

KEYWORD SEARCH PATTERNS IN SPONSORED LINK ADVERTISEMENTS

Research-in-Progress

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Abstract

Over time, an online user searching for information about an idea or product may enter multiple search engine queries, thus creating a keyword search pattern from which the user's intent may be inferable. Our research seeks to establish the relationship between these patterns and user actions, specifically their purchase behavior. To test our hypotheses, we examine a unique dataset from a large Asian travel agency; the dataset includes search engine and on-site behavior from over a million users during a one year span. We have developed a typology for the coding of search queries used and determining the level of specificity and breadth as well as content type for each of well over two million unique searches. Once coded, our analysis will allow us to identify types of patterns and test our hypotheses, thus providing important findings regarding the relationship between search patterns and behavior.

Keywords: search, e-business, online search behavior, user behavior

Introduction

In a face-to-face context, individuals have the opportunity for rich interactions. In particular, if one is in need of information or advice and asks another, the second individual can follow up with a wide variety of questions to qualify the initial request and thus be sure to give the most appropriate answer. The same is true in face-to-face sales environments where salespeople can ask a wide variety of questions to better identify a useful response (Johnston and Marshall 2010). Web-based interactions, however, often do not allow for such rich information sharing. In particular, search engines can only provide results algorithmically identified based on search terms provided by the user. While a salesperson could be sensitive and attempt to discern the needs of each particular customer, a search engine will provide the same results over and over no matter who is asking, how many times the person has asked, or what prior information has already been requested and given.

Follow-up questions such as those asked in an inter-personal context are more difficult to support with Web technology. Often a “chat” feature needs to be engaged to start the process. Phone numbers are also sometimes available for asking the questions. Given those extra steps, some users might just give up and go to a physical agent instead. While follow-up questions may not be prevalent within Web interfaces, users may nevertheless give cues that suggest their own level of interest, amount of knowledge, and commitment to purchase.

Depending on the way the user interacts with a site, e.g., the pattern of terms used on a search engine across multiple sessions, it may be possible to ascertain the intent of a user’s search and/or their expectations from the interaction. While this understanding may be useful to the search engines themselves (e.g., it may allow them to deliver better-tailored results), it would certainly be useful to those companies that spend billions of dollars annually advertising through such services as Google AdWords or Bing.

This research aims to understand the correlation between user search query patterns and user actions. Research into specific keyword usage requires large data samples to capture the wide variety of search terms that may be used; using a data set of 2.4 million unique searches, we expect to uncover insights that will improve knowledge of such patterns and better predict user intent and actions.

Background

Within a search engine (e.g., Google), a user will *search* by entering one or more keywords (i.e., a *query*) into a text box to obtain results on a *search result page*. A *search session* is a sequence of related searches that usually takes place over a reasonably confined time period, typically less than a half hour, to achieve a particular search goal. Upon reviewing the results, a user might click on a *sponsored link*, i.e., a textual advertising unit triggered by the specific query entered. Advertisers typically assess advertisements based on metrics such as *click-through rate* (CTR; the ratio of clicks to advertisement impressions), *conversion rate* (CR; the ratio of completed sales to clicks), and *cost-per-click* (CPC; the ratio of cost to clicks).

This online search behavior is a phenomenon relevant to several fields of research, such as marketing, information science, and information systems. To understand search behavior more thoroughly, relevant literature from these areas was examined. This enables us to establish the precise meanings of several terms and simultaneously shed light on the behaviors that will be tracked in this study.

Marketing

Consumers' information search (or information acquisition) behavior has been an important subject in the marketing literature, in particular as it relates to new and/or repeated purchases. Kiel and Layton (1981) suggest three dimensions of search behavior – source of information, brand, and time – and identify key consumer segments. Research on walk-in retail stores has found that the amount of search is relatively limited and heavily influenced by consumers' knowledge and ability to acquire relevant information (Murray 1991).

Huang et al. (2009), who examined various aspects of search behavior in the online context, found that searches targeting experience goods reach greater depth and lower breadth than searches targeting search goods. Johnson et al. (2004) associated search depth, frequency of search within a session, and frequency of search categorized by different consumer expertise level. Bhatnagar and Ghose (2004) found that consumer learning occurred when consumers were seeking information about search goods, but not when they were seeking information regarding experience goods.

Information Systems and Information Science

Text-related search engine query behavior has received substantial scrutiny from researchers in the information science field. In one of the first analyses of search engine query data, Silverstein et al. (1999) studied six weeks of data from the AltaVista search engine query log and found that search engine users differed significantly in their query strategy from users of other data retrieval services, tended to use short queries (the majority used two terms or fewer), and generally only entered one query per search session. Several other log query-related studies have also been conducted. For instance, log query data can be used to develop subject-based categorizations (Ross and Wolfram 2000) to determine that a small number of terms are used with high frequency and a large number used very infrequently (Spink et al. 2001), and to identify differences in query behavior among users of different search engines (Jansen et al. 2008).

Understanding user intent has also been a subject of focus. In a seminal paper, Rose and Levinson (2004) suggested a framework for identifying the implicit goals underlying user search queries. They developed three discrete, broad categories of search goals: navigational, informational, and resource. They further argued that queries can be assigned to these categories based on four data points, (1) the query itself, (2) the pages provided on the search engine results page, (3) the result clicked on by the user, and (4) additional searches conducted by the user. Related research investigated methods for automating this goal identification process (Lee et al. 2005). Jansen et al. (2008) offered an alternative classification system, including navigational, informational, and transactional goal categories. Using these categories, they found that 80% of queries were informational in nature, but also that a quarter of queries were too vague to be easily classified.

Finally, researchers have also considered the effect of user-level variables on search behavior. This research has found significant differences in search behavior based on gender, cognitive complexity, and cognitive style (Ford et al. 2001) and based on psychological traits such as extraversion and openness to experience (Heinström 2003). It has also been found that these individual differences result in different search strategies depending on the complexity of the searcher's objective (Ford et al. 2005).

Keywords and Sponsored Links

The main focus of the research on sponsored links has focused on the factors affecting CTR, CR, and advertisers' keyword bidding strategies (Agarwal et al. 2011; Ghose and Yang 2009; Jerath et al. 2010; Liu et al. 2010). Ghose and Yang (2009) showed that the rank of an advertisement in the search result page had a significant effect on CTR and CR. However, they also found that the profitability of the keyword had an inverted U shape with the regard to the rank in the list, i.e., profits are often higher at the middle positions than at the top or bottom.

Rutz and Bucklin (2011) found evidence of a "spillover effect", in which users who begin with one category of search terms move to other categories, for example starting with a generic term (e.g., "sports car") and moving to a brand-specific term (e.g., "Honda S2000"). Ghose and Yang (2010) reported spillover between product categories. Rutz et. al. (2011) also found evidence of a "loyalty effect", wherein consumers who visit an advertiser's Web site through a sponsored link are more likely to revisit the site by directly typing its URL.

Keyword advertising is not a one-off proposition; users will often conduct several related searches, using different search queries, before completing a purchase. A common search pattern, called the "funnel search strategy," describes users who begin a search with general terms, then continue by searching ever more specifically (Blackwell et al. 2006). Previous literature in Information Systems and Information Science indicates that individuals' information search evolves as they acquire more knowledge (Browne et al. 2007). In addition, different patterns emerge in this process depending on user search goals, domain knowledge, and the search environment (Dou et al. 2010; Grant et al. 2007). These studies also suggest

that not all search patterns are linear (e.g., from general to specific) but that there are many different patterns. Because keyword search is a type of information search, it is expected that one of several different possible patterns may emerge during the evolution of a particular search. Moreover, analyzing the differences across these patterns will help us better understand search behavior in the context of sponsored link advertisements and provide valuable insights for practitioners. To the best of our knowledge, no study of sponsored links has attempted to investigate the relationship between such patterns and user intentions and behaviors including purchase.

Literature Gaps

Viewing the literature across disciplines reveals gaps that this research is intended to fill. The marketing literature has shown a difference among user types and search modes; we seek to build on this by examining the correlation between search specificity (narrowness) and the user's purchase behavior and time spent in searching. While other research has found evidence of this using aggregate data (e.g., Rutz and Bucklin 2011), we seek to test it at the individual searcher level. It has also been found that, in general, users with intermediate product knowledge seek information more extensively than those with low or high knowledge; this concept, however, has not been directly evaluated in the online context. Finally, while researchers have noted that "cognitive style" can impact search behaviors (Ford et al. 2001, 2005), the detection of such styles through a user's pattern of keyword choices have not been attempted, and, therefore, their impact in terms of measurable keyword search performance metrics (CTR, CR) has received little or no attention.

Hypothesis Development

Online search navigation has been categorized as being either goal-directed or exploratory (Hoffman and Novak 1996; Im and Hars 2007). In the sponsored link context, exploratory behavior occurs when users have a broad or ambiguous idea about their goal(s) (e.g., they have an interest in cars). Goal-directed users, on the other hand, have a clear sense of their objective (e.g., they know the brand and model of the exact car they intend to buy). Prior studies showed that individuals exhibit different search behaviors depending on their search mode (El Sawy 1985; Vandenbosch and Huff 1997). We expect, then, that those who conduct goal-directed searches tend to use queries that are both more narrow (focused on fewer subject matter areas) and deeper (more specific), while those conducting exploratory search tend to use queries that are broader (addressing a broader set of subject matter areas) and shallower (less specific). By "depth" we refer to the level of specificity rather than number of searches. Although deeper searches may often take more time than shallower searches, the depth of search is not necessarily correlated with the length of search. A deeper search could be shorter than a shallow search if the user searches with a small number of keywords closely related to one another. It is same for breadth and length; breadth refers to the number of subjects addressed and thus does not necessarily require a longer duration.

It is expected that goal-directed search will lead to a higher probability of purchase than exploratory search because people involved in goal-directed search are looking for solutions to specific problems and they are willing to buy the solution immediately, if found. Thus:

H1: Users searching more narrowly will exhibit a higher conversion rate (CR) than those searching more broadly.

Consumers searching for information tend to focus more on brands and models as they receive more exposure to them (Biehal and Chakravarti 1983). Once consumers accumulate enough information, their intent to purchase increases and, eventually, they make a buying decision. Using aggregated data, Rutz and Bucklin (2011) found evidence of a similar effect in online search, although they were unable to detect how an *individual's* search pattern changed over time or what provoked those specific changes. We expect, then, that users who begin their search with specific brand or model names must therefore be closer to making a purchase decision and, therefore, will require fewer searches (i.e., a shorter search pattern) before making a purchase.

H2: Eventual purchasers who start searching with specific brand or model names will spend less

time searching than those who start with more general keywords.

H3: Users who start searching with specific brand or model names will exhibit higher conversion rate (CR) than those who start with more general keywords.

Prior research has found that consumers having an intermediate level of knowledge about products search more extensively than those having a low or high level of knowledge (Morthy 1997; Punj and Staelin 1983). Experts search less because they need conduct only selective searches to confirm what they already know or to acquire specific information to complement existing knowledge. Those with little knowledge tend to search less due to the lack of knowledge itself; they do not know enough to know what they do not know. In the sponsored link context, then, we expect that users starting with search queries of intermediate specificity (e.g., “The North Face”) will search more extensively than people who start with broad keywords (e.g., “down jackets”) or people with very specific keywords such as model names (“North Face Korbu Jacket”).

We note that there is a substantial difference between on- and off-line searches in terms of the cost of search. For instance, in the off-line environment, consumers are restricted by physical mobility, which limits the number of searches that can reasonably be conducted due to the distance between stores, difficulty in finding products in stores, the availability of knowledgeable sales staff, etc. On the other hand, on-line consumers are not as subject to such limitations, since different information sources can be accessed through an Internet browser almost instantaneously. Therefore, it is expected that the differences among groups with different knowledge levels will be even more salient in the on-line environment.

H4: Users who start searching with moderately specific queries will conduct more searches than those starting with highly specific or highly unspecific queries.

One of the biggest benefits of a large dataset that can be tracked to individual users is its facilitation for discovery of new patterns and estimation of predictive power for those patterns. While prior research has discussed spill-over and funnel strategies, other studies have indicated that individuals’ searches can vary based on goal types and complexity as well as the user’s cognitive style (Ford et al. 2001, 2005). We expect, then, that users with different goals and cognitive styles will interact differently from one another in their search patterns as well, i.e., that some users may opt to become increasingly specific in their searches (a funnel pattern), while others may exhibit more complex patterns such as starting with specific terms, moving to more general terms, then reverting back to more specific terms. By better understanding the range of patterns, we can understand their relationships to dependent variables such as CTR and CR.

H5: There will be categorizable differences among user search behavior patterns with regard to specificity, breadth, depth, and session duration.

Data and Empirical Analysis

The research hypotheses developed in the above section will be tested by analyzing data from a leading online travel agency in Asia (XYZ Company hereafter), which conducts sponsored link advertising. From this advertising, they have accumulated individual user search and click data, which can be matched to online sales results for that user. The raw data contains information about each user’s search, including the search query entered, the time of the query, user IP address, and, if the user purchased a product, sales data (sales amount and type of product). The dataset contains a total of 2,399,391 raw search cases - 172,671 from users who made purchases and 2,226,720 from users who did not - collected during a one year span. The total number of unique keywords was 11,221. Repeated searches from particular customers exist in the database as well.

A travel agency data set of this size is expected to have a broad range of types of searches. Our underlying assumption is that any search is performed to find some data that helps the user make a decision about travel. The target element can be broad (e.g., looking for vacation packages or activities in a particular city) or very specific (e.g., pricing a flight from Shanghai to Orlando or determining the schedules of those

flights). In both case, the users do not know the answer. However, the searches still have a broad enough range to enable testing of all five of the hypotheses.

IP Address	N of Keywords	Keyword 1	Keyword 2	Keyword 3	...	Keyword 15
158.xxx.xxx.xxx	2	Airplane Ticket	Price Comparison		...	
210.xxx.xxx.xxx	15	Singapore Airtel	Guam Airtel	Airline Reservation	...	Hong Kong Travel
...
165.xxx.xxx.xxx	1	Tokyo Travel			...	

The keyword search cases can be sorted by IP address and time, which yields sequences of keywords, each of which represents a customer's search pattern. Examples of sorted keywords are shown in Table 1. These search patterns will be used for the analysis of this study. After sorting, the number of unique customers (based on IP address) was 1,176,115 (80,840 of whom made purchases). The average number of searches (keywords) per search session was 2.13 for purchasing customers and 2.01 for non-purchasing customers.

Keyword Coding

Coding of keyword data presented one of the biggest challenges of this study. This coding is critical because customers' search patterns are derived from the keywords they enter. Without similar previous studies for guidance, the researchers employed a two-phase approach for keyword coding. In Phase 1 (already completed), researchers determined a typology for keyword categories (e.g., "location specificity"). Based on the specific criteria and the information captured, each of these categories was designated as binary, categorical, or ordinal in scale. In Phase 2 (underway at the time of this writing), keywords are being coded by multiple coders, aided by automated processes and using the criteria developed in Phase 1.

In **Phase 1**, the typology of keyword categories was initially developed based on a thorough review of random samples of keyword search sequences. After establishment of this initial typology, a sample of 40 customers each from purchasing and non-purchasing customer groups were coded by the researchers individually by hand in order to verify the validity and replicability of these categorizations. Discrepancies among coding results were discussed and categories refined based on these discussions. A second round of sample coding was done in a similar way; Researchers coded sample keywords and any disagreements or possible problems were discussed and the coding scheme modified as appropriate. A total of three rounds of sample coding were carried out after which the coding scheme was deemed final. Those variables included in the final scheme include: travel location, location specificity, airline, type of activity, purpose of travel, reservation-related terms, recommendation-related terms, price-related terms, advertiser name (i.e., "XYZ Company"), and otherwise un-captured specificity. See Table 2 for more details.

Phase 2 consists of a screening stage and a coding stage. In the screening stage, seven undergraduate students were recruited as coders and asked to screen for and identify specific destinations, airlines, and other terms frequently appearing in search keywords. Once complete, these terms will be used in the coding stage.

In the coding stage, ten coders will code the keywords using Web-based software developed by the researchers specifically for this application. A portion of the coding can be completed automatically by a text-analysis program. For example, there are relatively small number of popular destinations such as "New York", "Shanghai", and "Hawaii" that can be programmatically identified and coded. Other common words and phrases will also be automatically coded in this manner.

For more accurate coding and to reduce any subjective bias that could arise, each keyword requiring manual coding will be coded by two randomly assigned coders as has been done in several prior studies (e.g., Boudreau et al. 2001; Shrivastava 1987).

Table 2. Keyword Coding Scheme	
Variables	Description
Travel Location	A number is assigned to each travel location. The number consists of 7 digits - the first digit for region, the next two digits for country, the next two digits for city, and the last two digits for specific attraction or location in a city. This coding system enables to identify the hierarchy of travel locations (e.g. Tokyo is a city in Japan and Japan is a country in Asia).
Location Level	0 – if not applicable (e.g., Airline ticket), 1 – Region (e.g., Europe), 2 – Country (e.g., Japan), 3 – City (e.g., Los Angeles), 4 – Attraction (e.g., Phuket Beach, Disneyland)
Type of Airline	0 – if not applicable (e.g., Backpack travel), 1 – Domestic airlines (e.g., Korean Airlines, Asiana Airlines), 2 – Other airlines
Type of Activity	0 – if not applicable (e.g., Japan travel), 1 – Package, 2 – Free travel, 3 – Backpack travel, 4 – Transportation (e.g., Airplane, Train), 5 – Lodging (e.g., Hotel, Ryokan, Airtel)
Purpose of Travel	0 – none, 1 – Business (e.g., Conference, Exhibition), 2 – Active leisure (e.g., Ski, Golf, Kayak), 3 – Inactive leisure (e.g., Beach, Cruise), 4 – Education (e.g., language program)
Schedule	0 – none, 1 – if there is a schedule related term (e.g., Schedule, Itinerary)
Reservation	0 – none, 1 – if there is a reservation related term (e.g., Reservation, Booking)
Purchase	0 – none, 1 – if there is a purchase related term (e.g., Purchase, Buy)
Price-related Terms	0 – none, 1 – if there is a weak price-related term (e.g., Price, Price check), 2 – if there is a strong price-related term (e.g., Discount, Hot deal, Lowest price)
Recommendation	0 – none, 1 – if there is a recommendation related term (e.g., Recommendation, Popular, Suggestion)
Advertiser Name	0 – none, 1 – if the advertiser name (XYZ Company) is specified
Other Specificity	0 – if not applicable, 1 – if there is specific term not captured by above variables (e.g., Package-specialized agency, Hilton hotel)

Data Analysis Plan

Measurements that gauge narrowness, breadth, depth, and shallowness of search are being developed. Generally, if a user narrows down, in terms of search specificity, the depth increases and if the user conducts searches on more and varied topics, the breadth increases. For example, if a user starts a search with “Japan travel” and then searches for “Tokyo hotel”, the depth will increase because the second search is more specific in terms of travel location. Then, if the user enters “Tokyo subway”, breadth increases because another search topic was added, i.e., a type of transportation was used in addition to the lodging-related topic used in the previous search. Once keyword coding is done, the breadth and depth of each customer search pattern will be calculated and those hypotheses related to breadth and depth will be tested using these measures.

An overall specificity of search also needs to be calculated at the search query level in order to test hypotheses H2, H3, and H4. There are several variables in Table 2 that indicate specificity of the customer’s search location – country is more specific than region and city is more specific than country, etc. If a customer specified “type of activity” or “purpose of travel,” the search terms gain specificity. The “specificity” variable will be calculated by summing the variables. Brand name can be measured by checking if a customer mentioned the advertiser name, “XYZ Company.” The difference between

customers who used keywords containing the advertiser name and those who did not will be tested using this variable, advertiser name.

Finally, search patterns will be considered not only in terms of specificity and depth, but also in terms of search content categories (e.g., whether the user searched for a location name vs. a travel activity). We can then perform cluster analysis to create a new typology of pattern types and to begin associating these types with behaviors (e.g., whether users who display a given pattern are more likely to purchase).

Expected Contributions

Our dataset is of particular interest because it tracks individual users' search behaviors over time, which sometimes leads to purchases of travel services. The dataset is very large but has two important limitations: it only generalizes to travel services and also generalizes only to searches in Asia. Nevertheless, the data enable us to contribute to research and practice in several novel and important ways. Our study will (1) provide a better theoretical framework for understanding patterns of keyword search behaviors and the ability of those patterns to predict user intent, (2) develop and test a model to predict purchase probability based on specificity, and (3) introduce semi-automated data coding and apply it to this large, advertiser-specific dataset. For practitioners, this study offers insight into user intent and a means of inferring that intent to a higher degree based on longitudinal search behavior patterns. This new insight should help practitioners optimize sponsored search programs as well as understand better how users seek to interact with their firms in an online environment.

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