. Dewarc, V. Kadirkamanathand, and G. Sanguinetti. Point process modelling of the afghan war diary. *PNAS*, 109(31):12414–12419, July 2012.

[36] Z. Zhang and O. Nasraoui. Mining search engine query logs for query recommendation. In *WWW*, pages 1039–1040, New York, NY, USA, 2006. ACM.

[37] J. Zhuang, Y. Ogata, and D. V. Jones. Stochastic declustering of space-time earthquake occurrences. *Journal of the American Statistical Association.*, 97(458):369–380, 2002.