An Empirical Study of Software Exceptions in the Field using Search Logs

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ABSTRACT

Background: Software engineers spend a substantial amount of time using Web search to accomplish software engineering tasks. Such search tasks include finding code snippets, API documentation, seeking help with debugging, etc. While debugging a bug or crash, one of the common practices of software engineers is to search for information about the associated error or exception traces on the internet. Aims: In this paper, we analyze query logs from Bing to carry out a large scale study of software exceptions. To the best of our knowledge, this is the first large scale study to analyze how Web search is used to find information about exceptions. Method: We analyzed about 1 million exception related search queries from a random sample of 3 billion web search queries. To extract exceptions from unstructured query text, we built a novel machine learning model. With the model, we extracted exceptions from raw queries and performed popularity, effort, success, query characteristic and web domain analysis. We also performed programming language-specific analysis to give a better view of the exception search behavior. Results: Using the model with an F1-score of 0.82, our study identifies most frequent, most effort-intensive, or less successful exceptions and popularity of community Q&A sites. Conclusion: These techniques can help improve existing methods, documentation and tools for exception analysis and prediction. Further, similar techniques can be applied for APIs, frameworks, etc.

CCS CONCEPTS

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

KEYWORDS

software engineering, debugging, web search, machine learning

1 INTRODUCTION

With the growing complexity of software systems, the use of web search has become ubiquitous in software engineering. More and more software engineers are relying on search engines for various tasks, including finding code snippets, API documentation, debugging, and understanding new concepts [49, 60, 66]. Prior research on code search [10, 18, 64] has shown that software engineers depend heavily on search engines for finding information. A study of Google search [60] also identified that developers use Web search heavily for code and code-related tasks. Researchers have proposed several approaches [24, 43] to improve code search. Despite all these efforts, recent study [56] on code-related search behavior identified that code search often requires more effort than more general search intents to find a solution. Prior study [56] also identifies that developers tend to search with error and exception messages to find solutions, but general-purpose search engines (GSEs) such as Google, Yahoo! and Bing are better at locating general code issues compared to specific errors or exceptions. Thus, error or exception search imposes unique challenges for developers to find solutions using GSEs.

Xin et al. [71] collected Web search logs from 60 developers and interviewed 12 developers to categorize software engineering related search tasks. According to the study, learning new topics is the first most popular task, while debugging errors and exceptions are the second most popular task developers accomplish using Web search. Software engineers heavily rely on Web search to find not only documentation for exceptions but also crowd-sourced information from websites like StackOverflow, GitHub, etc. This underlines the importance of characterizing exception search behavior to be able to improve and build new tools for improving exception debugging using the internet. However, such analysis is non-trivial and yet to be carried out, which motivates our large-scale study of exception search analysis.

In this empirical study, we address two key challenges: 1) Extraction of exceptions from unstructured text, and 2) Leveraging search metadata for characterization of various aspects of exception-related searches (e.g., popularity, effort, success). We collected search logs from Bing, a leading GSE. In GSE, search queries can be for a wide variety of intents and domains. To overcome the challenge of extracting exceptions from query logs, we propose a novel machine learning model for the extraction of exception names (e.g., NoClassDefFoundErrors) and identifiers (e.g., 500) from raw query text. To train and evaluate the machine learning model, we
extracted and labeled 348,559 (~0.3 million) search queries with a semi-automatic approach (See Section 4.3.1). Next, we defined the metrics for characterizing exception search behavior. Prior work on software engineering search analysis [56, 60, 71] worked on a limited amount of data and data collected in a controlled environment using browser plug-ins or via crowd-sourcing. Such data may not be a good representative of the actual behavior. To overcome this issue, we collected 50 days of user search queries from Bing and extracted exception names and identifiers with the machine learning model. We also performed Programming Language (PL) specific categorization for better analysis. For behavior analysis, we adopted standard metrics defined and used in the Information Retrieval (IR) [1, 8, 29, 62] community and performed behavior analysis based on these metrics. Through this empirical analysis, we address the following research questions:

**RQ1:** What are the most popular exceptions?
Seeking help through general-purpose search engines (GPSEs) is a complex process, and to understand developer needs, we need to have a study on how developers interact with GPSEs. Prior study [71] identifies that exceptions are one of the top-most searched items, but the study lacks the detail of exception search items and behavior. Through this research question, we identified mostly searched exceptions that can be more actionable for improving documentation and generate fix suggestions.

**RQ2:** In terms of search effort, what exceptions require the most effort?
Developers interaction with GPSEs are time intensive and recent study on developer search behavior [56] identifies that code-related search tends to use more time than non-code related search. In this RQ, we explored search effort for exceptions in terms of time to find an exception solution.

**RQ3:** Which exceptions are most difficult to debug in terms of search using Web search?
While searching for a query, people browse different websites for a satisfactory solution. Through this RQ, we tried to understand the successfulness of various exceptions from different PLs.

**RQ4:** What are the query characteristics of exceptions from various PLs?
Through this RQ, we tried to answer the search query property: number of terms in the query. Since for exceptions developers tend to search with exceptions generated by the compiler or framework, it can also help us to identify which exceptions are more verbose in nature.

**RQ5:** Which websites are the most helpful in debugging exceptions?
In this RQ, we discussed the most frequently used Q&A sites that are helpful in finding exception solutions. Though developers community considers StackOverflow, GitHub, etc. as the most used Q&A sites, this research question can identify other prominent sites for exception solution and the findings can also be helpful for the research community for solution mining and improving the documentation.

Through answering the above research questions, we characterize the exception search behavior and provide insights for software engineers as well as for researchers. For example, our analysis finds that Python exception search is more effort-intensive than Java and C# exception search, but have higher search success. Moreover, our analysis on exception search shows that Q&A sites are more frequently used than official sites for exception solution. Several research studies have been performed to understand how software engineers search for code [18, 60] and use Web search for various tasks [56, 71]. Yet, this is the first empirical study to analyze the usage of web search for debugging exceptions. In summary, we make the following contributions:

- We propose a novel machine learning model that can extract exception names and IDs from unstructured search query text. Based on the evaluation described in Section 4.3.3, the model has high accuracy with an F1 score of 0.82.
- We analyzed ~5 billion web search queries using metrics from the Information Retrieval (IR) community to understand and characterize software exceptions.
- We conducted the first study to analyze and characterize exceptions by leveraging commercial Web search data. The results provide useful insights for software engineers as well as researchers to provide better tool support and documentation for exceptions.
- We proposed a novel methodology for analyzing and characterizing exceptions, which can also be applied to other software artifacts like APIs, programming frameworks, etc.

The rest of the paper is organized as follows: We start by presenting related work and search log terminologies in Section 2 and Section 3, respectively. After that, we discuss the overview of our analysis, which includes collecting search query data, extracting exceptions for raw query text, training and evaluation of the machine learning model in Section 4. Section 5 presents the empirical findings of our study and Section 6 discussed possible implications of our proposed extraction model and study. Finally, we discuss threats to validity and conclusion in Section 7 and Section 8, respectively.

2 RELATED WORK
Web search is heavily used today for various purposes by software engineers such as code search, debugging, downloading, etc. [13]. Prior research works on code search [10, 63, 65] identified that developers widely use GPSEs during development. In a survey, Stoele et al. [65] reported that 85% of developers perform source code search in GPSEs at least weekly. Similar behavior was also reported by Sim et al. [63] that 50% of developers perform search for code frequently. Moreover, prior study [63] identifies that code-specific search engines such as Koder and Krugle [6] perform better searching for subsystems of code, while GPSEs perform better for code blocks.

To analyze search behavior, search logs of GPSEs are widely adopted by the different research communities [12, 30, 57]. Research work [53] on the healthcare domain utilizes search log for detecting devastating diseases, while recent work [15] uses search log to measure employment demand. In software engineering research, search logs are also used to analyze search behavior. Bajracharya et al. [11] analyzed the logs of a code search engine from a 12 months period. They do topic and lexical analysis to understand the
usage of code search engines. Further, they compared code search engines with Web search engines and identified aspects unique to code search. Research work to measure developer focus [18] used search log of 150 developers over four months period of time. Recent work by Rahman et al. [56] also utilizes search log to characterize code search behavior over non-code search. To analyze the behavior, they collected search logs from 150 developers that contain nearly 150,000 queries. For the analysis, they collected logs from a controlled environment. In contrast, we collected data from general users to analyze exception search behavior and did the analysis on a very large set of data (5 billion).

In a study on Google developers, Sadowski et al. [60] utilized a combination of survey and log-analysis methodologies to analyze code search behavior. The study identified that programmers frequently search code with an average of five sessions with a total of 12 queries each day. In a recent large-scale study, Xin et al. [71] collected Web search logs from 60 developers and interviewed 12 developers to categorize software engineering related search tasks. They found that exception debugging is the second most frequent task performed by software engineers using web search. In this work, we analyze logs from a Web-scale search engine to do a large scale study of software exceptions. Further, we use an ML based approach to automatically extract exceptions from the raw search query text. To the best of our knowledge, this is the first empirical study to analyze and characterize millions of search queries to extract exceptions and characterize them based on various metrics like popularity, effort and success. Further, similar techniques can be applied for APIs, frameworks, etc.

3 WEB SEARCH LOGS

For the analysis of exception search behavior, we collected web search logs from Bing, a leading commercial general-purpose search engine (GPSE). The logs contain a rich set of metadata along with associated click information. The logs are anonymized and do not contain any personally identifiable information (PII) like IP addresses, MAC addresses, etc.

3.1 Web Search Terminology

Since we use web search logs for our analysis of exception search behavior, we have adopted some key terms from the web search domain. In this section, we describe the definitions that will be used frequently in the rest of the paper.

- **Search Query**: A search query is the raw query text entered into the search engine by a user.

- **Search Session**: For a given client, a search session is defined as a series of search queries that extend until either the browser is closed or there is a 30-minute inactivity [32, 55].

- **Result Urls**: Ordered list of Urls displayed by the search engine in response to a search query.

- **Clicked Urls**: List of Urls clicked by the user from the result Urls, ranked based on the order in which they were clicked.

- **Dwell Time**: Amount of time spent by a user on the clicked result page. Dwell time is considered as one of the key metrics for web search effort [1, 32, 36] and has a high correlation with task difficulty and user satisfaction [21, 40].

- **SAT (Satisfaction) Click**: Click Urls with Dwell Time more than 30 sec are considered to be SAT clicks. Prior research on search behavior [21, 26, 44] adopted SAT Click as a signal for the relevance of the clicked Url.

- **Search Success**: Prior work on search analysis [29, 39] found that if the last clicked Url answered the user query, they do not explore the search results further. Hence, we consider a search query to be successful if the last result click for that query is a SAT Click.

4 METHODOLOGY

In this section, we discussed the two steps of our study: 1) Exception query extraction and categorization, and 2) Exception search analysis. Figure 1 shows an overview of the study. Our exception search query extraction process and categorization is described in Section 4.3. Based on extracted exceptions, we investigate the search behavior to answer RQ1-RQ5 in Section 5. We use two datasets from different time periods. The first dataset (May 15-May 30, 2019) is used to train the models to label, extract, and tag the exceptions. The second dataset (June 1-July 20, 2019) is used for the empirical analysis of web search behavior related to exceptions.

4.1 Data Filtering

Web search is ubiquitous in nature and is used in different domains as well by a diverse set of people. Also, web search patterns vary based on demographics, locales, clients, etc. Since in this work, we are focusing on exception search behavior, we applied the following filters to remove variation and noise:

- **Locale & Region**: We only used search logs from users with English locale and the US region. We determined locale-based search request HTTP header [47]. Lastly, We also filtered out search queries that contain non-English characters based on character encoding.

- **Keywords & Clicks**: Since we want to analyze exception related search queries, in order to select error and exception related queries, we applied keyword-based filtering. Prior research works [31, 61] on error and exception handling also applied keyword-based search approach to filter related issues or bugs. For exceptions, based on manual analysis, we used the keywords: error, errno, and exception. The keyword “error” is used in Python, Javascript, C/C++, Ruby, R, TypeScript as part of exception, while “exception” keyword is used as part of Java, C#, Php and Perl exceptions. Keyword “errno” is used mainly for ID-based exceptions. These keywords are very generic in nature and covers wide range of exceptions from large set PLs. So, we extracted all the queries which contain at least one of these keywords in either the query text or the clicked Url. Further, to remove noise from the dataset, we filtered out all the search queries, which did not result in at least one click. Prior research works [7, 9, 42] on search behavior also removed such data to avoid cases where users abandon the search query or remain inactive. This behavior can mislead search behavior analysis.

4.2 Study Subject

We collected search queries from Bing to train and evaluate our machine learning model for extraction of exceptions from raw search query texts. Apart from this dataset, we collected a separate set of search logs from the same Web search engine for exception search behavior analysis.

For **model training**, we extracted a random sample of search queries from a 15 days period in May 2019. We applied the filters
Figure 1: Overview of the Study

Table 1: Regular expressions for extracting exceptions from Search Queries

| No. | Regular expression | Sample search query | Exception type |
|-----|--------------------|---------------------|----------------|
| 1   | error code         | error 2006 (hy000) at line 462 | error          |
| 2   | ssrs 2016 error: an attempt has been... | ssrs 2016 error: an attempt has been... | error          |
| 3   | java.lang.TypeNotPresentException: Type javax.xml.bind.JAXBContext not present | java.lang.TypeNotPresentException: Type javax.xml.bind.JAXBContext not present | error          |
| 4   | 0x000A0555 | 0x000A0555 | error          |
| 5   | 0x000A0555 | 0x000A0555 | error          |
| 6   | 404 GET /nbextensions/widgets/extension.js | 404 GET /nbextensions/widgets/extension.js | error          |

remove these noisy exception queries, we performed manual inspection of exception types. For example, when we applied regular expression based annotation, we found more than thousands “cyberterror” related query as exception query and those are grouped as “cyberterror” exception. With manual analysis, we evaluated each exception group and identified that “cyberterror” is not an exception. So, we removed exception annotation of all the queries that are falsely identified as exception queries by regular expression-based approach. In this process, we tried to minimize the labeling effort of a large number of queries by looking at exception categories, not by each individual search query.

To create the annotated training dataset for the model, we performed labeling using the regular expressions on the 1.1 million search queries from the training period mentioned in Section 4.2. After applying regular expressions based labeling, we collected 348558 (~0.3 million) queries with exception and non-exception query in the ratio 1:1. Two of the co-authors manually validated exception types or groups for training data. We refer to this data as semi-automatically annotated data.

4.3.2 ML Model for Extracting Exceptions. To parse search queries, we need to have a machine learning model to extract the exception entity. In natural language processing, an entity is considered as a basic information element and often considered the main subject of the text. Named Entity Recognition (NER) is a Natural Language Processing (NLP) technique to identify entities from text and classify them into the defined categories. NER is widely used in
different languages processing applications, such as newspaper content classification [46], Q&A systems, and machine translation [25], extract software project artifact information from document [27]. NER solutions can be divided into two broad categories: i) rule-based and ii) statistical pattern-based. Rule-based methods are mainly for common entities like persons, locations, organizations, etc. using specialized dictionaries as the reference for identification. For entities that are not included in the dictionary, it may require experts to rewrite the handcrafted rules. On the other hand, the statistical pattern-based approach needs a larger annotated corpus for learning but doesn’t need experts. Different supervised machine learning algorithms including HMMs [17], SVM [33], CRF [35] have been used for learning of statistical pattern-based NER systems. With our semi-automated tagging approach as described in Section 4.3.1, we annotated the exception entity corpus for NER training.

The conditional random fields (CRF) algorithm proposed by Lafferty [35] is widely used for reliable sequence labeling [38, 69, 70] for NER task. CRF utilizes undirected statistical graphical model, which is Maximum Entropy-based linear chain model that evaluates conditional probability given a sequence of observations. In our study, we used the first-order Markov linear chain CRF [59] with L-BFGS [37] training algorithm using the scaling method [54]. To regularize the classifier, we used Elastic-net(L1+L2) [22] penalty in order to reduce model complexity. Based on the Hammersley-Clifford theorem, CRF computes the conditional probability of a state sequence as follows:

\[ p(y|x) = \frac{1}{Z_\theta(x)} \exp \left\{ \sum_{t=1}^{T} \sum_{k=1}^{K} \theta_k f_k(y_{t-1}, y_t, x_t) \right\} \] (1)

where \( x = (x_1, \ldots, x_T) \) denotes the input sequence and \( y = (y_1, \ldots, y_T) \) is the output sequence, hereafter referred to as the sequence of labels. \( \{f_k\}_{1 \leq k \leq K} \) is an arbitrary set of feature functions and \( \{\theta_k\}_{1 \leq k \leq K} \) are the associated real-valued parameter values. For our study, we used CRFSuite [51], which is a commonly used Python library for CRF. As part of feature extraction, tokens and parts of speech (POS) tags are the basic features to extract. The basic features have less contextual information and less text patterns. So, in addition to basic features, we extract three other features, including contextual features [20], gazetteer features [14], and orthographic features [41]. For hyper-parameters, we used 0.1 as Elastic-net L1 penalty and 0.01 as Elastic-net L2 penalty based on prior work on domain-specific parser [4]. Due to large data size, we used maximum iteration count 200 for training.

4.3.3 Model Evaluation. In this section, we describe the evaluation of the performance of CRF model described in Section 4.3.2. We evaluated the model using a manually annotated dataset. For this dataset, we randomly sampled 500 queries with exception and non-exception queries in the ratio 1:1 collected from the analysis period (June 1, 2019 to June 5, 2019). Two researchers separately annotated those queries and resolved the disagreement by discussion. We performed Cohen’s kappa coefficient [68] to find an inter-annotator agreement. Coefficient value 1 indicates a complete agreement and value of 0 indicates complete disagreement. In our annotation, we found the coefficient value as 0.88, which indicates high confidence of agreement.

| Class     | Precision | Recall | F1-Score | Support |
|-----------|-----------|--------|----------|---------|
| Exception ID | 0.89 | 0.69 | 0.80 | 169 |
| Exception Name | 0.78 | 0.97 | 0.86 | 61 |
| Avg.     | 0.83 | 0.83 | 0.82 |       |

Since we categorized exceptions into two broad categories: i) ID-based Exception and ii) Name-based exception, we evaluated the performance of both categories. Table 2 shows the performance of the machine learning model on manually labeled data. According to the Table, average Precision, Recall, and F1-Score are 0.83, 0.83 and 0.82, respectively. Since our evaluation performed with a dataset collected from real-world user search data and large scale in nature, the performance of our model is reasonable and can be used for exception data collection for empirical analysis of exception search behavior.

4.3.4 Exception Tagging for Analysis. Using the machine learning model described in Section 4.3.2, we tag the analysis dataset. If the model can extract any exception from the query, then we consider that as an exception query. In many cases, search queries can have multiple exceptions IDs or names due to search exception trace from IDEs. In those cases, we only consider the root or first level of exception. With the machine learning model, we extracted 118315 ID-based exception queries and 32887 Name-based exception queries from 980155 search queries.

4.3.5 Programming Language Categorization. Every programming language (PL) can have its own format for exception names and IDs. To perform PL specific exception analysis, we categorized search queries into various PLs based on the exception, query text and the clicked Urls. For this, we picked three popular programming languages 1) Java, 2) C#, and 3) Python. To categorize search queries into these programming languages, we performed a keyword-based search with keywords (java, c#, and python). We search the keywords in raw query and also in the clicked Urls. If a match is found, then we assign the corresponding PL to the query. For instance, for “Search query: python ImportError: cannot import name” we found the PL name was mentioned in the query. So, we assigned this exception query to the Python PL category. If PL name was not found in the search query or the clicked Urls; we look-up the exception tagged in the search query in exception lists for Java [3], C# [2] and Python [5]. If we find a match with any of these lists, then we assign the corresponding PL name to that query. For example, in query “Search query: System.ioFileNotFoundException addinutil.exe “, no PL name occurs in the search query or the clicked Urls. So we cross-reference the exception name with the C# exception list and found a match. So, we assigned C# as PL type for that query.

4.4 Exception Analysis

Based on the exceptions and PL tagging of search queries, we performed empirical analysis on exception search behavior. We analyzed the following five aspects: 1) Popularity Analysis, 2) Effort Analysis, 3) Success Analysis, 4) Exception Query Characteristics and
5) Website analysis for debugging of exceptions. The results of the study are presented in Section 5.

5 EMPIRICAL STUDY

In this section, we present our analysis of exception search queries. Some exceptions can be rare or their search results could not have yielded a meaningful result. To avoid such unusual cases, we only considered exceptions that appeared in at least twenty distinct search sessions.

5.1 RQ1: What are the most frequently searched exceptions?

5.1.1 Metric. To find frequently searched exceptions, we used unique session count as a metric as the same exception can be searched for with different text.

5.1.2 Analysis. Exceptions can be presented in two text formats: ID-based exception and Name-based exception. We measure the frequency of both ID-based exceptions and Name-based exceptions. Based on the unique session count, Figure 2 shows the most frequently searched ID-based exceptions. Among the top ten ID-based exception list, six of the exceptions (500, 404, 400, 403, 401, and 502) are Http protocol exceptions and rest are Windows OS related exceptions. Figure 3 shows the most frequently searched Name-based exceptions. In Name-based exceptions, typeerror is the most searched exception. A reason might be due to the fact that both Python and JavaScript throw typeerror exception. Other popular Name-based exceptions are also related to Python and Java.

We also performed programming language (PL) specific popularity analysis. Figure 4 shows the top searched exceptions of Java, C#, and Python. For Java, noclassdefoundererror is the most popular exception. Another exception we would like to call attention to is exception 65542, which is thrown from the Java utility library for use with OpenGL. For C#, invalidoperationexception is the most frequently searched exception. Even though cs1061 and cs0029 both are C# compile-time exceptions, they are also frequently searched. Also, the C# exception ad0001 that is thrown from the code analyzer also shows up in the top searched for exceptions. For Python, typeerror is the mostly searched exception, which is raised when an operation or function is applied to an object of inappropriate type. Other frequent exceptions are also from Python built-in exceptions. Python’s typeerror exception is searched 4.64 times more frequently than Java’s most frequent exception and 8.47 times more frequently than C#’s top searched exception. This also indicates that Python exceptions are more frequently searched than Java and C#. Prior studies [19, 48] on programming language popularity found that Python is more popular than Java and C#, which aligns with our exception search popularity findings.

Finding 1: Most popular ID-based exceptions are related to HTTP Connection and OS related errors. Python exceptions are more frequently searched than Java and C# exceptions.

5.2 RQ2: What is the exception search behavior based on effort?

5.2.1 Metric. For effort analysis, we use Total Dwell Time (described at Section 3.1) in seconds as the evaluation metric. We limit effort analysis to within the first 10 minutes of a session.

5.2.2 Analysis. Our exception search effort analysis is divided both by exception format (ID/Name) as well as programming language. According to Figure 5, overall exception search takes an average effort of 157.39 sec. While for ID-based exceptions, it takes 155.22 secs, Name-based exceptions take 164.57 secs of effort, which is 6.02% higher than ID-based exception search. Name-based exceptions are more effort-intensive than ID-based exception (confirmed by t-test with p-value(ID,Name) = 8.86e − 13, which is lower than threshold 0.05). This could be since IDs are usually unique and more easily “searchable” due to easy matching. For programming language-specific effort analysis, Java and C# take a mean effort time of 160.59 sec and 161.57 sec, respectively. While Python exception searches take 169.18 sec, which is 5.34% higher than Java and 4.71% than C#. Based on our analysis Python exceptions are more effort-intensive exceptions(confirmed by t-test with p-value(ID,Name) = 0.002 and p-value(C#,Python) = 0.03, which are lower than threshold 0.05). Java and C# exceptions take similar effort for search, which we confirmed by t-test with p-value(Java,C#) = 0.79. Prior work [21] on effort with Dwell Time finds that it has a high correlation with task difficulty and user satisfaction.
Figure 4: PL specific most popular exceptions

(a) Java
(b) C#
(c) Python

5.3 RQ3: What is the exception search behavior based on success?

5.3.1 Metric. Search success can be defined as the user found information for a query that the user entered. To evaluate the exception search success behavior, we will use the Search Success metric, which we defined in Section 3.1. The value for this metric is either 0 for fail and 1 for success.

5.3.2 Analysis. For exception search success analysis, we analyzed the overall dataset of exceptions, format-based exceptions and PL specific exceptions. Figure 7 shows the mean success rate of all the groups of exceptions. The overall success rate for exceptions is 0.57, while ID-based exception shows the mean success rate of 0.56 and Name-based exception shows the mean success rate of 0.58. So, ID-based exceptions are less successful than Name-based exceptions in terms of finding a solution from search engines (confirmed by t-test with p-value(ID, Name) = 2.45E−13, which is lower than threshold 0.05). In terms of PL specific analysis, Python exceptions are the most successful in terms of finding a solution from the search engines with a mean success rate of 0.61. Among the three programming languages, C# shows the least success rate, which is 0.54. Mean success rate of these three programming languages are also statistically significant with t-test p-Value(Java,C#) = 2.05e−31, p-Value(Java,Python) = 0.01, and p-Value(C#,Python) = 1.35e−98.

Figure 7: Exception search success comparison

Apart from group-specific success analysis, we also performed an analysis to find the least successful exceptions of Java, C#, and Python. According to Figure 8, verifyerror is the least successful exception among Java exceptions. java.lang.VerifyError can occur when

Finding 2: ID-based exceptions take less effort to find a solution. In terms of PL specific analysis, C# exceptions and Java takes similar effort, while Python takes higher effort than Java and C#.
the compile-time and run-time environments are different. Another less successful exception of Java is saxparseexception, which might be caused during XML parsing and the solution also depends on XML content. For C#, top four least successful exceptions are due to code analysis (ad0001 and compile-time exceptions (cs1061, cs0266, and cs1003). This might be an indication that the C# development environment finds a lot more exceptions during code analysis and compile-time than before the run-time executions, which is good from a deployment perspective. For Python, connectionerror is the least successful exception and it is also an exception that depends on the connection environment rather than on the code alone.

Finding 3: ID based exceptions are less successful than Name-based exceptions. Also, among the three Programming Languages C# has the lowest search success.

5.4 RQ4: Characterizing exception search queries

5.4.1 Metric. We used the number of words or terms in the exception search query as the query characteristics. To count number of words, we tokenize the raw query into words with space used as the delimiter.

5.4.2 Analysis. Figure 9 shows the word count characteristics of overall all exceptions, IDException, NameException, and the three PL specific exceptions. As shown in the graph, ID-based Exceptions are least wordy due to the uniqueness of the exception code. ID-based exception mean word count is 6.93, while Name-based exception word count 9.13 (confirmed by t-test with p-value (ID,Name) = 0.0, which is lower than threshold 0.05). C# exceptions mean word count is 12.72, Java mean word count is 8.53, and Python mean word count is 9.25. Among the three programming languages, C# exceptions are the most verbose and Java is the least verbose, which is also confirmed by t-test with p-Value (Java,C#) = 2.37e − 141, p = Value(Java,Python) = 3.93e − 07, p-Value(C#,Python) = 1.95e − 213. Users search exceptions with exception text messages generated by the compiler or during run-time. This indicates that C# compiler or run-time generates more wordy exception message than Java and Python.

Figure 10 shows the most verbose exceptions of Java, C#, and Python. Even though gameerror is not Java’s built-in exception, it’s the wordiest exception of Java. For C#, cs1061 is the most verbose exception that is thrown when trying to call a method or access a class member that does not exist. For the case of Python, environmenterror which is the base class of IOError, OSError exception is the wordiest exception.

Finding 4: C# generates more verbose exceptions than Java and Python.

5.5 RQ5: What are the popular web domains for finding solutions to exceptions?

5.5.1 Metric. For this analysis, we used the metric click count to a certain web domain for analysis and ranking of its helpfulness in finding solutions to exceptions.

5.5.2 Analysis. Figure 11 shows the most popular exception solution web domains. According to our analysis, stackoverflow.com is the topmost web domain to provide a solution or help with exceptions. The next popular web domain is from Microsoft community help site answers.microsoft.com site, which covers troubleshooting help for a wide range of Microsoft products. Github is the fourth most popular web domain for helping find solutions to exceptions.

Figure 11: Most popular websites used for debugging exceptions

For the Java programming language, stackoverflow.com is the most popular web domain, which is 17.44 times more popular than the Java official community site. stackoverflow.com is also the most popular solution web domain for C#, even though Microsoft maintains several forums and official help sites. For Python exceptions,
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6 IMPLICATIONS

In this section, we discuss the implications of our exception extraction and categorization model and exception search behavior analysis. Followings are the list of actionable items inferred from the study:

- In recent works [16, 34, 72], researchers have been working on code recommendation systems to assist developers in writing code faster. These works mainly focus on APIs. Through RQ1, we identified the most frequently searched items from different PLs. Also, we identified that ID-based exceptions such as 400, 500, etc. are searched frequently. These frequently searched items can be base for recommending code for exception solution. From our analysis, we also found several Windows errors, such as 0x80004005, searched very frequently. These type of analysis can be helpful to identify emerging issues such as OS upgrade problem, framework version synchronization problem, etc.

- Analysis from RQ2 indicates that ID-based exceptions take less effort or time to find a solution than Name-based exception. In terms of PL specific analysis, C# exceptions and Java takes similar effort, while Python takes higher effort than Java and C#. RQ3 indicates that ID based exceptions are less successful than Name-based exceptions. Also, among the three Programming Languages, C# has the lowest search success. Prior work [21] on search effort analysis finds that effort has a high correlation with user satisfaction. That indicates that C# exceptions searches are less successful, so developer tends to put less effort or time for searching and abandon search at some point. This is a very critical finding to have the necessity to improve C# exception handling documentation and posts in Q&A sites. The same issue is also identified for ID-based exceptions.

- Analysis from RQ4 indicates that C# generates more verbose exceptions than Java and Python. According to the recent study on web search [71], developers search though exception messages generated by the compiler or framework with partial message from client code. Prior study [56] finds that code-related searches are more verbose than non-code related searches. So, the exception search success rate for C# should be higher than the other two programming languages. But RQ3 analysis finds that the success rate of C# search is lower than Java and Python. Findings of these two RQs sheds light on the necessity of reviewing the context and information generated by C# framework exceptions.

- Although several research works [34, 45, 50, 58, 67] have used stackoverflow.com and GitHub.com for different software engineering research purpose such as code recommendation, developer intent analysis, mining code repository, etc., but this is the first work with such a large set of user search data and the study identifies the popularity of these community-based Q&A sites. Also recognizes that the necessity of community engagement for making a framework popular and easy to work with.

- Finally, with our proposed exception extraction model, exception type can be extracted without manual effort. This approach can also be extended for APIs, frameworks, etc. for user search behavior analysis.

Figure 8: PL specific exceptions with least success

Figure 9: Word count comparison for exception search queries

Finding 5: Even though Java, C#, and Python have their own documentation websites and social forums, stackoverflow.com is the most popular website for debugging exceptions in these languages.
7 THREATS TO VALIDITY

Our empirical study has some limitations that we would like to recognize:

Construct validity: Our metrics defined for success might not directly be identifiable with success in all scenarios. This is alleviated to a large degree by the fact that these are standard metrics [21, 29] defined and used in the IR [1, 52, 55] community for several years.

External Validity: There are three main external validity concerns. Temporal: Our results are obtained in the given time frame only. It is possible that the results might vary for a different time frame. Given our unintentional and 50 day time period selection, we hope to alleviate this problem. Geographic: Our data is based on search queries from the United States with only English language queries. Analyzing differences in behavior across different locales, geographies and client form factors is an interesting and important topic but is out of scope for this work. Selection bias: The results could possibly be different should another GPSE be used. We think this is alleviated by the fact that we performed our analysis on a large sample of 5 billion search queries.

8 CONCLUSION

In this paper, we have investigated for the first time how users search and find information about exceptions using web search. Our study identified one key implication that even with having more verbose exception message, exception search could suffer from less search success. Development community should look carefully at the reasons behind the low search success. Also, our study identifies the importance of community Q&A sites for faster development and debugging. This information helps identify and motivate the importance of improving the documentation support for exceptions. Developer websites like StackOverflow and GitHub can also leverage the methodology and metrics proposed in this work for improving developer experience. Given the large body of work on software engineering recommendations [28], adding tool support in IDE’s to have better suggestions for fixing exceptions would be of strong interest to the broader community. Additionally, in public forums, enhanced exception documentation or solution suggestions for most frequent, most search effort-intensive, or less successful exceptions can reduce developer effort. In the future, we plan to incorporate qualitative study to analyze exception search expectation from developer’s point of view.

Data sharing and availability: The search data unfortunately cannot be shared publicly. This is due to legal laws and not due to independent choice. Search queries are very personal data and GDPR [23] in Europe and equivalent privacy laws in other countries strictly govern the access to, usage and research that can be carried out on this data without specifically identifying an individual or groups of individuals. Interested researchers should contact us about the availability of similar data. Upon completion of the necessary legal steps and the legal paperwork, it may be possible to give access to similar search data for academic researchers.
