The Usage of Web Search for Software Engineering

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ABSTRACT

Internet plays a key role in accomplishing many tasks. For many such tasks, web search is integral in finding relevant information. Similar to other domains, web search is also heavily used in software engineering (SE) to help with various SE specific tasks such as debugging, finding documentation, installation, etc.

In this paper, we present the first large scale study on how web search is used in software engineering. We analyze the query logs from a major commercial web search engine. Being able to disambiguate software engineering queries from other queries is important for understanding the usage of web search in software engineering. We build a machine learning based classifier for distinguishing software engineering related search queries from other queries. We then define a taxonomy of intents behind the usage of web search by software engineers. This allows us to develop a better understanding of the various contexts in which web search is used in software engineering. We also analyze 1 million web search sessions to understand how software engineering related queries and sessions differ from other queries and sessions. Our results show that web search is heavily used for SE related search tasks. Finally, we discuss implications of this work on improving search engine support for developers and providing more effective and contextual assistance to developers using web resources. To our knowledge, this is the first study to fully characterize online search tasks in the software engineering context with a focus on query and session level differences.

CCS CONCEPTS

• Software and its engineering; • Information systems → Web search engines; Query log analysis;

KEYWORDS

software engineering, web search, machine learning, query logs, query intents

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1 INTRODUCTION

The Internet plays a key role in accomplishing many tasks. To use internet for task completion, web search is integral in finding relevant information. The typical knowledge worker frequently searches for experts, information, and tools to help with their work [27]. In software engineering (SE), web search is heavily used to help with various tasks such as debugging, finding API usage [23] or examples [7, 32], navigating to resources, etc. Previous work has extensively studied several aspects of web search usage and user behavior as well as Web search usage across demographics (see Section 2 for details). While there has been some work on Web Search Usage in domains such as e-commerce, little is known about how Web search is used in software development. Several papers looked into how software engineers search for code specifically [5, 28, 31] and many tools have been built to facilitate code search [4, 11, 15, 20, 26]. However, software engineers use web search for more than just code. They often search for bug fixes, tools, documentation, discussions, and more [33]. The most definite work so far on how software engineers search on the Web is by Xin et al. [33] who collected search logs from 60 developers and interviewed 12 software engineers to categorize search tasks and assess the difficulty and frequency of these search tasks.

In this paper, we present the results from a large scale study of millions of search queries and sessions from a major commercial web search engine (Section 3). To learn more about how web search is used in software engineering, we have built a classifier that recognizes SE-related queries with high accuracy. We then identified a taxonomy of intents for why software engineers search on the Web. Lastly, we compare how SE queries are different from non-SE queries. This is the first large scale study to analyze web search usage for SE tasks and not just code search. Specifically, we make the following main contributions:

(1) We propose a machine learning based method for distinguishing software engineering related search queries from other queries. Our evaluation shows that the classifier has high accuracy. (Section 4)
(2) We define a taxonomy of intents behind the web searches of software engineers. The taxonomy includes the following intents:
queries related to debugging, how-tos, learning, APIs, and installation as well as navigational queries. (Section 5)

(3) We present the results from a large-scale analysis using the query logs of a major commercial web search engine. We characterize and compare how software engineering related search queries and sessions are different from other queries and sessions. (Section 6)

2 RELATED WORK

There have been a significant amount of work from the data mining and information retrieval communities around characterizing and improving Web Search. In this work, we leverage insights and metrics from this work to better understand web search in context of software engineering. In the empirical software engineering community, the primary focus has been on analyzing code search by developers. In this section, we discuss related work from all these areas.

2.1 Web search query understanding

Previous work has extensively studied several aspects of Web search usage and user behavior while using Web search. For instance, previous work has studied how users behave with respect to several characteristics of Web search queries. Ong et al. [24] studied different user behavior for Mobile search and Desktop search queries; highlighting several usage differences on the type of queries and the interaction with the results. Other work focused on characteristics of the results such as the effect of snippet length and content [21] and the effect of the number of documents in the result list [14]. Other studies focused on query characteristics such as the query interface and query difficulty [3]. These studies are very generic in nature and aim to provide a general characterization of how people use and interact with Web search.

Previous work also tried to study Web search usages for more refined segments. For example Mehrotra et al. [22] studied search engine usages across different ages, genders and other demographics. Additionally, the difficulty of the search task was also shown to have a significant impact on interactions with search engines [2, 16]. Even though, these studies try to study Web search usage in more defined segments, they create the segments based on domain independent factors such as demographics, task type or task difficulty. Another area of interest has been characterizing Web search usage for specific domains. For example, Jansen and Molina [12] studied Web search usage in the e-commerce domain. More specifically, they evaluate the effectiveness of search engines in the retrieval of relevant e-commerce links. Web search for health and medical queries has also received significant attention (e.g. [29, 30]). Spink et al. [30] provided general characterization of medical and health queries; showing that the top five categories of medical or health queries were: general health, weight issues, reproductive health and puberty, pregnancy/obstetrics, and human relationships. It also compares usage of general Web search vs. specialized medical/health websites for finding health related information.

In this work, we build on previous work on characterization of web search engine usage. Unlike previous work, we focus on search engine usage for software engineering tasks. Additionally, we discuss implications of this characterization on how to improve existing tools and build new tools to better support software engineering tasks.

2.2 Code search

In software engineering community, there has been significant amount of work in understanding and improving code search [4], [20], [15], [11]. Bajracharya et al. [5] analyzed usage of Koders.com, a specialized code search engine, by developers. They do a lexical analysis of the search queries and also use topic modelling to extract 50 topics from the search queries. Similarly, Stolee et al. [31] surveyed developers on the tools used for code search and found that 69% of the participants use Web Search for code search and the existing code search tools were not satisfactory. [28] studied code search by developers at Google. They surveyed 27 developers to understand the intent behind code search and also the properties of code search queries. Perhaps the closest work to our work is the study by Xia et al. [33]. They collected search logs from 60 developers and interviewed 12 software engineers to categorize search tasks into 34 buckets across seven different categories. They also carried out a survey to understand the difficulty and frequency of these search tasks. They also found that developers are more likely to search for code on web search engines than on specialized code search engines. This supports our work by showing the importance of web search engines in software engineering.

Our work differs from existing work in the software engineering community in several aspects: a) Ours is the first large scale study to analyze web search usage for SE tasks and not just code search. As we discuss in Section 5, web search is used for multiple other SE related tasks like navigation, learning and installation. Similarly, by using the search logs from a major web search engine, we are able to analyze a large set of population without limiting ourselves to developers in a commercial setting. b) We propose a novel method for labeling search queries for SE tasks and train a ML classifier for classifying SE queries. c) We also carry out a large scale study on millions of search queries and sessions to understand how they differ in key Web Search metrics.

3 WEB SEARCH LOGS

In this paper, we leverage the web search logs from a major commercial search engine. The search engines logs a rich set of metadata for all the search queries made by the users. In this work, we leverage a subset of them described below, for our study. Also, the search logs have been anonymized to remove any user identifiable information before any analysis was conducted.

3.1 Definitions

Below, we define some of the terms that will be used throughout the paper:

- **Search query**: A search query is the raw query text entered into the search engine by the users.
- **Client**: A client is a user facing application used for browsing the search engine and doing search queries. Clients are uniquely identified by using various tracking mechanisms, for instance, browser cookies.
Web search is used from a wide variety of demographics, locales, clients, etc. The search usage patterns may vary heavily based on these parameters. So, we filter the query traffic to remove any variability & noise due to factors such as languages, geography and client form-factors.

Locale & region - We only use search logs from users with English locale and from the US region. We also filter out any search queries which contain non-English characters by checking for non-ASCII characters.

Clients & traffic sources - Since we are focusing on analyzing real user behavior, we filter out automated traffic from bots and services which query the search engine via APIs. Lastly, as Kamwar et al. [13] have showed, web search patterns and usage differ vastly between different client form factors like desktop, mobile, etc. Since the majority of tasks related to SE are carried out on desktop, we only focus on search traffic from desktop clients in this study.

We have access to rich set of metadata for search queries such as the query text, result URLs, clicked URLs, dwell times, etc. However, we only use the features derived from the query text for training the classifier, so that we can classify queries even when other information is absent. For instance, not all queries lead to clicks on the search results. Also, since our heuristics rely on the clicked URLs, we explicitly remove that from the model features to prevent information leak. Before extracting features from the query text, we pre-process the text by replacing non-alphanumeric characters with space. We then transform the query text into a vector representation by first extracting a token count vector and then transforming it to a TF-IDF representation. TF-IDF representation helps reduce the weightage of frequently occurring words such as stop words.

4.2 Data
As described earlier, we have sample 2 million search queries from April 1st, 2019 to April 5th, 2019. We restrict the queries to en-US and normal traffic as described in Section 3. These queries are sampled in a stratified manner with 1:3 ratio of SE:Non-SE queries. We decided to do stratified sampling instead of random sampling because SE queries form a small fraction of the overall web search traffic. So, effectively our train and test data contains 1.5 million non-SE and 0.5 million SE queries. Finally, we do a 70:30 random split of the data for the train and test datasets.
Table 2: 10-fold cross-validation comparison

| Model      | Precision | Recall | F1 | AUC        |
|------------|-----------|--------|----|------------|
| AdaBoost   | 0.891     | 0.516  | 0.653 | 0.826     |
| DecisionTree | 0.911    | 0.890  | 0.900 | 0.935     |
| LinearSVC  | 0.941     | 0.920  | 0.930 | 0.989     |
| LogisticRegression | 0.940 | 0.891  | 0.915 | 0.988     |

Table 3: Evaluation results of LinearSVC model on test data

| Class | Precision | Recall | F1-score | Support |
|-------|-----------|--------|----------|---------|
| SE    | 0.94      | 0.93   | 0.93     | 149558  |
| Non-SE | 0.98     | 0.98   | 0.98     | 450442  |

4.3 Model selection

We formulate the task of distinguishing SE and non-SE queries as a binary classification problem. In order to select the best machine learning algorithm, we experiment with 4 commonly used ML based classifiers: AdaBoost, Decision Trees, Logistic Regression, Linear SVC (Support Vector Classification). For training and evaluation the classifiers, we use the Scikit-learn 0.20.0 package for Python 3.7.1. Note that our goal is not to find the best-fitting classifier, but to explore the feasibility of classifying SE related search queries. So, we use the default hyper-parameters for these classifiers.

To compare the classifiers, we use 4 metrics: Precision, Recall, F1 and AUC. These metrics are widely used for classification tasks. Here, AUC is the area under the ROC curve, which measures the overall discrimination ability of a classifier. It has been widely used to evaluate classification algorithms in prediction tasks [27]. A machine learning model is considered applicable to classify a given dataset, if the AUC score is larger than 0.7. Following existing studies [17], we use the widely used 10-fold cross-validation to evaluate the classification models. Table 2 shows the metrics for each of the classifier. As we can see, the LinearSVC classifier clearly outperforms all the other models. Also, all the classifiers achieve AUC score more than 0.7. LinearSVC achieves a F1-score of 0.93 and an AUC of 0.989. Based on these results, we chose the LinearSVC model for classification of SE and non-SE queries and do further evaluation in next section.

4.4 Model evaluation

In this section we evaluate the efficacy of the LinearSVC model for classifying SE and non-SE queries. Firstly, we do further analysis of the model on manually annotated data. Secondly, we do an evaluation of the model on automatically labeled data. Lastly, we do a qualitative analysis of the feature weights learnt by the model to show that it’s highly generic.

Evaluation on inferred labels - As shown in Table 2, the LinearSVC model has high accuracy on the test data created using the inferred labels as described in Section 4.1. Since, the data has a class imbalance, we also separately computed the metrics for both SE and non-SE classes. The metrics are shown in Table 3. Here, support refers to the number of samples that belong to a given class. As we can see, for both the classes, the LinearSVC model has > 0.93 F1-score. This shows the model can classify both SE and non-SE queries in the test set with high accuracy.

Manual evaluation - The evaluation we have done so far was based on the automatically labeled dataset. It’s plausible that the ML classifier simply learns to distinguish search queries from the SE websites listed in Table 1 vs queries from other websites.

So, we did a manual evaluation, where we randomly sampled 200 search queries from the test dataset. Then, two of the authors manually and independently annotated the data with SE and non-SE categories. We used Cohen Kappa [8] coefficient to measure the inter-rate agreement and the score was 0.91. Finally, we evaluated the accuracy of the ML model on this dataset and the accuracy was 0.93 which proves that the model is generic and highly accurate.

Feature coefficients - For training the ML classifier we used the unigram features extracted from the search queries. To further analyze the model, we looked at the top 20 features, shown in Figure 1, and their coefficients learned by the model. Both the positively (for instance: python, github, string) and negatively correlated features (for instance: county, news, porn) were very generic. Also, they have a clear mapping to SE and non-SE topics respectively.

5 QUERY TAXONOMY

There are many reasons why software developers search the web, for example to learn more about a technology or to debug an error message they encountered. To better understand the motivations behind web searches related to software technologies and to derive an initial taxonomy of search intent, we manually labelled three sets of search queries. Each dataset contained the query and the URLs that the user clicked on (if any) for 50 web searches. When needed, the raters searched for the query and considered the entire web search results. In total, we labelled 150 search queries.

- TensorFlow #1. We randomly selected 50 queries that contained the term "TensorFlow". This dataset was labelled independently by two raters who followed an open coding approach, i.e., rather than predefined labels, the labels emerging during the coding of the web searches. For each web search, exactly one category was assigned. The raters then met and discussed the categories and agreed on an initial set of categories: debug, how-to, installation, learn, navigational, and misc.

- TensorFlow #2. This dataset of 50 web searches for "TensorFlow" was used to further validate the categories and to measure inter-rater agreement. Three raters independently labeled the dataset with the categories from the previous dataset. No new categories emerged. The pairwise Cohen Kappa agreement [8] between the three raters was 0.469, 0.530, and 0.637; the Fleiss Kappa agreement [9] among all three raters was 0.545.

- Xamarin. This dataset was used to validate the categories for a different technology. The dataset included 50 queries that contained the term “Xamarin”. Two raters independently labelled the dataset with the categories from the previous dataset. The Cohen Kappa agreement between the two raters was 0.524. For this dataset, a new category emerged: api for any searches related to documentation on how to use certain Xamarin APIs.

The agreement scores indicate a moderate agreement according to Landis and Koch [18]. When the raters disagreed, this was either because of lack of context ("3559a tensorflow", "tensorflow 1.13 rc0 .whl") or for queries where multiple
Debug. This category captures web searches that are related to debugging an error or issue. Typical searches include error messages ("tensorflow/core/framework/op.h: No such file or directory"), parts of stack traces ("Java org.tensorflow lite NativeInterpreterWrapper createErrorReporter"), and sometimes a description of the context of the error ("xamarin SIGSEGV after upgrading to visual studio 2019"), which often can be short and abstract ("tensorflow1.3 MKL libdl.so.2"). For this type of query, users typically often click on StackOverflow search results, the respective issue trackers, and discussions in web forums.

How-to. This category captures web searches that are related to accomplishing a specific task with a software technology. These queries often contain a short description of what the user wants to accomplish ("tensorflow get all tensors", "force tensorflow to use gpus", "launch camera on camera button click in xamarin forms") and in some cases the technology they want to use ("RandomShuffleQueue tensorflow"). For most of these queries, users click on StackOverflow search results and when available official web forums and blogs.

Learn. This category captures queries related to learning about an abstract topic related to the software. Example queries are "tensorflow python tutorial", "tensorflow tools", "tensorflow deep learning", or "xamarin testing".

API. This category represents web searches where the user wants to learn more about a specific API element in the software. Searches related to specific API were much more frequent in Xamarin than in TensorFlow, hence we created a separate category. Examples are "xamarin.controls.signaturepad/forms" and "xamarin ActivityIndicator".

Navigational. This category is related to queries where the search engine is used to navigate to a specific resource or web-page. Example queries are "TensorFlow: Large-scale machine learning on heterogeneous systems" and "o reilly TensorFlow for Deep Learning". In both cases, the user knew their destination and used the search engine as a shortcut/bookmark to get to a book or video respectively.

Installation. This category is for searches with the goal to install the software. Often these searches include the target environment ("tensorflow gpu keras 2019 windows 10"), version numbers, and simply the word download ("tensorflow 1.13 for windows download"). In many cases these searches end up at download or install pages on the official webpages but not always. For example, for the query "tensorflow gpu keras 2019 windows 10", the user clicked on a Medium.com post that in detail describe the nine steps necessary to setup the Keras deep learning framework on Windows 10 on both GPU and CPU systems. Interestingly searches related to installation were more common in our samples for TensorFlow than for Xamarin.

Misc. This category was used when none of the above intents was suitable or when insufficient context was available to make a decision. An example from this category is "3559a tensorflow".
As we can see in Table 5, software engineering related search sessions tend to be shorter than other sessions. This could be an indication that the user needs to browse more about related topics. 

To measure the similarity between pairs of queries in the session, we begin by performing standard text normalization where we lower case the query text, replace all runs of white-space characters with a single space, remove leading or trailing spaces, and remove stop words. Thus every query is represented as a bag of non-stop word terms. The similarity between any two queries can be computed using the Jaccard coefficient between the two bags of word terms. As we can see in Table 5, SE search sessions contain 27.17% more similar search queries than other sessions. This means that in SE search sessions, user browse more about related topics.

6.2 Query Characteristics

Number of Unique Queries: The number of unique queries can serve as a metric for both query popularity and session length. Total number of unique queries provide a good estimate of how popular a given query estimate is. Additionally, a high number of unique queries per session could indicate that certain searches result in longer sessions. This could be an indication that the user needs to explore different aspects related to the information need or that the user needs to try multiple queries before the information need is met. We compute the distribution over the number of unique queries for different segments of queries. We used unique queries to avoid counting the same query multiple times when the user refreshes the search page or hits the back button. As we can see in Table 5, SE search sessions contain on average 2.186 unique queries which is 28.33% lower than non-SE search sessions. This shows that the SE search sessions tend to be shorter than other sessions.

Also, we did an analysis of the word and character count. As we can see in Table 6, software engineering related queries have 37.8% higher word count on average compared to non-software engineering related queries. Based on our manual analysis, this can be attributed to majority of the queries being related to tasks like searching for error messages which tend to be more descriptive. Similarly, software engineering related search queries contain 27.17% more characters on average.

Query Similarity: One interesting characteristic of web search sessions may be the diversity of queries within the session. We might expect queries from a particular segment to contain less overlap as people revise their queries to explore alternatives. To examine this, we measure the similarity between every query in the session and the first query in the session. Our objective here is to assess how queries evolve as the user moves further into the session in both cases. Query similarity might also reflect how successful a user is with finding the needed information. If the user is struggling to find the information, we might expect strong resemblance to the first query to be present in future queries, but with terms being added or removed as the session proceeds.

To measure the similarity between pairs of queries in the session, we begin by performing standard text normalization where we lowercase the query text, replace all runs of white-space characters with a single space, remove leading or trailing spaces, and remove stop words. Thus every query is represented as a bag of non-stop word terms. The similarity between any two queries can be computed using the Jaccard coefficient between the two bags of word terms. As we can see in Table 5, SE search sessions contain 27.17% more similar search queries than other sessions. This means that in SE search sessions, user browse more about related topics.

Reformulation Strategies: The number of unique queries in a session and the similarity between queries shed light on the length of the sessions and how search progresses during the session. Additionally, we also consider the strategies employed by the user when they transition from one query to another. Reformulated queries are pairs of queries that have similarity larger than a threshold. When a query is reformulated, the user might employ one or more strategies. For simplicity, we investigate the following strategies for moving between queries:

- Term Addition: one or more words are added to the query
- Term Removal: one or more words are removed from the query

As we can see in Table 5, software engineering related search sessions have a significantly higher rate of term additions and removals. This is consistent with our previous finding of software engineering related sessions having higher percentage of similar search queries as shown in Table 5.

6.3 Interaction Characteristics

Number of Clicks: We suspect that SE search sessions might have different click distribution compared to other sessions. This may be related to difference in task types or because users may experience different levels of difficulty locating information. Our dataset has logs of all clicks performed by the user during the search session. We excluded all non-result clicks (e.g., clicks on sponsored results), as well as clicks that lead to another search result page (e.g., spelling corrections, related search clicks, etc.). We then computed the average number of clicks for different query positions in the session for different segments. As shown in Table 6, SE search queries have a lower click rate and, also a lower SAT click rate than non-SE search queries. This can be attributed to SE related search tasks being more difficult than other search tasks.

| Metric                          | SE          | Non-SE       |
|--------------------------------|-------------|--------------|
| Unique Session %               | 2.611       | 97.389       |
| Unique Client %                | 2.832       | 97.168       |
| Avg. unique query count (± SEM) | 2.186 (± 0.014) | 3.05 (± 0.005) |
| Avg. similar query % (± SEM)   | 4.278 (± 0.072) | 3.555 (± 0.01) |
| Avg. term addition count (± SEM)| 2.484 (± 0.068) | 2.183 (± 0.021) |
| Avg. term removal count (± SEM) | 2.184 (± 0.085) | 1.879 (± 0.025) |

Table 5: Comparison of SE and non-SE Search Sessions

| Metric                          | SE          | Non-SE       |
|--------------------------------|-------------|--------------|
| Avg. word count (± SEM)         | 5.245 (± 0.017) | 3.807 (± 0.002) |
| Avg. character count (± SEM)    | 30.521 (± 0.0111) | 24.088 (± 0.0163) |
| Avg. click count (± SEM)        | 0.41 (± 0.002) | 0.449 (± 0.003) |
| Avg. SAT click count (± SEM)    | 0.217 (± 0.001) | 0.236 (± 0.002) |
| Avg. total dwell time (in sec ± SEM) | 270.051 (± 2.072) | 307.549 (± 0.339) |

Table 6: Comparison of SE and non-SE Search Queries
Dwell Time: Another interesting question related to click characteristics is the difference in dwell time on clicked results. Dwell time is an important measure reflecting time spent by the user examining the clicked documents. Previous work has shown that the amount of time spent by users on the clicked document is an important indicator of whether they are satisfied with the content they encounter [10]. Dwell time can be estimated from click logs by computing the time between the click and the next seen click or query on the search engine. We calculated the dwell time for every click in our dataset and then we calculated the dwell time per query averaging the dwell time of all clicks corresponding to a single query.

As we can see in Table 6, SE search queries have 13.8% less total dwell time on average than other queries. Longer dwell time has been shown to correlate with success in finding the required information. Hence, SE queries are less effective than other queries.

7 DISCUSSION

There are several implications of this work. First and most notably, the analysis of 1 million web search sessions in Section 6 suggests that software engineering related queries are less effective than other types of queries: we observed higher rates of query reformulations, fewer clicks, and shorter dwell time. Custom search engines could be a way to provide a better experience for software engineers. For example, we observed that software engineering sessions more often contain queries similar to other sessions, which suggests that other search sessions could improve the search experience. The query taxonomy presented in Section 5, can inform different modes that search engines should support for software engineers.

On a large scale, search data also provides a pulse of what software engineers are searching for and what problems they face. This data can be analyzed to generate insight, for example identify frequent problems with software technology, compare the difficulty of different software technologies based on search query properties, or predict the satisfaction of developers with specific software technology, which are all avenues for future work. This information could be looped back to the creators and users of software technologies, similar to tools like Google Trends.

Lastly, the search history of individuals provides a wealth of information that can provide context for personal assistant like Siri, Cortana, etc. as well as software bots [19]. The search history can also be used for a personalized search experience and better software tools. Integrating context and task-aware search into software tools is another opportunity to improve their productivity. Search data can also be used as signal for task type detection [6].

8 CONCLUSION

In this paper, we presented the first large scale study on web search usage for software engineering. We demonstrated that it is possible to distinguish software engineering related search queries using machine learning without requiring any labeled data. Further, we showed that web search is mainly used in software engineering for 6 main tasks. These 6 category of tasks cover the majority of the software engineering queries. We further did a thorough analysis of a sample of 1 million web search sessions to better understand software engineering related search queries and sessions. We showed that software engineering related search queries and sessions constitutes a significant volume, over 2.6%, of the overall web search sessions. Lastly, we also found that software engineering related search tasks are less effective and require more effort than other search queries. We believe that these insights will be helpful in improving existing tools and building new tools for software engineers.

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