Characterizing Queries in Different Search Tasks (PDF)

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Characterizing Queries in Different Search Tasks

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Abstract

The purpose of this study is to explore the characteristics of queries of varied search tasks driven by different user intents. For this, the study collected empirical and descriptive evidence of twenty-nine subjects' information searching process on the Web. Several indicators have been employed to determine different characteristics of queries. The results indicate that there were statistical differences in query iteration, identical query, failed query, click-through query rate among different search tasks with different search intent. The results also indicate different search tasks result in different query interval lengths.

1. Introduction

The general information retrieval process starts with an individual having an information need. This need must be made more concrete in the form of an information request in some languages, i.e. a query. Then the query is passed on to an information retrieval system that is matched against the representation of information objects in a system. In this process, individuals face the difficult task of effectively formulating queries that represent their information needs [1] [35].

Searchers often engage in laborious iterations of query formulation to find their needed information; this certainly is needed in the web-searching environment, an abundant source of information where finding relevant information can be challenging. After entering a query into a search box and being presented with results, users may want to click on one of the results and/or follow up with other queries. During this process, users may become lost, and they can retrieve irrelevant results and miss out on relevant results.

To tackle the information overload problem on the web, personalization, which adapts the results according to each user's information needs, has become more of a necessity than an option. Recently, personalizing web search, which focuses on searchers' goals, background, interests, and preferences as the main factors of context, has received much attention in the research community. Many researchers have attempted to pursue and have applied personalization using prior user interactions with the search engine, such as user's past search queries, used search terms, or cached web pages [7] [15] [24] [29].

By adopting this idea, some search engines, such as Google or Yahoo, have implemented methods to suggest alternative queries to users. Typically, the list of suggested queries is computed by processing the query log of the search engine, which stores the history of previously submitted queries. However, this approach may not be adaptive enough to each user's individual needs, as suggested queries are based on what others have searched in the past. In addition, it may deter a user's desire to discover new topics [22]. Furthermore, it is not sufficient for gathering thorough insight into what a user really wants, because it is not based on a user's working context. Given this, more consideration has been given to user intent recently, as the goal of personalized IR is to help users formulate queries that better reflect their search intent as well as to return search results that better match their intent.

Addressing the variance in the information needs of people issuing queries is important [33]. In particular, web queries are heterogeneous and reflect various aspects of user intent that range from the specific desire to find a recipe for chocolate chip cookies to general interest in traveling in Italy. Many researchers have employed queries as a main source of information for understanding users' intent and behavior in web search. Previous studies focused heavily on inferring user intent behind each query instance, but couldn't prove how different user intents lead to different queries and the action following those queries.

So this study takes a different approach, beginning with user intent to provide additional insights into the intent itself. The focus of this study is to analyze and compare the factual characteristics of queries of varied search tasks driven by different user intents. In addition, this study examines how

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searchers' prior knowledge and perceived difficulty lead to different characteristics of queries.

2. Related Works

2.1. Studies on Web Queries

The main source of information for understanding users' behavior in web search has been users' queries. Early studies on web search queries focused on quantitative traits, such as session length, query length measured by the number of terms in query, and search result page viewing, etc. [30] [31]. Spink [32], outlined findings from studies conducted from 1997 to 2002 using large-scale web user data provided by commercial web companies. She reported that findings of the research conducted over the last five years were consistent with the earlier studies in that web searchers use short queries, do simple queries, searched one query only and did not follow with successive queries, and looked at the first few results only.

More attention has been paid to how people construct and change their queries during the web search, because query reformulation itself reveals search behavior characteristics. Several studies have reported some interesting findings: reformulation patterns on the web differ from those in traditional IR systems [27]; query reformulation involves conceptual and linguistic changes in the way a person approaches a search as it progresses [40]; and different reformulation strategies were effective depending on the action from the initial query [11]. A number of studies explored patterns of query reformulation and related strategies and tactics to understand searchers' behavioral characteristics and enhance search engines [9] [12] [13] [17] [40].

Recently, a few studies evaluated the effectiveness of query reformulation strategies: Huang and Efthimiadis [11] examined a clicking action after a query. Liu, Gwizdka, Liu, Xu, and Belkin [19] employed a bookmarking and tagging action as a predictor of search relevance. Furthermore, the information contained in queries has been used in different ways; for example, to provide context during search, to classify queries, to infer search intent, to facilitate personalization, to uncover different aspects of a topic, etc. [10].

However, most previous research was based solely on an analysis of anonymous search logs from the search engine site, such as Excite or Altavista, with a few exceptions [19]. Since transaction log data include user and system interaction from a large number of web searchers captured from the server side, it has been regarded as a non-intrusive method to study real-life user behavior [27]. On the other hand, the limitations of such studies are important to consider, because these logs provide no data related to personal characteristics of the searchers or insights into the searchers' thinking behind their observable behavior, such as what directs user actions and why. Consequently, these logs provide only limited explanation for the patterns of web searching identified [40].

2.2. Studies on User Intent

Understanding what the user is searching for (the need behind a search) has been a crucial area in classic IR. The term "user intent" has been used generally to represent such need behind a search for intelligent information retrieval and its concept is closely tied to why the user is searching for information and what motivates the user to make a search. Given that a query is the representation of a need or intent, there has been a growing interest in identifying the user's intent by analyzing queries, because the correct recognition of the user's intent can help the search engine provide the most relevant results. Thus, query intent classification has become an active research area to identify the underlying goal of a user when submitting a particular query.

Broder [4] is the pioneer who distinguished three intent categories: informational, navigational, and transactional. Later, Rose and Levinson [28] extended Broder's classifications and presented a more detailed level of classification for both informational and transactional intents. For instance, informational intents were further classified as directed, undirected, locate, advice, and list request. Recently, such previous approaches have been criticized as they are inadequate for capturing the complexity of information seeking in the real world. Calderón-Benavides, González-Caro, and Baeza-Yates [6] developed a wide range of terms that can be useful for user's intent identification, such as genre, objective, specificity, scope, etc. Many researchers have agreed on Broder's three intentions driving user queries; of consensus among their studies is that a large percentage of web queries are informational [2] [4].

In addition, many researchers have attempted automatic classification of user intent using web query logs, which have largely been studied to predict the user intent driven by the query. Some exploited users' behavioral features, such as click-through [5] [18] [20] [26] or mouse movement [8]. Others employed lexical and contextual query features, such as query length, use of verbs, or the meaning of particular terms [12] [34]. However, this is still challenging work because user intent is vague and multidimensional, making it difficult to classify [12]. In addition, different users often have different intents for the same query [37], and different queries of different users may represent the same intent.

A few studies employed different search tasks that reflect different user intents in their experiments to understand searchers' search behavior and process. For instance, Lorigo et al. [21] administered five navigational and five informational questions that varied in difficulty and topic, then analyzed searchers' transaction log file data and eye movement data. Their study reported that informational searches took more effort and time on average, despite no task influence found with respect to success. Joachims et al. [14] used the same 10 search tasks. They reported the average number of queries and clicks per question. Terai and his colleagues [38] employed one informational task and one transactional task in their study. The study found that participants visited more web pages for the transactional task than for the informational task, but their reading time for each page was shorter in the transactional task. However, all of the questions employed in previous studies were depicted as closed-ended questions (for example, "Who discovered the first modern antibiotic?" in Lorigo et al. [21]) and did not cover the full range of informational search tasks described in Rose and Levinson [28].

3. Research Methods

Data for this study was collected through a controlled lab experiment for a larger research project [16]. The research design related to this study is briefly described here.

There were a total of 30 LIS graduate students, all experienced searchers, who participated in the experiment, and each completed three search tasks from specific to general. Derived from work by Rose and Levinson [28], subjects were presented a set of three different informational search tasks, which implicitly specified the intent of the search from directed-closed to undirected, as presented in Table 1. However, the sequence of three tasks was randomized to reduce the potential order effect.

Unlike previous studies that assigned a short question-type search task to subjects in their experiments, tasks were placed in the context of "simulated work task situation" [3] because the intent of the experiment was to ensure that tasks are as close as possible to real-world situations. For the topic of each task, general areas rather than specific domain fields, which require professional knowledge, were given. This was also confirmed in Urquhart's study [39], which found open scenarios worked better generally when the topic was of universal interest. The content of task was chosen to provide reasonable coverage of the typical, desired, information seeking tasks on the web.

Table 1. Search tasks

Search Task	Intent	Scenario
Search Task 1	Directed-closed: I want to get an answer to a question that has a single, unambiguous answer	"You plan to visit San Francisco next week. One of your friends who has been there suggests that you visit the oldest seafood restaurant in town. You want to know the name of the restaurant."
Search Task 2	Directed-open: I want to get an answer to an open-ended question, or one with unconstrained depth.	"Your cousin, a typical teenage girl, said that one of her friends had started to smoke. You fear your cousin might begin smoking in the near future and decide to educate her, so you have to find some information on what could happen if she starts smoking."
Search Task 3	Undirected: I want to learn anything/every thing about my topic.	"You have recently moved to Boston and you are interested in buying a home. You have heard that most homes built before 1978 have some lead paint, but that their paint status is often reported as "unknown." You think you should learn about lead paint and housing. The web seems like a good place to locate this information."

Data was collected from multiple sources, including system-logging software that recorded user-system interaction; questionnaires that elicited subjects' background information, prior knowledge, and perceived difficulty; and a post-search interview to clarify and uncover each subject's reasoning for search behavior.

To analyze the factual characteristics of queries by different search tasks with different intents, several indicators were used:

- Query iteration: The number of queries in a search session
- Identical query: The number of queries previously issued by the same user
- Failed query: The number of queries that returned no results
- Click-through query: The number of queries for which a result was clicked on
- Click-through query rate: The rate of the number of queries for which a result was clicked on over the total number of queries issued; the higher rate may mean the more effective
- Save query: The number of queries for which a result was saved
- Save query rate: The number of queries for which a result was saved over the number of queries for which a result was clicked on; the higher rate may mean the more successful
- Query interval: The time (in seconds) between queries submitted by a subject within a session

Prior knowledge and perceived difficulty of search task were chosen as factors influencing intent and were measured through a pre-search questionnaire and post-search questionnaire as follows:

- Prior knowledge: Subjects' knowledge about a topic of search task, ranging from "1=nothing" to "5= quite a bit".
- Perceived difficulty: Subjects' perception of difficulty of the search task, ranging from "1=very easy" to "5=very difficult".

4. Results

4.1. Query Iteration

The number of queries in a total of 87 search sessions is reported in Table 2. During the search session, subjects issued queries on general search engines, databases, and specific web sites. A total 356 query iterations were obtained as the entire string of terms submitted by 29 subjects in this study[1], including 159 queries for T1, 104 queries for T2, and 93 queries for T3. The total number of query iterations for the search task with directed-closed intent, which is looking for an exact answer, was higher than the other two search tasks.

[1] One subject data was excluded from data analysis in this study due to its corruption.

Table 2. Query iterations

		Total	M	SD
Search Task 1	Search Engine	140	5.48	3.70
	Web Site	12		
	Database	7		
Search Task 2	Search Engine	67	3.71	2.88
	Web Site	27		
	Database	10		
Search Task 3	Search Engine	72	3.21	2.48
	Web Site	18		
	Database	3		

The number of query iterations averaged 5.48 on T1, 3.71 on T2, and 3.21 on T3. A one-way ANOVA test indicated that there were significant differences in query iterations among three search tasks (F = 4.40, P <. 05). A post-hoc analysis, using the Turkey HSD test, was conducted to evaluate pairwise differences among the means. It revealed that subjects submitted more queries in searching for T1 than for T3. This result implies that searchers employed more analytic search strategies on the search task driven by direct-closed intent as opposed to the search task driven by undirected intent.

A cumulative percentage was also calculated by ordering the number of query iterations from the lowest to the highest. Figure 1, Figure 2, and Figure 3 below are frequency histogram and cumulative percentage of T1, T2, and T3. Each bar in the histogram represents the number of query iterations and the line represents the cumulative percentages for query iterations. Fifty two percent of the subjects had no more than five query iterations for T1, whereas 20% and 14% of the subjects had more than four query iterations for T2 and T3, respectively.

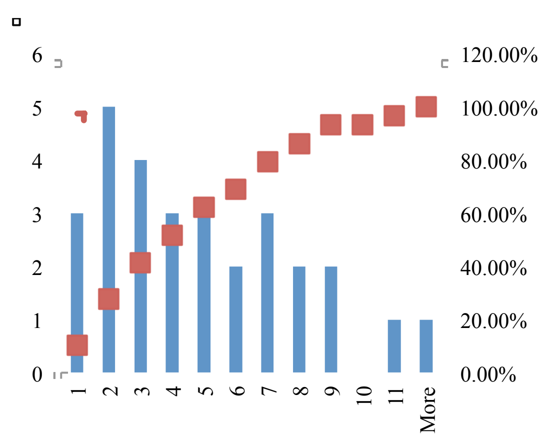

Figure 1. Frequency histogram and cumulative percentage of query iteration for T1

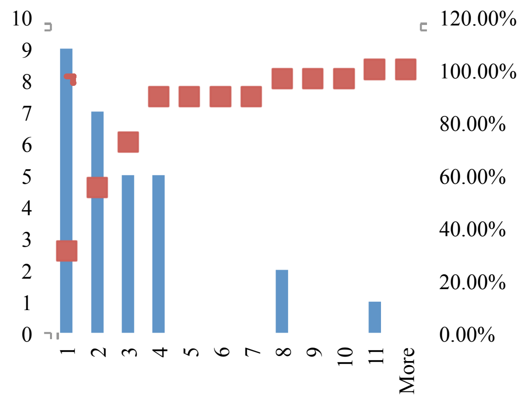

Figure 2. Frequency histogram and cumulative percentage of query iteration for T2

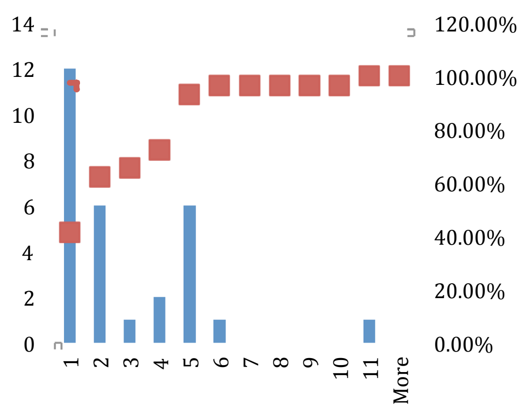

Figure 3. Frequency histogram and cumulative percentage of query iteration for T3

4.2. Identical Query

Searchers may submit the same query in their search session. Previous studies found the use of repeat queries was one of the frequently employed reformulation strategy. For example, Teevan and his colleagues [36] found in an analysis of web log data that 40% of all queries are re-find queries. He, Göker, and Harper [9] observed that the second most frequent type of reformulation in session is repeat queries, but they did not explain why.

We also observed in our experiment that some subjects often constructed the identical query as one that had been previously submitted. Going back to the previous result page by clicking on the back button was regarded as the use of the same query in this study, even though they did not enter the query in the search box again. A total of 26 queries out of 356 were calculated as an identical query. The number of identical queries was the highest in T1, with 14 identical queries issued by 10 subjects for T1; there were seven identical queries by six subjects for T2, and one identical query by one subject for T3. Even though we observed a very small number of identical queries, a one-way ANOVA was performed the compare the mean number of identical queries. The analysis was significant ($F = 3.46$, $P < .05$). Follow-up via Turkey HSD confirms that the number of identical queries for T1 was significantly different from that for T3.

Identical queries were observed when:

- Subjects wanted to return to the previous result page or webpage they had read (S002T1, S004T2, S005T1, S006T1, S011T1, S012T1, S013T1, S019T1, S023S3);
- Subjects thought the query was a general query that pertained to any resource in a different site and/or different search engine (S009T3, S015T2, S023T3, S024T3, S025T1, S028T2) and expected that the same query would bring up different results (S009T2, S011T1);
- Subjects refined the search results by adding other options with the same query (S002T1, S003T2, S021T2, S024T2);
- Subjects even did not notice that they typed the same query (S001T1, S014T1, S016T3, S019T1).

Further, the relationship between intent factor and the number of failed queries for T1 was explored. The Pearson Coefficient of Correlation was used to explore the possible relationship between intent factors and identical query. However, there was no relationship between intent factors and the use of identical query.

4.3. Failed Query

Sometimes subjects returned messages like “Your search did not match any documents,” “No pages were found containing your query,” or “No results.” Previous studies explored various aspects of failed query that returned no hits. Mastora, Monopoli, and Kapidakis [23], in their log analysis, found that failed queries represent 36% of the submitted queries. More specifically, 19.6% of failed queries occurred due to typing errors. Pu [25] compared the factual characteristics of successful and failed image queries. He reported that a failed image query is much longer than the average length of successful queries and failed searches has a much higher onetime query rate.

A failed query in this study is defined as a query that returns no results, that is, zero hits, though a zero-hit search does not necessarily mean that the search is a failure; moreover, all failed queries are not necessarily zero-hit searches. A total 21 failed queries were examined. Again, the number of failed queries was higher in T1 than T2 and T3; there were 17 failed queries issued by 16 subjects for T1, compared to four failed queries by two subjects for T2. None issued a failed query for the search task with undirected intent. Even though we observed a very small number of failed queries, a one-way ANOVA test showed that there were significant differences in the number of failed queries among the three search tasks ($F = 12.88$, $P < .01$). Follow-up via Turkey HSD confirms that the number of failed queries for T1 was significantly different from that of T2.

Since we observed the critical number of failed queries in T1, the relationship between intent factor and the number of failed queries for T1 was explored. The Pearson Coefficient Correlation test indicated that prior knowledge and failed query was negatively correlated ($r = -.45$, $P< .05$). Subjects who didn't know much about the topic of the task tended to produce more failed queries.

It is interesting to examine what a zero-hit message led subjects to do. Sixteen successive queries were modified by:

- Removing a certain term from the previous query (S003T1, S018T1, S019T1, S022T1, S027T1, S029T1);
- Adding a specific term (S005T1, S006T1);
- Changing the order of terms (S012T1);
- Or correcting a spelling (S017T1, S020T1, S026T2)
- Changing the search option or preferences (S002T1, S011T1);
- Returning to a previous result page (S001T1);
- Issuing a new unique query (S013T1);
- Ending the search session (S026T2)

4.4. Click-Through Query

The number of click-through queries and the click-through query rate were calculated per individual subject. For T1, 59% of issued queries (a total 94 queries out of 159 queries) led to a click-through of a link in the search results page. Seventy eight percent of queries (a total 81 queries out of 104) and 80% of queries (a total of 74 queries out of 93) were calculated for T2 and T3, respectively. The number of click-through queries averaged 3.24 on T1, 3.00 on T2, and 2.64 on T3. That is, the search task with directed-closed intent had the highest mean number of click-through queries as presented in Table 3. However, it had the lowest mean of click-through query rates ($M = 0.67$). A one-way ANOVA test indicated that there were statistically significant differences in the click-through query rate ($F = 6.12$, $P < .01$). A post-hoc analysis, using the Turkey HSD test, was conducted to evaluate pairwise differences among the means. It revealed that the click-through query rate was significantly lower in the search task with direct-closed intent than in the other two search tasks.

Table 3. Click-through query

	Click-through query		Click-through query rate	
	M	SD	M	SD
Search task 1	3.24	1.75	0.67	0.20
Search task 2	3	2.27	0.84	0.24
Search task 3	2.64	2.16	0.85	0.22

To see how prior knowledge and perceived difficulty are related to click-through query and/or click-through query rate, the Pearson Coefficient was calculated. For T1, pre-search difficulty was significantly related to click-through query ($r = -.40$, $P < .05$) and post-search difficulty was significantly related to click-through query rate ($r = .39$, $P < .05$). The more click-through queries subjects issued, the more difficult they evaluated the task. In addition, subjects who predicted the assigned task to be easy tended to have a higher click-through rate in their search sessions. For T3, only pre-search difficulty was significantly related to both click-through query ($r = .40$, $P < .05$) and click-through query rate ($r = -.44$, $P < .05$). The less difficult a subject expected the search task to be, the fewer queries they executed and the higher ratio of click-through query rate they had in their search sessions.

4.5. Save Query

Overall, there were only 27% queries (40 out of 159) for which a result was saved. However, 73% of queries (75 out of 103) for T2, and 62% of queries (58 out of 93) for T3 led to at least one saved link in the results page. The number of queries for which a result was saved averaged 1.38 on T1, 2.78 on T2, and 2.07 on T3, as presented in Table 4. A one-way

ANOVA test indicated that there were statistically significant differences in both save query ($F = 5.85$, $P < .01$) and save query rate ($F = 19.75$, $P < .01$). An independent-samples T test was conducted to ascertain if there is any difference in the number of save queries between T1 and T2. The result of T test confirmed that there were significant differences in the number of save queries between T1 and T2 ($t = 4.45$, $P < .05$).

Table 4. Save query

	Save query		Save query rate	
	M	SD	M	SD
Search task 1	1.38	0.78	0.38	0.31
Search task 2	2.78	2.12	0.81	0.24
Search task 3	2.07	1.44	0.74	0.27

It is not surprising that there is a difference in pages saved among the three tasks and that the search task with directed-closed intent has the lowest number of pages saved. This is because such search task is targeted for one answer. However, it is worthy to note that the search task with directed-open intent has more number of save queries than the one with undirected intent.

For the T2 directed-open search task, searchers' pre-search difficulty was strongly correlated with save query ($r = .41$, $P < .05$) and save queries rate ($r = .40$, $P < .05$). This result implies that subjects who predicted the assigned task to be difficult tended to issue more queries for which a result was saved and have a higher save query rate in their search session. For T3, pre-search difficulty was correlated with the number of save queries ($r = .42$, $P < .05$). Subjects who predicted the assigned task to be difficult tended to issued more queries for which a result was saved.

4.6. Query Interval

In this study, query intervals for each query iteration were measured in seconds and grouped into time frames of less than 30 seconds, 30 seconds to 59 seconds, 60 seconds to 119 seconds, 120 seconds to 179 seconds, 180 seconds to 239 seconds, etc., as shown in Figure 4. Overall, about half the issued queries (182 out of 356 queries) in all search sessions across three search tasks took no more than 1 minute.

For T1, 62% of queries (99 out of 159) had fallen into the less than one-minute interval, as presented in Figure 5. Among those less than one-minute queries, 41% of queries took less than 30 seconds. In addition, 92% of queries (145 out of 159) were under 3 minutes. For T2, as presented in Figure 5, 38% of queries had less than one-minute interval; i.e., 62% of queries had more than one-minute interval. Figure 6 shows that 45% of queries qualified for the less than one-minute interval for T3.

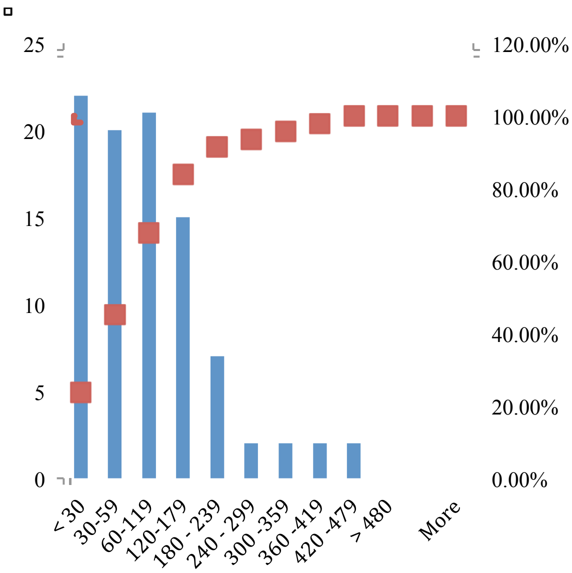

Figure 4. Frequency histogram and cumulative percentage of query interval lengths for T1

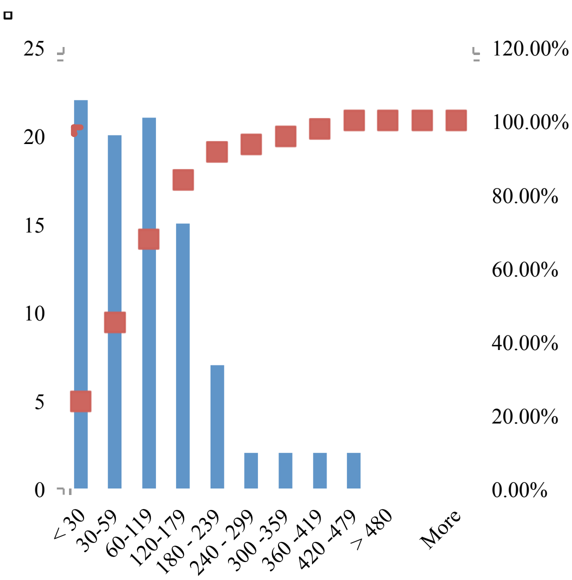

Figure 5. Frequency histogram and cumulative percentage of query interval lengths for T2

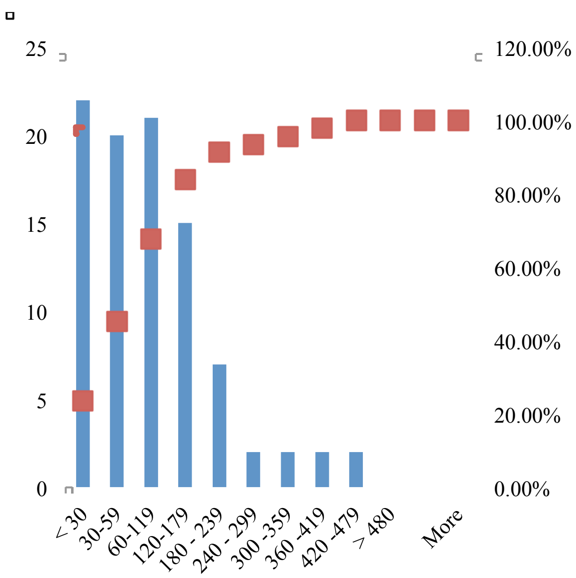

Figure 6. Frequency histogram and cumulative percentage of query interval length for T3

Overall, the search task with directed-closed intent had a shorter interval compared to the other two tasks, as shown in Figure 7. A chi-square was conducted to determine the differences among types of tasks in their query interval. The analysis revealed a significant difference between three different search tasks (χ^2 = 29.871, df = 18, P < .05). Further, Cramer's V tests were calculated to measure the strength of these relationships. The strength of the association between task types and method was .15 (Cramer's V = 0.21, P < .05).

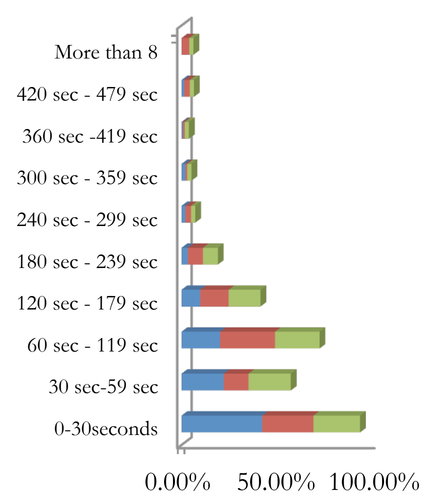

Figure 7. Query interval bar chart

5. Conclusions

This study examined the ways users express their intent in different search tasks. Several indicators were employed to characterize such intent: the number of query iterations, the number of identical queries used, the number of failed queries, the number of click-through queries, the number of save queries, and the query interval. This study found some clues that the user intent class might be related to those indicators. There were statistical differences among varied search tasks with different search intent in the factual characteristics of queries. For example, subjects who participated in this study issued more queries to complete the task with directed-closed intent than the other two informational tasks. They also issued more identical queries, failed queries, and click-through queries in their search sessions to complete the task with directed-closed intent than other search tasks.

While the small size of the test population and the short duration of the study do not represent a significant basis to establish reliable hypotheses, the study found interesting clues for further research.

6. References

[1] N. J. Belkin. "Anomalous States of Knowledge as a Basis for Information Retrieval." The Canadian Journal of Information Science, 5, 1980, pp. 133-143.

[2] R. Baeza-Yates, L. Calderón-Benavides, and C. González-Caro. "The Intention Behind Web Queries." Proceedings of the 13th String Processing and Information Retrieval, 2006, pp. 98-109.

[3] P. Borlund. "Experimental Components for the Evaluation of Interactive Information Retrieval Systems." Journal of Documentation, 56(1), 2000, pp. 71-90.

[4] A. Broder. "A Taxonomy of Web Search." SIGIR Forum, 36(2), 2002, pp. 3–10.

[5] D. J. Brenes and D. Gayo-Avello. "Automatic Detection of Navigational Queries According to Behavioural Characteristics." Workshop on Information Retrieval on LWA Congress, 2008, pp. 41-48.

[6] L. Calderón-Benavides, C. González-Caro, and R. Baeza-Yates. "Towards a Deeper Understanding of the User's Query Intent." SIGIR 2010 Workshop on Query Representation and Understanding, Geneva, Switzerland, 2010.

[7] P. Christa, C. Firan, and W. Nejdl. "Personalized Query Expansion for the Web." Proceedings of the 30th Annual

International ACM SIGIR Conference on Research and Development in Information Retrieval, 2007, pp. 7-14.

[8] Q. Guo and Agichtein. “Exploring Client-side Instrumentation for Personalized Search Intent Inference: Preliminary Experiments.” Proceedings of the AAAI 2008 Workshop on Intelligent Techniques for Web Personalization and Recommender Systems (ITWP), 2008, pp. 10-19.

[9] D. He, A. Göker, and D. J. Harper. “Combining Evidence for Automatic Web Session Identification.” Information Processing & Management, 38(5), 2002, pp. 727 - 742.

[10] K. Hofmann, M. de Rijke, B. Huurnink, and E. Meij. “A Semantic Perspective on Query Log Analysis.” Working Notes for the CLEF 2009 Workshop, 2009. Retrieved from http://taalunieversum.org/taal/technologie/stevin/documenten/duoman_clef2009.pdf

[11] J. Huang and E. N. Efthimiadis. “Analyzing and Evaluating Query Reformulation Strategies in Web Search Logs.” Proceeding of the 18th ACM Conference on Information and Knowledge Management, 2009, pp. 77-86.

[12] B. J. Jansen, D. L. Booth, and A. Spink. “Determining the Informational, Navigational, and Transactional Intent of Web Queries.” Information Processing & Management, 44(3), 2009, pp. 1251-1266.

[13] B. J. Jansen, A. Spink, C. Blakely, and S. Koshman. “Defining a Session on Web Search Engines.” Journal of the American Society for Information Science and Technology, 58(6), 2007, pp. 862-871.

[14] T. Joachims, L. Granka, B. Pan, H. Hembrooke, F. Radlinski, and G. Gay (2007). “Evaluating the Accuracy of Implicit Feedback from Clicks and Query Reformulations in Web Search.” ACM Transactions on Information Systems (TOIS), 25 (2), 2007, pp. 1-27.

[15] D. Kastrinakis and Y. Tzitzikas. “Advancing Search Query Autocompletion Services with More and Better Suggestions.” Proceedings of the 10th International Conference on Web Engineering, 2010, pp. 35-49.

[16] J. Kim. “Describing and Predicting Information Seeking Behavior on the Web.” Journal of the American Society for Information Science and Technology, 60(3), 2009, pp. 679-693.

[17] T. Lau and E. Horvitz. “Patterns of Search: Analyzing and Modeling Web Query Refinement.” Proceedings of the 7th International Conference on User Modeling, 1999, pp. 119-128.

[18] U. Lee, Z. Liu, and J. Cho. “Automatic Identification of User Goals in Web Search.” Proceedings of the 14th International Conference on World Wide Web, 2005, pp. 391-400.

[19] C. Liu, J. Gwizdka, J. Liu, and T. Xu, and N. Belkin. “Analysis and Evaluation of Query Reformulations in Different Task Types.” Proceedings of the 73rd Annual Meeting of the American Society for Information Science & Technology, 2010.

[20] Y. Liu, M. Zhang, L. Ru, and S. Ma. “Automatic Query Type Identification based on Click through Information.” Proceedings of Asia Information Retrieval Symposium, 2006, pp. 593-600.

[21] L. Lorigo, B. Pan, H. Hembrooke, T. Joachims, L. Granka, and G. Gay. “The influence of task and gender on search and evaluation behavior using Google.” Information Processing and Management, 42(4), 2006, pp. 1123-1131.

[22] J. Luxenburger, S. Elbassuoni, and G. Weikum. “Task-aware Search Personalization.” Proceedings of the 31st Annual ACM SIGIR International Conference on Research and Development in Information Retrieval, 2008, pp. 721-722.

[23] Mastora, A., Kapidakis, S., & Monopoli, M. “Failed Queries: a Morpho-Syntactic Analysis Based on Transaction Log Files.” First Workshop on Digital Information Management, 2011, pp. 1-7.

[24] N. Matthijs and F. Radlinski. “Personalizing Web Search using Long Term Browsing History.” Proceedings of the fourth ACM International Conference on Web Search and Data Mining, 2011, pp. 25-34.

[25] Pu, H-T. “An Analysis of Failed Queries for Web Image Retrieval.” Journal of Information Science, 34(3), 2008, pp. 275-289.

[26] F. Radlinski, M. Szummer, and N. Craswell. “Inferring Query Intent from Reformulations and Clicks.” Proceedings of the 19th International Conference on World Wide Web, 2010, pp. 1171-1172.

[27] S. Y. Rieh and H. Xie. “Analysis of Multiple Query Reformulations on the Web: The interactive information retrieval context.” Information Processing & Management, 42(3), 2006, pp. 751-768.

[28] D. E. Rose and D. Levinson. “Understanding User Goals in Web Search.” Proceedings of the 13th International Conference on World Wide Web, 2004, pp. 13-19.

[29] F. Qiu and J. Cho. “Automatic Identification of User Interest for Personalized Search.” Proceedings of the 15th International WWW Conference, 2006, pp. 727-736.

[30] C. Silverstein, H. Marais, M. Henzinger, and M. Moricz. “Analysis of a very large Web Search Engine Query Log.” ACM SIGIR Forum, 33(1), 1999, pp. 6-12.

[31] A. Spink, D. Wolfram, B. J. Jansen, and T. Saracevic. “Searching the Web: The Public and Their Queries.”

Journal of the American Society for Information Science and Technology, 52(3), 2001, pp. 226-234.

[32] A. Spink. “Web Search: Emerging Patterns.” Library Trends, 52(2), 2003, pp. 299-306.

[33] S. Stamou and A. Ntoulas. “Search Personalization through Query and Page Topical Analysis.” User Modeling and User-Adapted Interaction, 19(2), 2008, pp. 5-33.

[34] L. Tamine-Lechani, M. Daoud, D. Ba Duy, and & M. Boughanem. “Contextual Query Classification in Web Search.” Workshop in information retrieval, LWA, 2008, pp. 65-68.

[35] R. S. Taylor. “Question-negotiation and Information Seeking in Libraries.” College & research libraries, 29(3), 1968, pp. 178-194.

[36] J. Teevan., E. Adar, R. Jones, and M.A.S. Potts. “Information Re-retrieval: Repeat Queries in Yahoo’s Logs.” Proceedings of the 30th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, 2007, pp.151-158.

[37] J. Teevan, S. T. Dumais, and D. J. Liebling. “To Personalize or not to Personalize: Modeling Queries with Variation in User Intent.” Proceedings of the 31st Annual ACM SIGIR International Conference on Research and Development in Information Retrieval, 2008, pp. 163-170.

[38] H. Terai, H. Saito, Y. Egusa, M. Takaku, M. Miwa, and N. Kando. “Differences between Informational and Transactional Tasks in Information Seeking on the Web” Proceedings of the Second International Symposium on Information Interaction in Context (IIiX 2008), 2008, pp. 152-159.

[39] C. J. Urquhart. “Using Vignettes to Diagnose Information Seeking Strategies: Opportunities and Possible Problems for Information Use Studies of Health Professionals” Exploring the Contexts of Information behaviour: Proceedings of the 2nd International Conference on Research in Information Needs, Seeking and Use in Different Contexts, 1999, pp. 277-289.

[40] M. Whittle, B. Eaglestone, N. Ford, V. J. Gillet, and A. Madden. “Data Mining of Search Engine Logs.” Journal of the American Society for Information Science and Technology, 58(14), 2007, pp. 2382-2400.