# A New Clustering Technique based on User Search Histories

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**Abstract:** Most users want their search engine to incorporate three key features in query results. Relevant results(results they are actually interested in),Uncluttered(easy to read interface),Helpful options to broaden or tighten a search for accuracy. This paper addresses the third aspect with new improvement measures for an enhanced experience to the end user. A trivial query such as travel arrangement has to be broken down into a number of co-dependent steps over a period of time based on prior search patterns of the same user thus providing customized holistic view. For instance, a user may first search on possible destinations, timeline, events, etc. After deciding when and where to go, the user may then search for the most suitable arrangements for air tickets, rental cars, lodging, meals, etc. Each step results in one or more further queries, and each query results in one or more clicks on relevant pages. Current search engines cannot support this kind of hierarchical queries. We propose to implement Random walk propagation methods that can construct user profiles based on the credentials obtained from their prior search history repositories. Combined with click points driven click graphs of user search behavior the IR system can support complex queries for future requests at reduced navigations. Random walk propagation over the query fusion graph methods support complex search quests in IR systems at reduced times. For developing an interactive IR system we also propose to use these search quests as auto complete features in similar query propagations. Biasing the ranking of search results can also be provided using ranking algorithms(top-k algorithms).Supporting these methods yields dynamic and improved performance in IR systems, by providing enriched user querying experience. A practical implementation of the proposed system validates our claim.

***Index Terms:*** *query clustering, search engine, query reformulation, click graph, task identification*

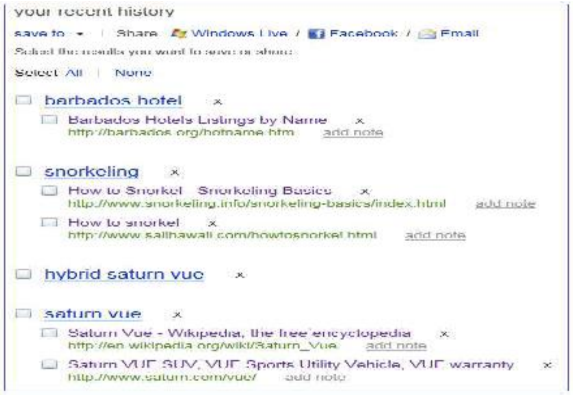
## I. INTRODUCTION

AS the size and richness of information on the Web grows, so does the variety and the complexity of tasks that users try to accomplish online. Users are no longer content with issuing simple navigational queries. Various studies on query logs (e.g., Yahoo's and AltaVista's reveal that only about 20% of queries are navigational. The rest are informational or transactional in nature. This is because users now pursue much broader informational and task-oriented goals such as arranging for future travel, managing their finances, or planning their purchase decisions. However, the primary means of accessing information online is still through keyword queries to a search engine.

To improve user's search experience, most major commercial search engines provide query suggestions to help users formulate more effective queries. When a user submits a query, a list of terms that are semantically related to the submitted query is provided to help the user identify terms that he/she really wants, hence improving the retrieval effectiveness. Yahoo's "Also Try" and Google's "Searches related to" features provide related queries for narrowing search, while Ask Jeeves suggests both more specific and more general queries to the user.

One important step towards enabling services and features that can help users during their complex search quests online is the capability to identify and group related queries together. Recently, some of the major search engines have introduced a new "Search History" feature, which allows users to track their online searches by recording their queries and clicks. This history includes a sequence of four queries displayed in reverse Chronological order together with their corresponding clicks. In addition to viewing their search history, users can manipulate it by manually editing and organizing related queries and clicks into groups, or by sharing them with their friends.

Once query groups have been identified, search engines can have a good representation of the search context behind the current query using queries and clicks in the corresponding query group. This will help to improve the quality of key components of search engines such as query suggestions, result ranking, query alterations, sessionization, and collaborative search. For example, if a search engine knows that a current query "financial statement" belongs to a {"bank of America", "financial statement"} query group, it can boost the rank of the page that provides information about how to get a Bank of America statement instead of the Wikipedia article on "financial statement", or the pages related to financial statements from other banks.


your recent history

save to ▾ | Share Windows Live / Facebook / Email

Select the results you want to save or share:

Select All | None

□ barbados hotel ×

□ Barbados Hotels Listings by Name ×
http://barbados.org/hotname.htm add note

□ snorkeling ×

□ How to Snorkel Snorkeling Basics ×
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□ Saturn Vue - Wikipedia, the free encyclopedia ×
http://en.wikipedia.org/wiki/Saturn_Vue add note

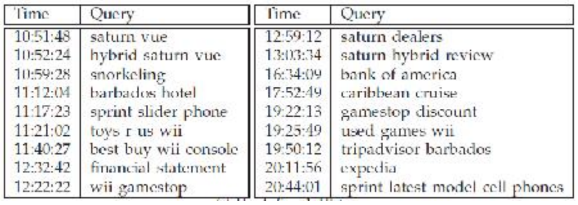
□ Saturn VUE SUV, VUE Sports Utility Vehicle, VUE warranty ×
http://www.saturn.com/vue/ add note

*Fig. 1. Example of search history feature in Bing.*

In this paper we motivate and propose a method to perform query grouping in a dynamic fashion. Our goal is to ensure good performance while avoiding disruption of existing user-defined query groups. We investigate how signals from search logs such as query reformulations and clicks can be used together to determine the relevance among query groups. We study two potential ways of using clicks in order to enhance this process: by fusing the query reformulation graph and the query click graph into a single graph that we refer to as the *query fusion graph*, and by expanding the query set when computing relevance to also include other queries with similar clicked URLs.

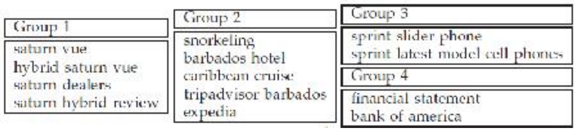
## II. RELATED WORK

Baeza-Yates et al proposed a query clustering method that groups similar queries according to their semantics. The method creates a vector representation Q or a query q, and the vector Q is composed of terms from the clicked documents of q. Cosine similarity is applied to the query vectors to discover similar queries. More recently, Zhang and Nasraoui presented a method that discovers similar queries by analyzing users' sequential search behavior. The method assumes that consecutive queries submitted by a user are related to each other. The sequential search behavior is combined with a traditional contentbased similarity method to compensate for the high sparsity of real query log data.



| Time | Query | Time | Query |
|---|---|---|---|
| 10:51:48 | saturn vue | 12:59:12 | saturn dealers |
| 10:52:24 | hybrid saturn vue | 13:03:34 | saturn hybrid review |
| 10:59:28 | snorkeling | 16:34:09 | bank of america |
| 11:12:04 | barbados hotel | 17:52:49 | caribbean cruise |
| 11:17:23 | sprint slider phone | 19:22:13 | gamestop discount |
| 11:21:02 | toys r us wii | 19:25:49 | used games wii |
| 11:40:27 | best buy wii console | 19:50:12 | tripadvisor barbados |
| 12:32:42 | financial statement | 20:11:56 | expedia |
| 12:22:22 | wii gamestop | 20:44:01 | sprint latest model cell phones |

*Fig 1: User Histories*



| Group 1 | Group 2 | Group 3 |
|---|---|---|
| saturn vue | snorkeling | sprint slider phone |
| hybrid saturn vue | barbados hotel | sprint latest model cell phones |
| saturn dealers | caribbean cruise | Group 4 |
| saturn hybrid review | tripadvisor barbados | financial statement |
|  | expedia | bank of america |

*Fig 2: Query Groups.*

Our goal is to automatically organize a user's search history into query groups, each ontaining one or more related queries and their corresponding clicks. Each query group corresponds to an atomic information need that may require a small number of queries and clicks related to the same search goal. For example, in the case of navigational queries, a query group may involve as few as one query. One major problem with the clickthrough-based method is that the number of common clicks on URLs for different queries is limited. This is because different queries will likely retrieve very different result sets in very different ranking orders.

**Dynamic Query Grouping:** One approach to the identification of query groups is to first treat every query in a user's history as a singleton query group, and then merge these singleton query groups in an iterative fashion (in a k-means or agglomerative way [8]). However, this is impractical in our scenario for two reasons. First, it may have the undesirable effect of changing a user's existing query groups, potentially undoing the user's own manual efforts in organizing her history. Second, it involves a high computational cost, since we would have to repeat a large number of query group similarity computations for every new query.

## III. EXISTING APPROACH

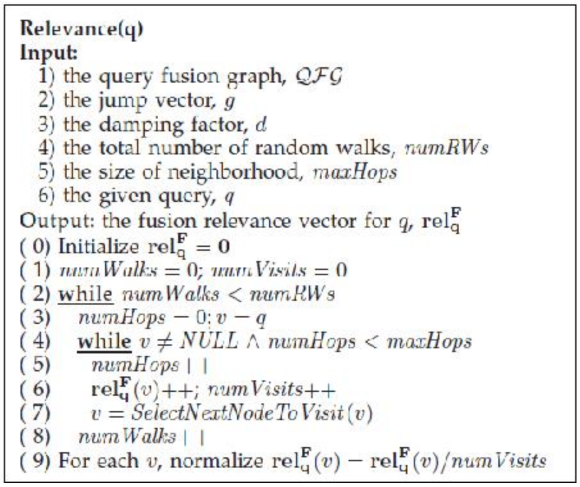
**Personalized Concept-Based Clustering:** We now explain the essential idea of our personalized concept-based clustering algorithm with which ambiguous queries can be clustered into different query clusters. Personalized effect is achieved by manipulating the user concept preference profiles in the clustering process. In contrast to BB's agglomerative clustering algorithm, which represents the same queries submitted from different users by one query node, we need to consider the same queries submitted by different users separately to achieve personalization effect. In other words, if two given queries, whether they are identical or not, mean different things to two different users, they should not be merged together because they refer to two different sets of concepts for the two users. Therefore, we treat each individual query submitted by each user as an individual vertex in the bipartite graph by labeling each query with a user identifier.

## IV. PROPOSED APPROACH

A user queries a search engine Search Engine tries to construct user profile based on his ipaddress/login credentials from its user search history repositories. If the user already exists, the search engine checks from its user search history repositories up to a certain threshold whether the user already queried the same query previously If the user did, then search engine further retrieves click points from user search history repositories and reformulates query results by generating click graphs. Click graphs contain useful information on user behavior when searching online. This step is called query fusion graph. Uses random walk propagation over the query fusion graph instead of time-based and keyword similarity based approaches. This entire process is called organizing user search histories into query groups. This approach helps users to pursue complex search quests online.

## V. QUERY REKEVANCE USING SEARCH LOGS

We now develop the machinery to define the *query relevance* based on Web search logs. Our measure of relevance is aimed at capturing two important properties of relevant queries, namely: (1) queries that frequently appear together as reformulations and (2) queries that have induced the users to click on similar sets of pages



```
Relevance(q)
Input:
  1) the query fusion graph, $\mathcal{QFG}$
  2) the jump vector, $g$
  3) the damping factor, $d$
  4) the total number of random walks, $numRWs$
  5) the size of neighborhood, $maxHops$
  6) the given query, $q$
Output: the fusion relevance vector for $q$, $\mathbf{rel}_q^F$
Initialize $\mathbf{rel}_q^F = 0$
$numWalks = 0; numVisits = 0$
while $numWalks < numRWs$
    $numHops - 0; v - q$
    while $v \neq NULL \wedge numHops < maxHops$
      $numHops$ | |
      $\mathbf{rel}_q^F(v)$++; $numVisits$++
      $v = SelectNextNodeToVisit(v)$
    $numWalks$ | |
For each $v$, normalize $\mathbf{rel}_q^F(v) - \mathbf{rel}_q^F(v)/numVisits$
```

*Fig 3: Algorithm for calculating the query relevance by simulating random walks over the query fusion graph.*

### 5.1 Search Behavior Graphs

We derive three types of graphs from the search logs of a commercial search engine. The *query reformulation graph*, QRG, represents the relationship between a pair of queries that are likely reformulations of each other. The *query click graph*, QCG, represents the relationship between two queries that frequently lead to clicks on similar URLs.

***Query Reformulation Graph:*** One way to identify relevant queries is to consider *query reformulations* that are typically found within the query logs of a search engine. If two queries that are issued consecutively by many users occur frequently enough, they are likely to be reformulations of each other.

***Query Click Graph:*** A different way to capture relevant queries from the search logs is to consider queries that are likely to induce users to click frequently on the same set of URLs. For example, although the queries “ipod” and “apple store” do not share any text or appear temporally close in a user’s search history, they are relevant because they are likely to have resulted in clicks about the iPod product.

***Query Fusion Graph:*** The query reformulation graph, QRG, and the query click graph, QCG, capture two important properties of relevant queries respectively.

## VI. PERFORMANCE ANALYSIS

**Experimental Setup:**

We study the behavior and performance of our algorithms on partitioning a user’s query history into one or more groups of related queries. For example, for the sequence of queries “caribbean cruise”; “bank of america”; “expedia”; “financial statement”, we would expect two output partitions: first, {“Caribbean cruise”, “expedia”} pertaining to travel-related queries, and, second, {“bank of america”, “financial statement”} pertaining to money-related queries.

**Using Search Logs**

our query grouping algorithm relies heavily on the use of search logs in two ways: first, to construct the query fusion graph used in computing query relevance, and, second, to expand the set of queries considered when computing query relevance. We start our experimental evaluation, by investigating how we can make the most out of the search logs. In our first experiment, we study *how we should combine* the query graphs coming from the query reformulations and the clicks within our query log.

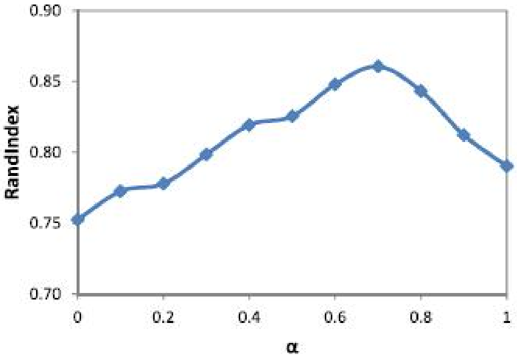


Fig 4: Varying mix of query and click graphs.

Above graph describes the horizontal axis represents _ (i.e., how much weight we give to the query edges coming from the query reformulation graph), while the vertical axis shows the performance of our algorithm in terms of the RandIndex metric.

## VII. CONCLUSION

The query reformulation and click graphs contain useful information on user behavior when searching online. In this paper, we show how such information can be used effectively for the task of organizing user search histories into query groups. More specifically, we propose combining the two graphs into a query fusion graph. We further show that our approach that is based on probabilistic random walks over the query fusion graph outperforms time-based and keyword similarity based approaches. We also find value in combining our method with keyword similarity-based methods, especially when there is insufficient usage information about the queries. As future work, we intend to investigate the usefulness of the knowledge gained from these query groups in various applications such as providing query suggestions and biasing the ranking of search results.

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