Big Code Search: a Bibliography

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Code search is an essential task in software development. Developers often search the internet and other code databases for necessary source code snippets to ease the development efforts. Code search techniques also help learn programming as novice programmers or students can quickly retrieve (hopefully good) examples already used in actual software projects. Given the recurrence of the code search activity in software development, there is an increasing interest in the research community. To improve the code search experience, the research community suggests many code search tools and techniques. These tools and techniques leverage several different ideas and claim a better code search performance. However, it is still challenging to illustrate a comprehensive view of the field since existing studies generally explore narrow and limited subsets of used components. This study aims to devise a grounded approach to understanding the procedure for code search and build an operational taxonomy capturing the critical facets of code search techniques. In addition, we investigate evaluation methods, benchmarks, and datasets used in the field of code search as well.

CCS Concepts: • **Software and its engineering → Maintaining software**;

Additional Key Words and Phrases: code search, code recommendation, code retrieval, find code, code snippet, code search procedure

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1 INTRODUCTION

Code search is one of the most frequent activities in software development since developers tend to write programs based on existing programs rather than writing them from scratch [94, 182, 234, 248, 252, 295]. Many programs consist

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of routines, data structures, and resources that are also implemented by other programs [70]. Developers are indeed recurrently writing code to address similar tasks or cloning (e.g., via copy/paste) other code. Towards easing software development, searching for source code on the internet became a typical activity for developers [19, 249, 262]. In particular, developers often search for source code to reuse or to consider as reference examples [72, 249] to help them identify the programming concepts that are required for solving coding tasks [14, 30, 94, 176, 248] or to fact-checking (i.e., in contrast to exploratory usages [174]) on the availability of different implementations for a given algorithm. Furthermore, the core concept and principles of code search research is also applied to other software engineering tasks such as *concept/feature/concern location* [58], *code clone detection* [126], *code completion* [32, 229], *match and transform* [207], *vulnerability detection* [37, 300], *bug localization* [3], and *automatic program repair* [161].

Developers often search other external sources rather than local sources for necessary code snippets. The external sources may include the internet, super-repositories (e.g., GitHub [289] and Bitbucket [25]), blogs, and Q&A forums (e.g., StackOverflow [257]). We define this type of code search as "Big Code Search" since it explores a large space of resources. In contrast to big code search, local code search, also called *concept/feature/concern location*, scans features and functionalities available only in the local projects or search space [58]. Local code search approaches often take a single software repository as the search base. This intra-project setting tends to provide high retrieval performance and fast speed since the search base is relatively small, and such approaches are implemented considering their characteristics [232]. Despite the high retrieval quality, such approaches (e.g., [65, 67]) have clear limitations with the variety of the source code and the generalization of the search engine. The research community started to propose *big code search approaches* to address these issues, containing at least two repositories as their search base to provide abundant source code. Especially, Many of the big code search approaches are built upon super repositories such as GitHub [289] or SourceForge [256] to cover various requirements from the developers and users.

Given the importance of code search in software development, the research community has invested substantial effort in the field of code search, developing new techniques, applying new methods, and collecting new data to improve efficiency and effectiveness. In broad terms, code search is a procedure composed of a series of activities aiming to retrieve relevant code snippets according to the user specification. These activities include; i) selection of the output type, ii) creation of a search base, iii) indexing the search base, iv) formulation of user specifications into search queries, v) obtainment of code snippets relevant to the user query, and vi) demonstration of relevant results to users. The ability to characterize the properties of each activity remains crucial towards understanding the core concepts and principles of code search. To that end, we summarize the properties and characteristics of code search approaches and use them to establish a procedure for code search. Eventually, we propose a grounded approach to establish a standard procedure for code search and build an operational taxonomy on this procedure.

Based on the observations above, this survey provides a comprehensive view of big code search by addressing the following challenges. First, practitioners often have difficulties selecting an appropriate tool or technique since there are too many code search approaches to consider. Second, the vocabulary mismatch problem [142, 221, 241, 253] still exists in the field of code search. Third, despite the substantial efforts by the researchers, code search benchmarks still remain low-quality. Fourth, recent studies invested less effort in extensibility (i.e., for multiple programming languages) and usability (i.e., for practical usage such as binary code search because of the obfuscation). Fifth, most existing approaches lack consensus for the specific requirements (e.g., a code snippet that is memory efficient).

It is still challenging to explore the world of big code search due to a lack of well-organized knowledge which links to the building/managing procedures and suitable literature. Yet, to the best of our knowledge, there has not been any attempt to undertake work that would address this issue and provide literature covering the big code search domain in its entirety. Although Liu et al. [158] recently submitted a survey that is based on the input and output of code search engines, their work focuses mainly on understanding the publication trend within the domain that provides a segmentation between the types of publication undertaken, venues, and trends. We believe that further in-depth analysis is necessary for a better understanding of big code search.

This survey aims to provide the reader with a complete view of the field, starting from the first known publication of big code search. We consider a total of 137 big code search approaches, which are all based on multiple projects (i.e., at least two projects as a search base). Due to the strict page limitation, we append big tables in our Appendix A[1].

Concretely, our work provides many essential contributions to the code search field, such as:

- A novel systematic literature review on 137 code search approaches published until the end of 2020.
- A profound literature search strategy with snowballing to bring to light unrevealed approaches of code search.
- An overview of the field of code search and its historical evolution trend to highlight what has been done so far.
- Identifying a general procedure of code search that can help understand fundamental concepts of code search.
- An operational taxonomy of code search that can guide researchers and practitioners to locate code search approaches that are most suited to their tasks.
- Analysis of existing dataset and the benchmarks of code search.
- Discussion of the open issues and potential research directions.

2 DIFFERENCES FROM OTHER SURVEYS ON CODE SEARCH TECHNIQUES

As there have been other existing surveys on code search, we clarify their insights and differences from our survey in this section. We found several surveys [5, 56, 125, 158, 219, 245] that can be directly or potentially related to the field of code search. We clarify the differences from the most relevant survey [158] as follows:

- **Survey scope:** We conducted a strict snowballing to collect the complete list of code search techniques by including DBLP and arXiv. Especially, arXiv contains major industrial publications on the field, which tend to have high research values. This allowed us to discover 137 studies, while Liu et al. [158] found 81.
- **Taxonomy:** Thanks to the complete list, we identify further categories of code search studies (e.g., Code Search based on Dynamic Information described in Section 5.2).
- **Procedures:** We not only provide a review of the techniques but also illustrate the full procedure of code search, which helps better understanding by linking each procedure with our taxonomy.
- **Deeper investigation:** Finding more techniques and illustrating the full procedure of code search allowed us to investigate deeper into the field, which led to the introduction of further techniques. For instance, Liu et al. [158] only introduce the "Inverted" technique for indexing of code search while we include all the other variants such as "Graph Indexing" and "ID-based Indexing". We believe this comprehensive and extensive investigation could help researchers and practitioners better understand and may motivate them to propose better approaches.
- **Better correlations:** Our code search procedure derives an intuitive understanding of the taxonomy of code search. For example, the query formulation phase in the procedure is directly related to the studies in "code search based on query reformulation" of the taxonomy. This can be an easy guide for the selection of the most suitable techniques during the design/implementation process of each task.
- **Opportunity discovery:** There exist missed and under-explored research opportunities we newly disclosed. For instance, a well-designed query language is good at modeling the structure (e.g., loops), and it can accurately

[1]https://github.com/FalconLK/BigCodeSearch/blob/main/Survey_Appendix.pdf

express more complicated search patterns than typical text-based queries. Although this is not a trendy topic for the code search field, these may further improve the performance of tools.
- **Additional issues:** We discover further phenomenons such as "There exist too many code search approaches to consider", which may disturb practitioners as they must select the most suitable one for specific tasks.

Furthermore, we also illuminate the differences from the most recent survey [56] in the following points:

- **Categorization:** We figure out a finer-grained categorization of code search techniques as a more detailed and nuanced categorization of techniques can help readers better understand the similarities and differences between different approaches to code search. This can be particularly helpful for both researchers and practitioners who are interested in implementing or comparing different techniques.
- **Comprehensiveness:**We have concrete tables for each category and diverse sub-techniques may help readers comprehend the field easier. This can be valuable as providing clear and organized information in tables can help readers quickly and easily understand the landscape of the field. It can also make it easier for readers to compare and contrast different techniques within each category.
- **Datasets:** We further support in-depth details of the datasets that can be directly and potentially used for code search engines. It is crucial for researchers to replicate experiments and build upon previous work. Our systematic literature review can provide a valuable resource for researchers who are interested in practical applications as well as developing or evaluating code search engines.
- **Complementary points:** The different open issues and challenges are found and both of them can be complementary to each other. For example, this paper raises vocabulary mismatch problem, extensibility, and usability as the issues in the field, while the similar survey [56] includes additional usage scenarios and cross-fertilization with other fields.

3 PAPER COLLECTION AND REVIEW SCHEMA

This section describes the survey scope, paper collection methodology, and brief statistics of the collected papers.

3.1 Survey Scope

The scope of our survey targets comprehensive internet-scale code search engines that take input from users and then retrieve/recommend/suggest code snippets/examples.

We apply the following criteria for the inclusion of papers in this survey.

- Papers that propose or discuss a general idea of code search.
- Papers that introduce an implementation of a code search/retrieval/recommendation techniques.
- Papers that propose an approach/study targeting specific code search techniques.
- Papers that present a dataset or benchmark especially designed for code search.

Some studies are considered beyond the scope of our work, even though they address code search ideas. These studies adopt code search engines to improve the performance for other research fields, such as code clone detection, which implies that such papers do not improve the field of code search. Furthermore, our survey excludes studies that introduce code search techniques but never retrieve code snippets or related information (i.e., we only cover end-to-end approaches). For instance, some approaches improve user queries by reformulating them (such as in [106]) but they do not retrieve code snippets. Such approaches are not being considered in the scope of the survey. Moreover, we excluded the papers that explicitly mention a single search base scope (i.e., approaches limited to a single specific software repository) as they are local approaches (e.g., feature location) rather than big code search.

Another criterion we have applied is discarding approaches that focus on locating specific code elements. Even if the same approach is applicable towards searching, detecting, or locating a code element, its use-cases differ. There are code clone detection and feature location techniques that closely resemble the code search. Also, some code search engines leverage them to evaluate the performance. However, we do not consider code clone detection as code search as their purpose is generally different from code search; they try to locate the concerned spot within a single project.

We also exclude a set of incomplete work from this survey. The literature of code search also consists of posters that present either work in progress or ideas by different authors at various venues. As most of the posters are later extended in the form of a conference paper or a journal, we do not consider posters in our study as separate ideas or approaches. However, we cover the short papers (i.e., papers that introduce interesting ideas to improve the code search without performing a proper/complete evaluation and they are usually less than 7 pages) as they also contribute to the field.

3.2 Methodology for Literature Identification

To collect the papers across different research avenues that would cover as many papers as feasible, we initiated the keyword search first on popular scientific databases. The databases are listed as follows: ACM Digital Library[2], IEEE XPlore[3], DBLP[4], Springer Link[5], Wiley Online Library[6], Elsevier Online Library[7], and arXiv[8].

Researchers have used diverse keywords for the fundamentally identical concept (e.g., 'code snippet'-'code example' and 'retrieval'-'recommendation'). Therefore, we employed keyword combinations for code-related keywords (i.e., source code, code snippet, code fragment, code example) and search-related (i.e., retrieve, recommend, and suggest) for the text searching across the repositories and published until 2020. We manually checked all the titles and abstracts to extract papers related to big code search.

To further ensure that we cover all the big code search [72] papers and avoid confusion from missing papers, we conducted snowballing on each paper found by text searching following a well-known guideline [293]. Snowballing is a process that traces citations of papers continuously until there are no missing papers in a domain. The main idea of such a process is to avoid missing related studies that are not discovered by keyword search. This process allowed us to add studies that satisfy our inclusion criteria in Section 3.1. For instance, CodeLikeThis [176] and Strathcona [95–97] are missing from the keyword search but found by such a process.

We observed an increasing trend in the number of code search approaches published in various venues since the inception of the year 2005. Figure 1 illustrates the trend. As these figures reports, the research within the code search domain gradually increased from 2006, reaching its peak in the recent years of 2019 and 2020. Finally, we ended up with 175 approaches code search approaches. We carefully exclude all duplicate papers (i.e., journal first and short versions of regular papers are not retained) for our taxonomy. Overall, 137 approaches are kept. These trends emphasize the importance of code search, and it is still in growth.

Conferences are popular venues for code search research papers. As shown in Figure 2, conference papers (including full and short versions) account for more than 70% of all papers we have studied. Other venues are academic journals

[2]https://dl.acm.org/
[3]https://ieeexplore.ieee.org/
[4]https://dblp.org/
[5]https://link.springer.com
[6]https://onlinelibrary.wiley.com/
[7]https://elsevier.com/
[8]https://arxiv.org/

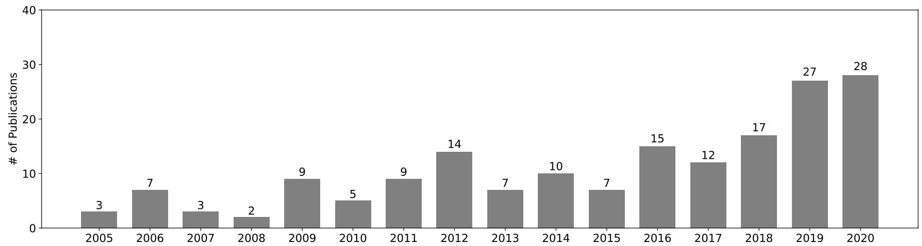


Fig. 1. Number of papers published ranged from 2005 to 2020.

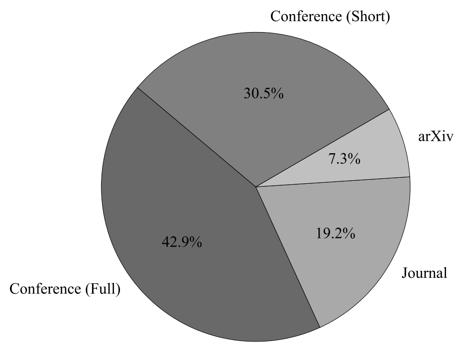


Fig. 2. Publication venue distribution of code search studies.

and e-Print archives; these account for 7% and 19% of all papers surveyed, respectively. Note that papers published at arXiv are non-peer-reviewed, but this should be included in our survey since it is one of the major industrial R&D publication venues. International Conference on Software Engineering (ICSE) has been the target of 20 out of 102 overall approaches that target the conference as a publishing venue. Similarly, the journals Transactions on Software Engineering (TSE), Empirical Software Engineering (EMSE), Journal of Systems and Software (JSS), and IEEE Access are the most target journals in the domain. The public repository that contains all the publications is available at our Github repository[9]. Conferences and journals that cater to the code search domain are listed in Table 1 of Appendix A[10].

4 CODE SEARCH ENGINES - GENERAL PROCEDURE

Figure 3 illustrates the typical process under which any general code search is conducted. This process is summarized from the literature, after taking into account all details in the manuscripts. A procedure of code search approach consists of several steps: (1) selecting search type, (2) search base creation, (3) indexing data, (4) formulating input (query), (5) building retrieval model and retrieve, and (6) presenting the results. These steps are therefore guiding the characterization that we will make in our review of the code search literature.

Providing a general procedure can derive a baseline (i.e., how to design a code search approach) for researchers while developers can understand the characteristics of each step and figure out the best approach to apply or use for

[9]https://github.com/FalconLK/CodeSearch_Survey.git
[10]https://github.com/FalconLK/BigCodeSearch/blob/main/Survey_Appendix.pdf

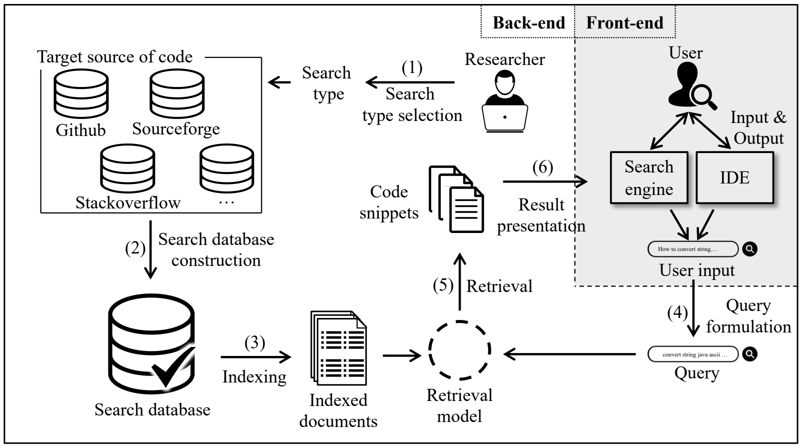


Fig. 3. General code search process.

conducting their own tasks. In other words, this should serve as a practical guide to researchers who are new to this field and developers who are confused about picking a code search approach.

Depending on the design of each step in the procedure, a code search approach can have a significant difference in terms of various performance metrics. For instance, creating a search base with good quality code snippets can improve the baseline performance, implying that poor code leads to poor results even though the other steps are well-designed. Formulating the query with a specific query language may help avoid a well-known vocabulary mismatch problem to enhance the relevancy of the code snippets. Designing the retrieval model with learning-based approaches significantly improves the performance, while classical models are still much faster to retrieve code snippets.

4.1 Search Target

The first step to designing a code search approach is to decide what kind of search targets it can provide. Developers want to search for various types of code, such as some need code snippets related to a specific API while the others require interface-related code. However, most developers search for available code snippets to address their problems or implement their tasks. These types vary by the desire of target users.

- **General Code Snippet**: Generally, code search approaches retrieve the most relevant general code snippets rather than other source code types (e.g., API usages, GUI code, or Binary code). Some representative examples are as follows: [13, 133, 253].
- **API Usage Example**: Many software developments leverage the use of APIs that provide standard functionalities toward smooth developments. The developers understand and learn about the API by referring to the API documentation and tutorials (e.g., JDK), looking towards Q&A forums such as StackOverflow, or searching for code examples on super repositories such as Github. Some representative examples are as follows: [194, 217].
- **GUI or binary code**: A code is used not just for writing software that provides specific functionalities; instead, it has also been used for user interface development that serves as the interface for the user's interaction with underlying software. Some representative examples are as follows: [37, 49, 299]. Moreover, there exists software

without its compilable source code; instead, they exist with only compiled binary files. Some representative examples are as follows: [22, 297].

4.2 Search Base Creation

The search base is a repository or dataset where a code search approach can search for and take the code snippets relevant to the user's specification. This is important because the overall performance of a search engine is influenced by the quantity and the quality of data [208]. Considering the importance of the data, we focus on how developers and researchers create their search base in this section and leave the description of the data itself used for code search in Section 6. Many approaches within the literature [133, 166, 220, 253] leverage the super repository such as GitHub [289] for their search base because such repositories are a rich and well-maintained source from the community.

Many studies [41, 66, 195, 211] implied that narrowing the search base allows the search engines to hit more relevant results to the queries. To do so, project metadata such as the programming language, creation date, and popularity are further considered in the code search domain. For some approaches, the researchers [133] consider specific repositories that a certain number of users have starred to avoid toy projects that contribute as noise within the data. Furthermore, some studies (e.g., [109]) leverage supplement information like commit logs (e.g., commit messages) to improve their engines' performance by narrowing the search base or mining them for specific topics. A dataset from Q&A forums where questions are mapped with answers containing code snippets is used in many studies (e.g., [133, 150, 160, 216, 217, 220, 221, 253]).

4.3 Index

Indexing is a process that makes the data access efficient within its search base. Generating and storing an index optimizes the speed and performance of finding the relevant results for a given query. Without such an index, the engine would need to parse every code snippet within the dataset for any given query, which leads to higher time and space complexity. Many studies leverage different indexing techniques to speed up source code retrieval in the code search field.

- **Inverted Indexing**: This is an index data structure containing a mapping from content such as words to its locations in a document or a set of documents. Inverted indexing is the most popular indexing technique that many search engines, such as Google, employ in the real world. Many code search engines also take this technique to index their source code snippets in their search base. To apply the inverted indexing, a number of researchers [12, 133, 237, 253] utilized Lucene [290], a representative open source search engine library. This library is commonly used to demonstrate many code search techniques (e.g., where they do not need specific indexing techniques).
- **B+ Tree Indexing**: This technique is an alternative mechanism to index a sequential set of data elements. A B+ Tree is primarily utilized for implementing dynamic indexing on multiple levels. It stores the data pointers only at the tree's leaf nodes, making the retrieval, addition, and deletion process more accurate and faster code search. Some researchers [22, 71, 143] in code search have relied on this indexing for boosting speed performance.
- **Graph Indexing**: Graphs have been used extensively to model the complicated structures and relationships between different entities within a programming code. Every query provided as input towards these approaches is transformed in graph structure to retrieve similar or related graphs from the search base. Researchers [124,

265, 297] have leveraged the graph structure and the graph indexing techniques for code search engines. The algorithm indexes all the reachable relationships between node labels.

- **ID-based Indexing**: This indexing mechanism (also called "File-based") is used to optimize an access to data managed in the form of a single file or access point. This mechanism typically leverages a specifically created index file that stores only the search key's value and a pointer towards the file's storage location. Within code search engines, the use of ID-based indexing means that for each of the potential searchable source code files, an index is stored that can point towards its location. Specific code search engines [34, 120, 274] leverage the ID-based index by assigning a unique searchable ID towards each file, class, or method that can be matched for optimized retrieval.
- **Positional Indexing**: Positional indexing is the mechanism that leverages the existence of tokens within a document. Each positional information (e.g., line number, the position of a token within a sentence) of every term is indexed and leveraged with the retrieval techniques.

4.4 Input (Query)

Formulating input to a query is one of the procedures related to the user side (also known as the Front-end). In particular, the client-side of code search starts with taking the input from the user. The form of input varies because each user has their own specific tasks. For instance, for developers who want to find a similar code to their code, a code search approach takes a code as the input is needed. Such tasks are mostly related to software maintenance (e.g., refactoring and performance optimization). If a developer has test cases to pass, the perfect-fit code search engine may take the test case as the input. It is crucial to design the input variety in code search according to these situations. We report the inputs and their properties used to design code search approaches.

- **NL query**: Developers often find it easier to formulate the query in natural language for the desired search describing the expected code snippet. An NL query allows a developer to enter terms in any form, either a statement, a question, a list of keywords associated with programming elements (e.g., class or method name). As many developers do not always have the knowledge about the technical expression required to express their search formats, most code search approaches are designed for NL queries. Community-driven forums for developers such as Stackoverflow [257] and super repositories like Github [289] take NL input for the user query.
- **Code Fragment**: We define "code fragment" as the source code that the search engine takes as input and "code snippet" as the source code that the search engine retrieves as output; code-to-code search engines leverages the fragments and snippets as query and results, respectively. The code-to-code approach is beneficial for research directions in code transplantation, code diversity, patch recommendation to find essential ingredients for their techniques. One of the popular commercial engines, Krugle [134], has its snippet-based search in the advanced option, while SearchCode [244] is capable of taking input as both NL and code fragment in its main interface.
- **Query Language**: A query language is specifically designed to model the structure and properties (e.g., loops, method calls, and exception handling). Modeling such properties can express more complicated search patterns such as '*find all code examples that call the ABC method in a loop and handle an exception of type abcException*'. In the case of typical text-based input, this cannot be accurately expressed [239, 255].
- **Binary Code**: In some cases, developers may need to search for code similar to functions within an existing binary file. Developers mostly use the use-case of binary code search to search for critical vulnerabilities or find code snippets that implement the given binary input file's functions. Researchers have proposed approaches

(i.e., [37, 49, 300]) that take a binary file as input and perform code search to retrieve code snippets that implement semantically similar functions.

- **Test Case**: A test case is executed and reaches a state of pass if the output from the code and the provided output matches are considered to have failed. Test cases are used heavily in software development and form the basis of Test-Driven Development (TDD) [21]. In many cases, Test-Driven Code Search (TDCS) approaches take either test cases or a set of keywords that can define a required test case. Test cases are beneficial as they provide instant feedback about the suitability of a particular code result.
- **Class/Interface Type**: Similar to test cases, Interface-Driven code search (IDCS) approaches leverage the interface types existing within the input snippet. These interface or class types are similar to existing interfaces within a function such as '*string f(string)*' in Java. In the example, the types (as input of a code search) are 'string'. Some researchers [95–97, 144] have leveraged the use of interface or class types for matching which reduces the potential search space and provide effective code search engines.
- **Software Specification**: Software specification is what the user specifies as their requirements and conditions towards the search. For example, a user may wish to retrieve code with only a limited set of parameters or asynchronous-only API code. Researchers [173, 263] have leveraged software specifications to specify the security constraints (i.e., method pre- and post-conditions) for retrieving results aligned with the user's needs.

4.5 Retrieval model

A retrieval model predicts and explains what a user desires given the input (i.e., it matches the query and retrieves the source code). The correctness of the model's predictions can be validated in various experiments. Moreover, different retrieval models usually categorize code search approaches as they take the position of the principle behind them. The retrieval phase of code search generally consists of matching text, computation of matrix, or vector similarity measure depending on a specific technique.

- **Textual Similarity**: In code search, the textual similarity consists of matching tokens, keywords, or even a sequence of tokens between the user query and source code from the search base. As for the standard models, the Boolean Model (BM) [136] and Vector Space Model (VSM) [238] are famous classical information retrieval models adopted many times by code search engines. Query and the target code files are conceived as sets of terms in the BM model, and the retrieval is based on whether or not the code files include the terms from the query. It has an explicit limitation that at least one of the query terms must be present on the document side when an OR connective is used. On the other hand, VSM represents the document (source code files) as the vector of identifiers such as method name, class name, or tokens. Generally, the comparison between such two vectors is derived using the cosine similarity. It does not support structural queries which consist of complex AND/OR relations. Therefore, researchers revised the VSM integrating with BM to address the limitations by weighting both query and document terms.
- **Graph Similarity**: As the tokens in source code are not just text, one might need a different form of representation to capture the semantics in the code. Graph representation [6] is an optimal way to model the different source code elements and leverage them for the code search. The code search approaches that leverage graph-based retrieval do not explicitly accept input in a 'graph' form; instead, it accepts a typical query in the form of NL or code fragments. The query is transformed into a suitable graphical representation such as AST before being passed as input for the underlying search technique. The type of graphical representation selected for a particular

search engine depends on the context of the targeted input. For instance, a binary code search engine is likely to transform the binary input into a Control Flow Graph (CFG); a code search engine targeting object-oriented programming language would use Data Flow Graph (DFG). In the form of similarity computation, this comparison consists of leveraging graph traversing techniques for optimized results.

- **Matrix Computation**: Matrix computation is an elaborate method used as a retrieval technique in some code search approaches [241, 291]. The result of the computation provides a characterized correspondence between the matrix elements. Many applications have adopted these matrix computations because of their scalability that retains the results' predictive accuracy. Similarly, code search employs the matrix computation for measuring the co-occurrences of specific features (such as terms) within the source code.
- **Embedding Vector Similarity**: Recently, code search approaches (e.g., [33, 80, 160, 233]) using neural networks have been a trend. Common across such approaches is the idea of embedding user queries and code into vectors (i.e., an embedding refers to a real-valued vector representation [132]). The computation of the distance between the embedding vectors is the correlation that forms the basis of retrieving the suitable candidates. As code search approaches based on neural networks show that they can adequately learn the features of both the query and code from a large dataset, it helps address the issues from the previous techniques.
- **Execution Trace**: A source code in binary format is hard to read and understand [147]. An efficient way towards understanding what a binary file is performing is to trace its execution flow, known as the execution trace [31]. This execution flow provides information on the behavior of a program, such as the logical sequence of execution, and changes in the data variables. The similarity between the execution traces of two syntactically different programs provides information on how similar (or dissimilar) the two binary programs are.
- **Clone Detection**: Code search is another way to identify similar or identical source code snippets. Generally, code-to-code approaches sometimes leverage code clone detection techniques in the middle of their retrieval process to narrow down the search space by clustering similar source code [4, 127, 162, 188]. Clone detection techniques are also directly used to determine the lexical similarity between the query code and candidate snippets [218].
- **Type Link**: Type Link [10] is a methodology that resolves a given function name by referencing the function and attempting to link it with its canonical form for the same type. For example, a class extending another class may have complex inheritance and nested types from its parent class. Such a type of class or code context requires a different approach when searching within them.
- **Solver**: Solver or SMT solvers [261] (short for satisfiability modulo theories) are instances represented as a formula in first-order logic. These formulas represent functions and symbols that follow specifications in the form of input and output of a program. For any given query, represented in the input and output of a program, the solver finds programs for which these specifications and constraints are satisfied. The satisfied candidates thus form part of the results presented to the user.

4.6 Implementation

The final step of the code search procedure delivers and presents the results in an appropriate platform. As each user has different requirements and feasibility, code search approaches should be provided on different platforms such as independent code search engines, integrated development environment (IDE), or presented as an idea in a research paper. Independent code search engines can be either local or online to interact with developers with the underlying techniques, while some others are implemented as a plugin of different IDEs allowing them to leverage the search within the development process. Finally, others are presented just as an idea form as potential work in code search.

- **Search Engine**: A search engine catered explicitly towards the code search is the popular means of presenting the search approach results. These search engines are either working online (accessible over the internet) or offline (where the engine is deployed locally over the dataset chosen by the user).
- **IDE Extension**: Rather than providing the code search in a search engine, some researchers have attempted to provide code search facilities within the integrated development environment such as Eclipse as a plugin. The majority of the code search implementation in the form of IDE extensions take as input either a pure NL query or a code fragment to output a relevant code snippet. The usage of the IDE plugin allows the code search to leverage the written code tokens as given input for the approach to find similar or potential code examples.
- **Idea**: Among all the different code search approaches, not all propose an evaluation or implementation; instead, there are ideas that can be incorporated into a potential code search implementation. Such approaches are classified as 'Idea' that proposes an approach without any evaluation or implementation details described. Such ideas are valuable contributions within the field since some of them are later implemented as part of a code search engine or an IDE plugin.

5 TAXONOMY OF CODE SEARCH TECHNIQUES

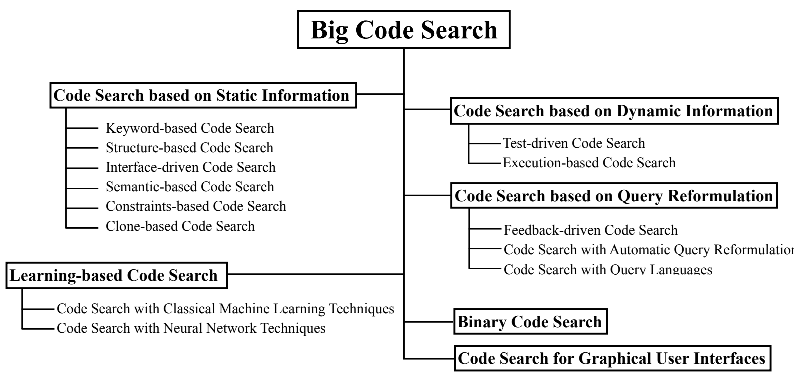


Fig. 4. Taxonomy for big code search techniques.

This section presents a taxonomy of code search tools and techniques. The taxonomy provides an overview of different techniques and their categories in the code search literature. Since there are hundreds of code search techniques, it can be challenging to figure out their characteristics and details. A clear taxonomy can help understand the techniques with a concise view on their key differences.

Based on the general procedure of code search, we have identified that code search approaches are broadly differentiable based on the kind of information that is used to drive the search (i.e., the query). Beyond that, the method under which the query is matched is also a key differentiator. Overall, we have defined six top-level categories to classify code search techniques. These categories represent the most common and popular ideas used in many code search techniques, while other details of each individual technique would be different from others. The overall taxonomy is presented in Figure 4, demonstrating the orders and sub-categories for better understanding. When a specific technique leverages ideas of multiple categories, we classify the technique as one category, which is the principal idea of the technique. Note that all the big tables for our taxonomy are located in Appendix A[11]

5.1 Code Search based on Static Information

Code search can leverage static information such as text in source code, which is similar to general-purpose search engines [74, 185]. For example, a code search tool can scan source code files and make an index of class, name, variable names, and parameter types. Recent code search techniques with static information consider more information, such as code comments; they generate code summaries to match against the query. We have identified six sub-categories of code search engines utilizing static information: keyword-based, structure-based, semantic-based, interface-based, constraints-based, and clone-based approaches. The details for each technique is represented in Table 2 of Appendix A.

5.1.1 Keyword-based Code Search. Many early code search engines rely on general text retrieval approaches; they treat source code as either plain or structured text. To that end, those approaches build an index of the textual information, i.e., keywords. Given a user query, the approaches try to compute a token-level similarity between the query and index. This type of code search is categorized into Keyword-Based Code Search (KBCS) in this study. The earliest known KBCS approaches [65, 67] were based on retrieving code snippets without considering any code-specific information (e.g., structure, sequence, etc). Although these approaches cannot be classified as big code search approaches, it is meaningful to consider in the survey for historical trends. Later, KBCS techniques often leverage additional information available after parsing Abstract Syntax Trees (ASTs) [251]; when building an index, those techniques annotate keywords with code entity information such as package, interface, class, method, constructor, field, initializer, etc. In addition to tokens in source code, it is able to use tokens in other sources such as API documentation [77, 78, 180, 183, 253], which are linked to source code as code search inevitably suffers from the vocabulary mismatch problem [253]. KBCS techniques are also applied to code search in Q&A posts [311], code-to-code search [191, 193, 272], and code summarization [114].

5.1.2 Structure-based Code Search. In contrast to tokens and keywords used in general search engines, source code often has specific structures such as call graphs, code trees, developer activities, and common API usage patterns. It might take some time to extract such information, but it is much less than dynamic information (see Section 5.2) as the information is essentially static ones.

Graphical information is one of the most common structures used for code search. For example, function [45, 166, 171, 181, 184, 236, 274] or API call graphs [36, 151] are common structure information used in code search engines. This information helps expand the search space, followed by the graphs, compared with keyword-based code search in which the search space is limited to code entities containing tokens in a given query. System dependency graph (SDG) [212] and Program Expression Graphs (E-PEGs) [212] are used for code search as well. Computing tree similarity is another way of utilizing static structural information as source code is fundamentally a tree form after parsing. Code search can leverage tree similarity based on hashing [4] or intermediate models [55, 235, 275, 276]. Hierarchical structures are also used for code search, such as code blocks [100] and class hierarchy [163], as they can expand the search space.

There have been code search approaches combining structural information and other entity types together. Sourcerer [12] provides a ranked list of code entities and the ranking is computed by keywords, structures, and graphs available in source code. Another approach [192] collects developer activities recorded in development tools and incorporates them

[11] https://github.com/FalconLK/BigCodeSearch/blob/main/Survey_Appendix.pdf

with structural information such as classes, types, and parameters available in source code to compute a degree-of-interest (DOI) model, which improves the code search performance. Barbosa et al. [17, 18] proposed an approach to searching for exception handling structures. This approach combines matching keywords in a user query with exception handling blocks.

Leveraging API usage patterns is another line of structure-based code search. By mining API documents (or other types of documentation) and usage patterns together, code search approaches [10, 140, 173, 186, 194, 198, 206, 214, 296] figure out relationships between them. For a given user query (e.g., what a user wants to implement, described in a natural language), an approach in this category first searches for similar API descriptions to the query and then retrieves API usage cases corresponding to the descriptions.

5.1.3 Interface-Driven Code Search. Functions (also known as *methods* in some languages such as Java) are often a target unit of code search. Interface-Driven Code Search (IDCS) approaches take an information of a function signature (i.e., interface) [312]. The information may include function name, parameters (with type information), and return type. Based on the information, IDCS can reduce the search space (e.g., by restricting the parameter and return type of a function to *int*) and generally improve the performance of code search. Strathcona [95–97] is an example of IDCS. Another approach [144] extends Sourcerer [13] to implement IDCS.

5.1.4 Semantic-based Code Search. While keywords and structural information often represent functional aspects, other types of information convey semantic aspects of source code. The semantic information includes part-of-speech (POS), topics, and source code types. These data can identify latent semantics of queries and code entities corresponding to the semantic. Thus, code search tools based on semantic information often extract the information both from user queries and source code.

Several code search engines have utilized diverse semantic information available in source code. For example, it is common to use semantic information collected from natural language processing. Part-of-speech [159, 279] and phrasal concepts [92] after parsing entity names (e.g., function signature, variable names, and types) are often leveraged to extract semantics of queries and source code. Since the meaning of the collected words cannot be discovered directly from the source code, those code search engines often adopt word models such as the Software Word Usage Model [90]. Topics are another standard semantic information used in code search. Topic modeling can identify common topic information from a bunch of documents. Several recent code search tools [9, 182, 278, 315] extract topics by using Latent Dirichlet Allocation (LDA) [26], Latent Semantic Analysis (LSA) [53], feature identification approach [60], or N-gram model [87] to identify code entities highly relevant to a given query even though they share very few keywords. Another semantic information used in code search is production and test code relationships. Test Recommender [209] identifies the relationships by collecting changesets in versioning histories. The changesets are used for ranking search results.

5.1.5 Constraints-based Code Search. Some code search approaches [43, 121, 260–263] attempt to use example-based query models to conceptualize what users want to search for. The approaches encode source code snippets as constraints. Each query (e.g., an input/output example) is transformed into constraints and sent as input to an SMT Solver [51] along with the encodings of the source code repositories. The SMT Solver identifies the code from the repository that meets the I/O example, which forms the results.

5.1.6 Clone-based Code Search. Code clone detection [231] and code search share several common ideas and techniques. Thus, many code search approaches [127] employ techniques used in code clone detection. For example, CodeNuance [162] directly uses CCFInderX [123], a code clone detector, to identify similar code (i.e., code clones) and build an exploration graph based on non-duplicate methods. Other approaches [188, 218] in this category are designed in a similar way to support code search. Sometimes, code clone detection techniques help overcome the limitations with non-compilable code or play a compensatory role of other similarity measures. It can say that the approaches in this category leverages static information since code clones used in code search are mostly Type-1, Type-2, and rarely Type-3 clones rather than Type-4 clones [231]. Note that the Type-4 clones are semantic clones while other clone types are defined by lexical similarity.

5.2 Code Search based on Dynamic Information

Code search engines driven by dynamic information focus on behaviors captured after running programs, while search engines based on static information utilize data collected without executing the programs. To extract dynamic information, it is necessary to run a program with concrete inputs (e.g., from test cases), which may cause an additional cost. Despite the cost, dynamic information can improve the performance of code search. For example, the dynamic information can assist developers who lack the expertise of the desired code [71] and non-native speakers of the language in which the repository is based [143], assure faster retrieval of code snippets [137], provide more guarantee the correctness of the behavior of retrieved code snippets [137]. Table 3 of Appendix A illustrates the details of code search techniques based on dynamic information.

5.2.1 Test-driven Code Search. What if a user can specify input/output example pairs (i.e., test cases) when searching for a certain source code snippet? Test-driven Code Search (TCDS) is one of the dynamic approaches in code search that takes a test case(s) and identifies the appropriate code snippets that pass the given test case. The use of test cases helps (1) define the behavior of the desired functionality to be searched; and (2)test whether the search results are suitable in the local context [137]. Typically, TDCS consists of the following procedures: (i) define test cases, (ii) feed the test cases to the search engine, and (iii) run the test cases on each search result (e.g., code snippet or function), given by the search engine, to validate whether it satisfies the search requirements specified by the test cases.

There have been several TDCS techniques. CodeGenie [137–139, 141] is one of the earliest technique that leverages Sourcerer [12], a well-known code search engine, as it carries out keyword-based code search with keywords extracted from test cases. Then, CodeGenie runs the test cases for each search result. This technique has been extended by using *thesaurus-based tag clouds* [143] as well to mitigate the vocabulary mismatch problem (VMP). Code Conjurer [111, 117] attempts to implement a more proactive code search based on TDCS than CodeGenie. EQMINER [120] generates random test input generation by using symbolic [148] or concolic execution [135], then checks the abstract memory states [131] to compute function similarity based on execution outputs. In addition, code search engines (such as S6 [28, 29, 223–226], HUNTER [287], and [129]) augment TDCS ideas to enhance search performance.

5.2.2 Execution-based Code Search. Code search engines can leverage dynamic information extracted after running a program. Program source code is not just text, and it is meaningful once it is executed. Fundamentally, the users of code search engines want to locate programs that carry out the meaning specified in the queries rather than those containing the same tokens. DyCLINK [265] is one of the examples of code search engines utilizing execution traces. This tool takes a code snippet as a query and constructs its Dynamic Dependency Graph (DDG) that captures behavior at the instruction level. The query's DDG is compared with DDGs of other programs to identify similar code snippets. CodeHint [71] is another code search engine leveraging execution traces. This engine exploits the Java runtime capabilities by executing the debugger at runtime to collect data. This data is used for matching the information specified in a user query.

5.3 Code Search based on Query Reformulation

The users of code search engines often try several different queries for a single search campaign when their first queries are not effective searching for necessary code snippets. Some code search engines proactively help or simulate the trials of different consecutive queries. This process is often called ‘query reformulation’. Search approaches in this category reason about more precise query strings based on initial user queries. A subset of the approaches leverage interactions between search engines and users to improve search queries (i.e., feedback-driven code search). Another subset of the approaches automatically reformulate the initial query and provide the search results (automatic query reformulation). Other approaches in this category use domain specific query language to enhance the query reformulation process. The related particulars are exhibited in Table 4 of Appendix A.

5.3.1 Feedback-driven Code Search. Code search tools in this category assume that the first user queries are highly likely to be incomplete. Instead, these tools provide a series of feedback (or clarification questions) to improve the user queries. The feedback includes adding, removing, or editing their initial queries [15, 30, 94, 247, 258]. This process is iterated until the developer is satisfied with the results. Note that developers often do not have a clear idea of what they are working with [50, 250]. Thus, the feedback loop can help the users complete the search queries [50, 63, 167, 188]. Multiple researchers have investigated an approach towards building feedback-driven (i.e., iterative) approaches based on such observation [1, 39, 85, 91, 93, 150, 164, 176, 177, 230, 239, 255, 264, 284].

5.3.2 Code Search with Automatic ery Reformulation. A query plays one of the most critical roles for the code search engines [93, 210], and many researchers have worked towards improving the search quality by reformulating the queries automatically (i.e., without the user’s intervention). Query reformulation is conducted because the vocabulary mismatch problem [88] (multiple words for the same topic), polysemy (one word with multiple meanings), and the general words in the query complicate the code search engines. A query can be reduced, expanded (augmented) [2, 34, 61, 105, 107–109, 122, 133, 142, 160, 169, 201, 216, 220, 221, 240–242, 253, 254, 294, 302, 304, 313, 317], or even entirely alternated by their properties [35, 84, 153, 165, 172, 217, 298, 303].

5.3.3 Code Search with ery Languages. When creating search queries, the users can benefit from a domain-specific language for code search. This type of language is called ‘query language’. A query language defines the structure of a query and the property of a token in the query. A user can annotate additional information of each element in a query. For example, SnipMatch [292] incorporates crowd-sourced source code and introduces a simple markup language used for indexing and matching relevant code snippets. Another example is the Dependence Query Language (DQL) [283, 286]. This language allows users to formulate the queries by describing dependence properties on top of textual properties. AutoQuery [282] alleviates the burden of users when creating a query based on a query language.

5.4 Learning-based Code Search

Leveraging machine learning (ML) techniques is popular in building a code search engine. Code search is fundamentally a prediction task for a given input (search query) to provide a set of code snippets as output so that ML techniques fit the task. In addition, code search techniques benefit from the recent advancement of deep learning. Nevertheless, machine learning techniques such as support vector machine [47] are useful for code search campaigns as well. The encapsulated details are shown in Table 5 of Appendix A.

5.4.1 Code Search with Classical Machine Learning Techniques.

Code search can be modeled as supervised (e.g., classification of a given query string into a set of files) or unsupervised (e.g., clustering of similar source code files) learning tasks. Thus, many classical machine learning techniques are applied to code search approaches to improve the quality of search results. The approaches leverage different ML techniques such as collaborative filtering [291], clustering [81, 102, 268], classification [119, 124, 197, 199], graph embedding [318], and Bayesian networks [190].

5.4.2 Code Search with Neural Network Techniques.

Deep neural networks opened a new research direction for code search as they do the same for other computer science topics. Like the code search approaches utilizing classical machine learning techniques, many recent approaches define code search as supervised and unsupervised learning tasks especially for deep learning. Those approaches use diverse deep learning techniques such as embedding (for word, sentence, or paragraph) [3, 33, 59, 80, 89, 154, 200, 233, 305], recurrent neural networks [80, 154, 160], convolutional neural networks [52, 104, 149, 246, 281], long short-term memory (LSTM) [79, 80, 86, 103, 112, 115, 146, 154, 228, 243, 246, 267, 280, 305, 307, 316], auto-encoders [42], transformers [285, 309], feed-forward neural networks [68, 104], graph neural networks [40, 155, 280], and generative adversarial networks [314].

5.5 Binary Code Search

Static information is not limited to source code. Some code search approaches [37, 49, 130, 152, 299, 300] address binary code as the search space instead of source code. These approaches are helpful when available resources have only complied binary files. The approaches often create additional indices after decompiling the binary code or retrieving CFGs from the binary files. The detailed information per each technique is demonstrated in Table 6 of Appendix A.

5.6 Code Search for Graphical User Interfaces

Researchers have proposed different approaches that aim to simplify and automate exploring and building GUI's by lettering users reuse similar GUI's within data repositories. The retrieved result is provided in the form of an interface for users to interact with the code to replicate them. Some approaches [22, 297] take input sketches from the user, identify its features, and apply various code search techniques to retrieve similar designs from the search space. While another approach [227] empowers the search by seeking users to 'draw' the required interface design within the search engine, potentially with additional context such as keywords relevant towards the search. Each characteristics are displayed in Table 7 of Appendix A.

6 DATASETS AND BENCHMARKS FOR CODE SEARCH

The choice of datasets in which performing the search has a high impact on the performance of code search techniques. In addition, those play a crucial role in evaluating the techniques from the research perspectives. For instance, using a readily available dataset allows reproducibility of the approach, and the larger the dataset, the better the coverage of the code search approach is. This phenomenon makes the dataset a crucial component when designing a code search engine as it directly impacts its performance. The dataset may also contain additional information such as Q&A posts of open developer forums and software metadata, while benchmarks can incorporate other features such as fixed queries and metrics. This section explains the source code dataset, non-code dataset, and benchmarks used within the code search domain to create search bases or evaluate the code search engines. Figure 5 illustrates the statistics of dataset types used in the code search studies.

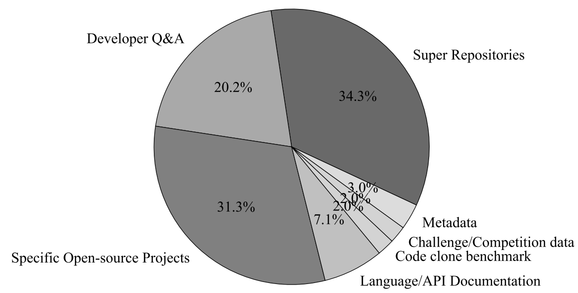


Fig. 5. Statistics of dataset types used in code search studies.

6.1 Specific Open-source Projects

In an earlier time before the rise of open-source software, only a limited number of projects and their source codes were actively maintained and accessible to the public. As a result, researchers intending to apply code search ideas had to leverage these sparsely available open-source projects. These projects ranged from different communities such as Apache HTTP Server [273] and Linux operating system [73]. The Portfolio [181, 184] and Coogle [235] are representative examples of approaches that utilize specific open-source projects to demonstrate their results.

6.2 Data Sources from Super Repositories

There has been widespread use and adaptation of open-source software in the last decade. This has created thriving open-source software development communities that leverage collaborative coding systems and are made centrally available for everyone to use. Similarly, researchers within the code search have adopted the data sources that form a large set of different open-source projects when testing their approaches [12, 274].

The leveraged data source, known as the dataset, is in a file archive, where most of the source code files are extracted from different software projects. These repositories are often accessible online on code hosting services such as `Github` [289] or `Sourceforge` [256]. The hosting services are built upon version control systems (VCSs) such as `Git` [156]. Software repositories are a rich source of code snippets created and curated by developers around the globe. Furthermore, the curated source code snippets in the form of datasets provide opportunities to investigate and research new ways for code search techniques.

Many of commercial code search approaches [44, 134, 204, 244] and research prototypes [133, 169, 177, 178, 186, 189, 214, 215, 218, 221, 253, 262, 288, 304] have utilized source code files collected from the code repository platform `Github` as their search base. `Github` is one of the largest super-repositories built on top of the `Git` VCS [16]. It is the most superior hosting service [222], with more than 100 million repositories hosted as of January 2020. `Github` also hosts huge and popular projects such as Homebrew [179] (a package manager) or Django (a web framework) [98].

`Sourceforge` is another super repository used for constructing code search datasets. It hosts more than 500 thousand projects. Similar to `GHTorrent` for `Github`, the `FLOSSMole` [99] project supports creating a dataset [187] from `Sourceforge`. Exemplar [180], Lukins et al. [168], and Hsu and Lin [101] crawled and utilized the data from `Sourceforge`.

For Android-centric code search approaches, there exists a website named F-droid[12]. It is a repository of Android applications of various sizes and categories. The dataset[13] contains meta-data (name, description, and version), the

[12] https://f-droid.org
[13] https://gitlab.com/fdroid/fdroiddata

source code of each major version, and its most recent 'apk' file. Some code search approaches [119, 201] leveraged such datasets for android code search.

Although these super repositories have been used frequently to construct various code search approaches, their use has several disadvantages. For example, users tend to upload (commit and push) files unrelated to source code, such as security-related tokens or documents containing personal information. These can affect the quality of the search base. Such accidental exposure of information can have dire consequences (e.g., disclosing personal information to the public) [271] even through the code search engines. Another disadvantage of super repositories for research is that the quality of the projects and developers within such community is hard to validate. A significant amount of time needs to be dedicated to curating good candidate projects.

6.3 Other Data Sources

Other resources have been leveraged for different approaches towards code search problems. Resources such as the developer Q&A forums, benchmarks, metadata, and API documents are applied for some approaches. Such additional resources have demonstrated an increase in the code search techniques' efficiency and accuracy.

6.3.1 So ware developer Q&A forum. Question and Answer (Q&A) forums are community-driven platforms that allow users to share knowledge with other users who participate in them. Q&A forums offer social mechanisms to evaluate and improve the quality of both the question and answer that implicitly leads to brevity in questions and qualitative answers, potentially with source code snippets [133]. The posts within such forms tend to include code snippets within the question and its answer. It makes them ideal for forming the part of the dataset for some code search approaches.

Many of the code search approaches [9, 116, 127, 133, 144, 151, 169, 175, 186, 201, 202, 218, 253, 259, 262, 263, 278, 279, 311] have utilized the developer Q&A forum called `Stackoverflow`. `Stackoverflow` is the largest Q&A forum that mainly contains questions and answers on programming-related topics [76]. Answers from `Stackoverflow` often are an alternative explanation for corresponding official product documentation wherein the documentation is either insufficient, does not exist, or lacks in-depth information [19]. Furthermore, a significant portion of answers includes code snippets that demonstrate the solution for the corresponding programming problem.

Recently, a large and systematically mined dataset using Stackoverflow are proposed, and learning-based code search approaches [52, 86, 103, 281, 314] leveraged these in their evaluation. CoNaLa dataset [310] by Yin et al. consists of two parts, a manually curated parallel corpus of training and test examples as well as systematically mined pair examples. Unlike CoNaLa, StaQC [306] is specifically intended for code search (i.e., not for code generation or summarization) and it consists of 148K systematically mined Python and SQL question-code pair datasets.

Even though such data from Q&A forums have advantages for code search, they are not primarily designed for code reuse or the search for particular code snippets [19]. Thus, not all the posts include source code, as some are mere questions and answers either with incomplete code or devoid of any code. For example, there are multiple instances where the code is written with ellipses (i.e., "…") [253]. It implies that some people prefer to express natural language expressions that make it hard to leverage the data. Furthermore, pervasive unqualified names [266] and ambiguity in enclosing class names of method calls [48] for code snippets can affect the accuracy of the overall source code approach.

6.3.2 Language/API documentation. Some code search studies [38, 132, 175, 180] leveraged well-known Application Programming Interface (API) documentation. Generally, developers refer to the API documentation for examples [151] of a concerned project where such documents are the official source of information, such as the `JavaDoc` [205]. These documentations are known and followed by all vendors for consistencies usually written by multiple people [54].

6.3.3 Code clone benchmark. Several researchers have used a benchmark designed explicitly for code clone detection to evaluate their code search approaches. For example, `BigCloneBench` [8, 269, 270] is a benchmark that clearly distinguishes between the actual java clones mined from a cross-project dataset, `IJaDataset` 2.0 [7, 8]. FaCoY [133], a semantic-based code search approach uses `BigCloneBench` in a different perspective (i.e., code clone detection using code search approach). Its evaluation consists partially of the `BigCloneBench`'s data as its search base and is evaluated against the state-of-the-art clone detection tools (e.g., [237]).

6.3.4 Challenge/Competition data. Coding competitions are events where participants try to code a program based on specific problems. For example, Google Code Jam [75] is an annual online coding competition hosted by Google. Each submission for a defined problem is expected to perform semantically similar even though they may syntactically be different. Researchers have leveraged the problems and the different solutions to evaluate the code search engines. For example, DyCLINK [265] and FaCoY [133] applied the code written for CodeJam to identify code relatives at the granularity of methods. The latest challenge known as CodeSearchNet [113] aims to encourage researchers and practitioners to study and propose new approaches towards code search. Several learning-based approaches [79, 155, 267] leveraged this challenge dataset.

6.3.5 Metadata. Software project metadata includes information such as the project name, owner, description, etc. [23, 24, 46, 62, 83, 234]. Code search studies [27, 72, 82, 128, 133, 177, 181, 253] have leveraged project metadata by claiming that metadata can play an important role in designing and implementing code search approaches.

6.4 Benchmarks for Code Search

Common benchmarks are necessary to compare the performance of different code search approaches. Many studies on code search collected their datasets from various sources and incorporated several evaluation metrics. Approaching this direction leads to inconsistencies for fair comparison because their search base has different snippets, and different metrics may indicate different results. Furthermore, different queries for the same task make the retrieved results vary. These problems motivate researchers to build benchmarks for code search using common search bases and metrics or to have the same queries and answer code snippets. Therefore, the ideal benchmarks should provide the dataset, metrics, and sample results that lead the users to a fair comparison in the code search evaluation phase.

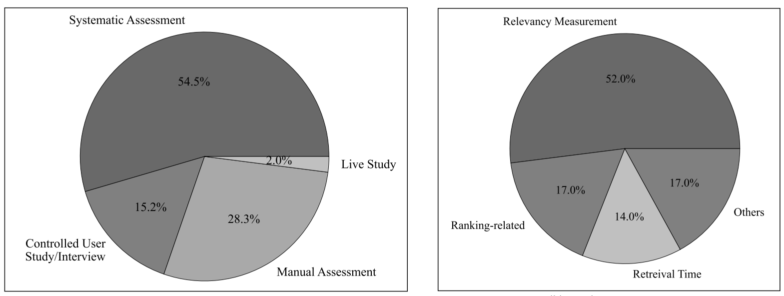
There are several code search benchmarks proposed recently. For instance, Li et al. [145] introduced a benchmark in the field of code search by providing the results of their neural code search approaches [33, 233]. The benchmark consists of a dataset as a natural language query (from Stackoverflow) and code snippet pairs about Android software development (from Github). They further employed two neural code search engines named NCS [233] and UNIF [33] to build the benchmark providing the results. Another benchmark CosBench [301], combines a search base (from GitHub), query and answer pairs (from Stackoverflow), and a set of metrics. To show the usefulness of the benchmark, they employed four IR-based [165, 169, 201, 290] and two learning-based [80, 308] approaches to compare in the evaluation. A recent deep-learning approach [149] has leveraged this benchmark to study user query and source code interactions.

There is another notable benchmark dataset: Project CodeNet [213]. This dataset stands out from other similar datasets as it is exceptionally large, with code samples written in over 50 programming languages. The code samples in Project CodeNet are also extensively annotated, providing information such as code size, memory footprint, and

CPU run time. The dataset also includes benchmarks that potentially can be leveraged to evaluate new code search approaches built upon AI techniques.

7 EVALUATION

Evaluating the performance of the approaches provides an overview of how efficient and accurate the code search engine is compared to others or over a particular dataset. In particular, code search approaches should be evaluated in several different aspects such as the accuracy of the relevancy between the query and retrieved source code, the time consumed for the retrieval, or if the results pass specific test cases. To quantify such aspects, researchers leverage several ways (e.g., systematic assessment or live study) to measure the satisfactory performance of the approaches. This section investigates the different evaluation methods and the metrics used within the code search approaches.



(a) Evaluation methods. (b) Evaluation metrics.

Fig. 6. Distribution of evaluation methods and metrics used in code search studies.

7.1 Evaluation Methods

The evaluation methods are essential when disseminating the results of a particular approach. The research community has invested considerable efforts to find appropriate ways to measure the various performances. Evaluation of classical search engines has been limited towards manual relevancy checks by domain experts [172]. Similarly, code search engines' performance was manually measured (e.g., [96, 236, 274] in the early stage until researchers found out systematic ways to remove the subjective bias. Since then, systematic evaluation methods (e.g., comparison against the state-of-the-art approaches and models) were used to provide a more precise evaluation of the proposed approach [33]. Moreover, other methods such as controlled user study/interview provide opinions and insights from experts, developers, or a more significant portion of people capable of providing adequate evaluation [93, 279]. Recently, with the development forum's high growth, the live study method is being applied to leverage crowd knowledge [253]. Figure 6a presents how many approaches take which evaluation methods and Table 8 of Appendix A demonstrates the details per each approach.

7.1.1 Manual assessment. One of the practical evaluation methods known as *Manual internal assessment* requires the researchers' manual efforts. In this method, the researchers manually validate the results returned by the code search engines, determining their relevance to the user query and assigning a score for each of them. However, this method is known as inefficient and expensive [160] (i.e., the evaluation's manual process is very time-consuming). Furthermore, as the evaluation subjects are usually the authors, it may have a subjective bias.

7.1.2 Systematic assessment. To overcome the potential issues of bias in the manual assessment, researchers undertook a systematic evaluation of the results. The essential systematic evaluation consists of a comparison against other state-of-the-art approaches and models. For example, researchers (e.g., [34, 169, 217]) utilize the dataset (e.g., queries and search space) and configure similar environments (e.g., Computing power, parameters) used in other state-of-the-art. Yet, a significant challenge when conducting the systematic assessment lies in the lack of a replication package of the state-of-the-art [157]. Another challenge is the non-agnostic nature of search engines, i.e., specific target programming languages or different software paradigms. Similarly, the learning-based approaches [33, 80, 233] utilize specific learning models or a combination of models from different approaches to bring new insights into the learning algorithm's characteristics.

7.1.3 Controlled user study/interview. Practical evaluation of a new approach can be challenging as there might not be state-of-the-art techniques available to compare. To address this issue, researchers [141, 169, 177, 282] conducted a *Controlled user study/interview* session that provides researchers with opinions and insights on the approach from real-world users who are likely to be domain experts. As there is no standard or defined process/rule on the number or occupation of involved users, type of queries, or topics, researchers have tried to involve as many users as possible to understand the generic opinions. This type of evaluation can be subjective but the results are acceptable if the evaluation method is designed concretely with solid rationale, and the users are professionals within the software domain. Large industrial entities like Microsoft tend to leverage this method to evaluate their approaches [113].

7.1.4 Live study. The goal of the *Live study* is to evaluate the approach in the real world where any user (professional or otherwise) would use and evaluate the results. These users generally are in the form of utilizing the users of popular developer forums. For example, Sirres et al. [253] took the questions from *StackOverflow* as their testing queries and posted the code snippets from their code search engine CoCaBu as the answer. The public (i.e., developers from *StackOverflow*) judges the questions and answers by voting and commenting in the system. Researchers utilize this method on various platforms (e.g., *StackOverflow* and *GitHub*).

7.2 Evaluation Metrics

There exist several metrics to assess code search engines. We split them into four dimensions: overall performance, ranking, retrieval time, and others (e.g., simple counting, statistical metrics, and user satisfaction). These metrics are adopted for various purposes, such as to measure how the results of a code search engine are relevant for a given query, how fast it can perform, or how much query range it can cover. Figure 6b shows the distribution of the metrics for assessing code search approaches. The overall performance metrics are primarily based on utilizing the confusion matrix. Table 9 of Appendix A illustrates the list of performance metrics mainly used in the code search domain.

Precision [11] concerns multiple codes relevant to a query, while *Mean Average Precision (MAP)* measures the average. *Recall* [11] quantifies the number of correct predictions made out of all positive examples in the dataset. *F-measure* [277] is the harmonic mean of the precision and recall. Similarly, *Normalized Discounted Cumulative Gain (NDCG)* [118] measures the performance considering the recommended candidates' order (weight-based). *Accuracy* [11] is the proportion of correct predictions (both true positives and true negatives) among the total number of cases. *SuccessRate* [11] measures the percentage of queries for which more than one correct result could exist in the results. *ROC curve* [64] is created by plotting the true positive rate against the false-positive rate with various thresholds. Furthermore, two approaches leveraged *False positive and negative rates* to check the errors of the search engine.

The ranking metrics primarily consider the location of the correct answers among the results. Several approaches are evaluated by checking the rank of the correct answers manually. *FRrank* (also known as *best hit rank*) is the rank of the first hit result in the result list [214]. *Rank of the first correct (RFC)* and *Expected Reciprocal Rank (ERR)* are measured to check if the user should review a specific number of results. *Mean Reciprocal Rank (MRR)* [11] is the average of the reciprocal ranks of results for a set of queries. The reciprocal rank of a query is the inverse of the rank of the first hit result. Differently, a paper [22] measured the quality of a candidate ranking against users' opinions to prove the ranking performance. Table 10 of Appendix A shows the ranking metrics utilized within the code search field.

The metrics used to evaluate code search approaches varies based on the context of the approach. Table 11 of Appendix A introduces all the details of the other metrics that have been used within the code search. Other metrics includes *Retrieval Time*, several statistical tests like *Mean Squared Errors (MSE)*, relevancy score-based and measuring metrics such as *Kendall's Correlation Coefficient (KCC)*, *Spearman Correlation Coefficient (SCC)*, *Pearson Correlation Coefficient (PCC)*, *Mann-Whitney U test*). Furthermore, user studies in code search utilized user satisfaction metrics such as *experience score* and *mouse clicks*. Other quality capturing metrics such as *METEOR* score and *BLEU-4*, *Rate of passing the test cases*, *Query Coverage (QC)*, and metrics based on an External library (specifically, `org.eclipse.compare-plug-in`) are also shown to be used in particular code search approaches (e.g., [40, 223, 235])

8 OPEN ISSUES AND POTENTIAL RESEARCH DIRECTIONS

Researchers have put tremendous effort into the field to avoid serving a poor-quality code search engine that can drag developers out, as documented in many published studies. Despite these proposed approaches and advancements, the following open issues we discovered may impede rapid and efficient software development.

Specific Tasks vs. Code Search Techniques: Given a wide variety of existing approaches to each code search procedure, developers may not be sure which one is the best code search technique for their specific tasks. For instance, developers who are new to their field may need a code search engine that can adequately reformulate their queries because of their lack of knowledge. Some developers need a feedback-driven code search engine to address multiple and complex requirements. As another example, code-to-code search approaches can be utilized to refactor the existing code by finding either syntactically or semantically similar code snippets. These task-characteristic pairs should be analyzed, and as a result, the best way to address a specific task remains an open issue.

Vocabulary Mismatch Problem: One of the crucial issues that affect information retrieval, in general, is the vocabulary mismatch problem (VMP). During our review process, we found out that VMP applies to most of the code search techniques as well. Specifically, techniques investigated in multiple Sections (i.e., 5.1, 5.3, and 5.4) focus on addressing this specific problem. VMP states that the likelihood of two people choosing the same keyword for a familiar concept is only between 10-15% [69]. Recently, researchers have focused on addressing this with learning-based techniques, especially to lower the gap between NL and code. However, we observed that the recent results of the approaches indicate that the VMP problem within the code search needs further efforts on tokenization and translation of NL-to-code to improve the retrieval performance.

Benchmarks: A trustworthy conclusion for the code search will be drawn with a high-quality benchmark [12], yet there is a glaring lack of such a benchmark for code search engines. Our investigation on the dataset (Section 6) for evaluations of each technique explicitly revealed there exist many different and individually collected dataset. However, these recent benchmarks also have open issues: 1) these are not validated yet by code search researchers; 2) they focus on learning-based approaches, i.e., classical and learning-based approaches are different; and 3) they still need standard and concrete metrics to test various approaches. Furthermore, other considerations such as different NL queries for a specific set of tasks should provide a similar set of results. Every user has a unique way of describing a problem, especially when representing in NL. Thus, generating a set of techniques that would consider different NL representations for the same set of questions would provide a more normalized set of results.

Extensibility: Software development consists of using multiple different programming languages for developing one full product. Consequently, code search approaches do not always prove to be a good solution because of their limitation on specific programming languages. We substantiate this in our taxonomy and the tables (i.e., Tables 2 to 7 of Section 5) in Appendix A[14] show this information as the last column. The extensibility of code search approaches toward all viable programming languages is an important issue, yet to be addressed in the domain. Note that the literature reviewed in this survey always retrieves/targets one language at a time. Applying a particular search approach to different programming languages (i.e., multi-language) would provide more usefulness and convenience.

Usability: We observed that specific code search approaches such as binary code search are limited in their usability in a real-world scenario while reviewing binary code search approaches in Section 5.5. While finding similar binary code is useful for specific domains such as vulnerability detection, code search is rather severely limited. This is mainly because a majority of the approaches rely on an essential assumption that the binary code is not obfuscated. Furthermore, the rise in compiler-level optimization or even hardware-specific optimization would prevent disassembly techniques from limiting the searching capabilities of code search approaches.

Replicability: Although this survey encompasses many approaches that support code search, most do not have publicly available replication packages. This poses an obstacle for developers who need to apply such an approach. A shared replication package helps developers in two significant ways: (1) a time-efficient way to deploy and test the approach and (2) a reference implementation to check for errors and issues. Re-implementation of an approach is a time-consuming and error-prone task, even if the approach is well-explained. Therefore, sharing source code can improve efficiency in the field of code search.

Multi-modal Query Supported Code Search: Code search techniques can utilize multiple query models. For example, such techniques could allow users to input different formats of queries, e.g., free-form text, query language, and input-output examples, at the same time. The more detailed information the user provides, the higher probability the tool could give accurate recommendations while this direction is not studied by previous studies though according to our taxonomy illustrated in Section 5. Thus, we need a new code search system that can support multi-modal queries and which may bring substantial improvements.

9 CONCLUSION

Through the comprehensive study undertaken in this survey, we expect it to serve as a thorough introduction for the newcomers, helping them familiarize themselves in the field. At the same time, the practitioners can extend their understanding towards identifying techniques based on the context of their exploration. Moreover, existing code search researchers can identify the different contributions and advances made within the different categories. To this end, we undertook a procedure-driven systematic literature review process to identify 137 code search approaches that form the bases of our operational taxonomy. The taxonomy classifies all the approaches to permit a fair comparison and identifies potential future research areas that can be explored. Furthermore, the survey shed light on the existing open issues within the code search, such as the lack of a standard benchmark that provides a fair evaluation between various code search engines. Additionally, the survey establishes the directions that researchers can tackle further in

[14]https://github.com/FalconLK/BigCodeSearch/blob/main/Survey_Appendix.pdf

code search. Finally, our procedure-driven systematic literature review provides analysis on each phase, and it should deliver insights for the overall field.

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A APPENDIX

This section includes supplementary information for our survey and it consists of 14 pages.

A.1 Paper Collection and Review Schema

This section contains a figure for the cumulative number of papers published ranging from 2005 to 2020 and a table for the publication venues of code search studies.

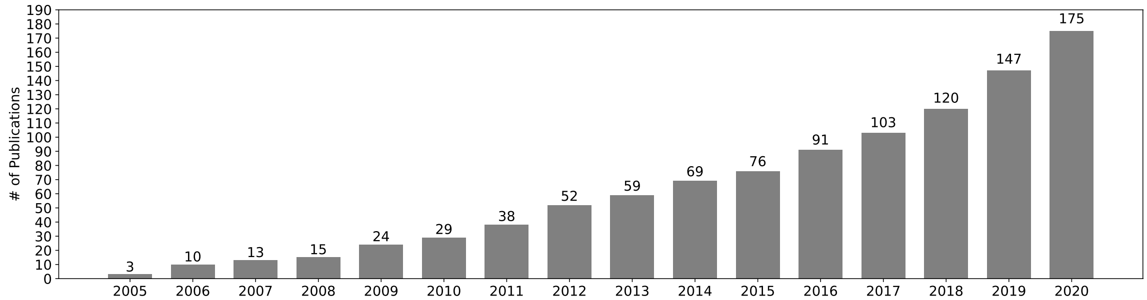

Fig. 7. Cumulative number of papers published ranged from 2005 to 2020.

Table 1. Publication venues of code search studies.

Category	Abbreviation	Full Name	Count
Conference	ICSE	International Conference on Software Engineering	20
	ASE	Automated Software Engineering	13
	MSR	International Conference on Mining Software Repositories	8
	SUITE	Workshop on Search-Driven Development-Users, Infrastructure, Tools and Evaluation	5
	PLDI	ACM SIGPLAN Conference on Programming Language Design and Implementation	4
	OOPSLA	Object-Oriented Programming, Systems, Languages & Applications	4
	RSSE	International Workshop on Recommendation Systems for Software Engineering	4
	SANER	IEEE International Conference on Software Analysis, Evolution and Reengineering	3
	COMPSAC	Annual Computer Software and Applications Conference	3
	CSMR-WCRE	IEEE Conference on Software Maintenance, Reengineering, and Reverse Engineering	3
	ESEC/FSE	European Software Engineering Conference and Symposium on the Foundations of Software Engineering	2
	SAC	ACM Symposium on Applied Computing	2
	WWW	The World Wide Web Conference	2
	SBES	Brazilian Symposium on Software Engineering	2
	SCAM	International Working Conference on Source Code Analysis & Manipulation	2
	VL/HCC	Visual Languages and Human-Centric Computing	2
	ISSTA	International Symposium on Software Testing and Analysis	1
	MAPL	ACM SIGPLAN International Workshop on Machine Learning and Programming Languages	1
	FASE	International Conference on Fundamental Approaches to Software Engineering	1
	RecSys	ACM Conference on Recommender Systems	1
	ACIIDS	Intelligent Information and Database Systems	1
	UIST	ACM Symposium on User Interface Software and Technology	1
	WEH	International Workshop on Exception Handling	1
	SBCARS	Brazilian Symposium on Software Components, Architectures, and Reuse	1
	ACL	Annual Meeting of the Association for Computational Linguistics	1
	ICoICT	International Conference on Information and Communication Technology	1
	WSDM	ACM International Conference on Web Search and Data Mining	1
	ICCIT	International Conference on Computer and Information Technology	1
	CCS	ACM SIGSAC Conference on Computer and Communications Security	1
	RCoSE	International Workshop on Rapid Continuous Software Engineering	1
	Programming	International Conference on the Art, Science and Engineering of Programming	1
	Internetware	Asia-Pacific Symposium on Internetware	1
	MOBILESoft	International Conference on Mobile Software Engineering and Systems	1
	IWSC	International Workshop on Software Clones	1
	SERVICES	IEEE World Congress on Services	1
	ASC	ACM Southeast Conference	1
	ICSEW	International Conference on Software Engineering Workshops	1
	IJCNN	International Joint Conference on Neural Networks	1
	CIRCLE	CEUR Workshop	1
		Subtotal (Conference)	102
Journal	TSE	Transactions on Software Engineering	3
	EMSE	Empirical Software Engineering	3
	JSS	Journal of Systems and Software	3
	IEEE Access	IEEE Access	3
	SPE	Practice and Experience	3
	TOSEM	Transactions on Software Engineering and Methodology	2
	ASE_Journal	Automated Software Engineering Journal	2
	IST	Information and Software Technology	2
	TSC	IEEE Transactions on Services Computing	2
	SCIS	Science China Information Sciences	2
	JIFS	Applications in Engineering and Technology	1
	ISF	Information Systems Frontiers	1
	JPCS	Conference Series	1
	PACMPL	ACM on Programming Languages	1
	IEEE Software	IEEE Software	1
	KBS	Knowledge-Based Systems	1
	KIES	International Journal of Knowledge-based and Intelligent Engineering Systems	1
	WUJNS	Wuhan University Journal of Natural Sciences	1
	JIT	Journal of Internet Technology	1
	SEKE	International Journal of Software Engineering and Knowledge Engineering	1
		Subtotal (Journal)	35
		Total	137

A.2 Taxonomy of Code Search Techniques

This section presents detailed information reflecting the proposed taxonomy. Each table classifies all the investigated techniques based on their characteristics.

Table 2. Dissection of code search techniques based on static information.

Category	Approach	Output		Dataset					Indexing				Input							Retrieval					Presentation			Languages
		General Code	API Usage	Specific Open Source Projects	Super Repositories	Developer Q&A	Language/API Documentation	Others	Inverted	Database (B+ Tree)	Graph Index	File Prefix	Natural Language	Code Fragment	Input/Ouput	Software Specification	Query Language	Binary	Class/Interface Type	Textual Similarity	Graph Similarity	Solver	Type Links	Embedding Vector Similarity	Search Engine	Idea	IDE Extension	
Keyword-based	Jsearch [251]	3									3			3						3							3	Java
	CoCaBu [253]	3			3	3			3				3							3					3			Java
	Murakami et al. [192]	3		3						3				3						3						3		Java
	McMillan et al. [183]		3	3					3				3							3					3			Java
	Exemplar [77, 78, 180]	3			3				3				3							3					3			Java
	Example Overflow [311]	3				3			3				3							3					3			Java
	Selene [191, 272]	3		3					3					3						3					3		3	Java
	SoCeR [114]	3		3					3				3							3				3	3			Python
Structure-based	Aroma [166]	3			3					3				3							3			3	3			Java, Javascript, Python
	Prospector [171]	3					3												3		3						3	Java
	Portfolio [45, 181, 184]	3		3					3				3							3	3				3			C, C++, Java
	XSnippet [236]	3					3			3									3		3						3	Java
	PARSEWeb [274]	3				3	3					3							3		3						3	Java
	Chan et al. [36]		3	3							3		3							3	3				3			Java
	RACS [151]		3	3		3	3			3			3							3	3				3			Javascript
	YOGO [212]	3				3				3				3							3				3			Python, Java
	Akhin et al. [4]	3		3							3			3							3					3		
	Coogle [235]	3		3										3							3						3	Java
	Mendel [163]	3		3										3							3				3			
	Hsu and Lin. [100]	3			3				3				3							3					3			Java
	Sourcerer [12]	3			3				3				3							3					3			Java
	Murakami et al. [192]	3		3						3				3						3						3		Java
	Barbosa et al. [17, 18]	3			3					3				3						3					3			Java
	AUSearch [10]		3		3												3						3		3			Java
	MAPO [296]	3	3										3							3					3			Java
	SUSHI [198]	3						3						3				3		3				3	3			Android
	PropER-Doc [173]		3	3												3							3				3	Java
	PRIME [186]	3	3	3									3							3					3			Java
	LibFinder [206]	3			3									3										3			3	Java
	SWIM [214]	3	3		3								3							3					3			C#
	APIREC [194]	3	3											3						3	3						3	Java
	Lee et al. [140]		3		3								3							3							3	Java
Interface-driven	Strathcona [95–97]									3				3					3								3	
	Lemos et al. [144]	3			3					3			3						3	3					3			Java
Semantic-based	ANNE [279]	3				3							3							3					3		3	Java
	CodeMatcher [159]	3			3				3				3							3					3			
	Hill et al. [92]	3		3									3							3					3			Java
	JECO [9]	3				3							3							3					3			Java
	Vinayakarao [278]	3				3				3				3						3						3		Java
	McMillan et al. [182]	3			3					3			3							3					3			Java, C#
	Lancer [315]	3			3					3				3						3	3						3	Java
	Test Recommender [209]	3		3						3				3						3							3	Java
Constraint-based	Satsy [260–262]	3		3					3					3	3							3			3	3		Java, C
	Extended Satsy [263]	3		3					3		3				3	3					3	3			3			Java
	Quebio [121]	3			3									3	3						3	3			3			Java
	Extended Quebio [43]	3			3	3							3		3					3		3			3			Java
Clone-based	Keivanloo et al. [127]	3			3				3											3					3			
	CodeNuance [162]	3			3				3											3								
	Rahman and Roy [218]	3			3				3					3							3						3	Java
	MUSE [188]		3	3																	3						3	Java

Table 3. Dissection of code search techniques based on dynamic information.

Category	Approach	Output		Dataset		Index			Input						Retrieval				Presentation			Language
		General Code	Test Case/Test Code	Specific Open Source Projects	Super Repositories	Database (B+ Tree)	Graph Index	File Prefix	Natural Language	Code Fragment	Query Language	Test Case	Class/Interface Type	Software Specification	Textual Similarity	Graph Similarity	Test Case/Tested Input	Linear Programming	Search Engine	Idea	IDE Extension	
Test-driven	CodeGenie [137–139, 141]	3				3				3						3					3	Java
	Lemos et al. [143]	3			3	3				3					3						3	Java
	Code Conjurer [111, 117]		3			3				3					3						3	Java
	EQMINER [120]		3	3				3		3						3	3		3			C
	S6 [28, 29, 223–226]					3			3					3		3			3			Java
	Marcus and Atkinson [129]	3			3	3				3							3			3		
	HUNTER [287]	3			3	3					3	3						3	3			Java
Execution-based	CodeHint [71]	3		3		3								3	3						3	Java
	DyCLINK [265]	3		3			3			3						3					3	MYSQL

Table 4. Dissection of code search techniques based on query reformulation.

Category	Approach	Output		Database						Index				Input			Retrieval				Presentation			Language
		General Code	API Usage	Specific Open Source Projects	Super Repositories	Developer Q&A or Tutorial	Language/API Documentation	Code Clone	Challenge/Competition	Inverted	Database (B+ Tree)	ID-based	Positional	Natural Language	Code Fragment	Query Language	Textual Similarity	Matrix Computation	Graph Similarity	Embedding Vector Similarity	Search Engine	Idea	IDE Extension	
Feedback-driven	Mica [264]		3	3			3			3				3			3				3			Java
	SAS [1]		3		3									3			3				3			Java
	Conquer [230]	3		3										3			3						3	Java
	Extended Conquer [93]	3		3										3			3						3	Java
	Wang et al. [284]	3		3										3			3				3			C,C++
	CodeExchange [177]	3			3					3				3			3				3			Java
	CodeLikeThis [176]	3			3					3				3			3				3			Java
	INQRES [164]	3		3										3			3				3			Java
	Cosoch [150]	3				3								3			3				3			Java
	Contextual Search [91]	3			3									3			3						3	Java
	Refoqus [85]	3		3						3				3			3						3	Java, C++
	ALICE [255]	3		3										3		3				3			3	Java
	SNIPR [239]													3		3	3					3		
	DeepAPIRec [39]		3		3										3					3	3			Java
AQR *dagger*	QECK [201]	3			3	3				3				3			3				3			Android
	Yang et al. [302]	3		3										3			3				3			Java
	Durão et al. [61]	3		3								3		3			3						3	Java
	NLP2CODE [34]	3	3			3								3			3						3	Java
	SCP [254]	3		3									3	3			3				3			Java, C, C++
	QExpandator [241]	3		3										3				3			3			Java
	FWSMF [242]	3		3						3				3			3				3			Java
	CodeX [240]	3		3						3				3			3					3		N/A
	SnippetGen [105, 294, 304]	3			3					3				3			3				3			C#
	CodeGenie 2.0 [142]	3			3					3				3			3						3	Java
	CoCaBu [253]	3			3	3				3				3			3				3			Java
	FaCoY [133]	3			3	3		3	3	3					3		3				3			Java
	CodeHow [169]	3			3					3				3			3						3	C#
	RACK [220, 221]	3			3	3	3							3			3						3	Java
	NLP2API [216]	3				3				3				3						3	3			Java
	NQE [160]	3			3	3				3				3						3	3			Android
	SENSORY [2]	3			3							3		3			3				3			Java
	QESR [122]	3			3		3			3				3			3				3			Android, Java
	QECC [109]	3			3					3				3			3				3		3	Java
	GKSR [107]	3			3					3				3			3				3			C#, Java, Android
	QESC [108, 317]	3			3		3			3				3			3				3			Java
QL †	AutoQuery [282]	3		3							3				3				3		3			C, C++
	SnipMatch [292]	3		3										3			3						3	Java

†: AQR and QL are short terms for Automatic Query Reformulation and Query Language based, respectively.

Table 5. Dissection of learning-based code search techniques.

Category	Approach	Output		Dataset							Index		Input		Retrieval				Presentation			Language
		General Code	API Usage	Specific Open Source Projects	Super Repositories	Developer Q&A	Language/API Documentation	Code Clone	Challenge/Competition	Existing Benchmark	Inverted	Graph Index	Natural Language	Code Fragment	Textual Similarity	Graph Similarity	Matrix Computation	Embedding Vector Similarity	Search Engine	Idea	IDE Extension	
	MMMF [291]	3		3										3			3		3			Java
	Surisetty [268]	3		3							3		3					3		3		
	ROSF [119]	3		3							3		3		3			3	3			Java
	Source Forager [124]	3			3							3		3				3			3	C/C++
Machine Learning	Zou et al. [318]	3				3	3					3	3					3	3			Java
	CodeKernel [81]		3	3			3					3		3				3	3			Java
	CODEC [190]	3			3									3	3	3		3	3			Java
	ExAssist [197, 199]	3		3										3	3				3		3	Java
	CodeMF [102]	3				3							3		3				3			C#, SQL
	Nguyen et al. [200]		3	3			3						3		3			3	3			Java
	CODEnn [80]	3			3								3					3	3			Java
	MP-CAT [86]	3				3							3					3	3			Python
	CSDA [228]	3			3								3					3	3			Java
	CARLCS-CNN [246]	3			3								3					3	3			Java
	BVAE [42]	3				3							3					3	3			C#, SQL
	SCOR [3]	3			3						3		3					3	3			Java
	SLAMPA [316]	3						3						3				3	3			Java
	SCS [112]	3		3									3					3	3			Python
	NCS [233]	3			3	3					3		3					3	3			Android
	UNIF [33]	3			3	3					3		3					3	3			Android
	Fujiwara et al. [68]	3						3						3				3	3			Java
	MMAN [280]	3			3								3					3	3			C
	AdaCS [154]	3			3								3					3	3			Java
	CoaCor [305]	3				3							3					3	3			Python, C#
	CODE-NN [115]	3				3							3		3				3			C#, SQL
Neural Network	Ye et al. [307]	3				3							3					3	3			Python, SQL
	TranS^3 [285]	3			3								3					3	3			Python
	Yin et al. [309]	3				3							3					3	3			Python, SQL
	CDRL [104]	3			3								3					3	3			Java
	Schumacher et al. [243]	3			3								3					3	3			Python
	HECS [146]	3				3							3					3	3			Python, C#
	MSR [59]	3		3									3		3			3	3			Java
	PSCS [267]	3							3				3					3	3			Python, Javascript, Java
	Heyman and Cutsem [89]	3				3							3					3	3			Python
	COIL [149]	3			3					3			3					3	3			Java
	CoNCRA [52]	3				3							3					3	3			Python, SQL
	COSEA [281]	3				3							3					3	3			Python, SQL
	DGMS [155]	3			3	3			3	3			3					3	3			Java, Python
	APIRec-CST [40]		3		3		3						3						3			Java
	Zhao et al. [314]	3				3							3					3	3			Python, SQL
	CRaDLe [79]	3							3				3					3	3			Python
	NJACS [103]	3				3							3					3	3			C#, SQL, Java, Python

Table 6. Dissection of binary code search techniques.

Approach	Output	Dataset			Index		Input	Retrieval				Presentation	Language
	Binary Code	Specific Open Source Projects	Super Repositories	Others	Inverted	Graph Index	Binary	Textual Similarity	Graph Similarity	Execution Trace	Embedding Vector Similarity	Search Engine	
Tracelets [49]	3		3		3		3		3	3		3	Binary (x86)
Rendezvous [130]	3			3	3	3	3	3		3		3	C, C++
BINGO [37]	3			3			3		3	3		3	Binary C
BINGO-E [300]	3			3			3		3	3		3	Binary C
Gemini [299]	3	3				3	3				3	3	Binary C

Table 7. Dissection of code search for graphical user interfaces.

Approach	Input	Dataset		Index			Input			Retrieval		Presentation		Language
	Sketches/GUI	Specific Open Source Projects	Super Repositories	Inverted	Database (B+ Tree)	Graph Index	Sketch File	Natural Language	Code Fragment	Textual Similarity	Graph Similarity	Search Engine	IDE Extension	
GUIFetch [22]	3		3		3		3	3		3		3		Java GUI
SUSIE [227]	3		3					3	3	3		3		Java GUI
Xie et al. [297]	3	3		3		3	3			3	3		3	Java GUI

A.3 Evaluation

This section demonstrates various evaluation methods and metrics used in the field of code search per each approach with tables.

Table 8. Evaluation methods used in code search techniques.

Evaluation Method	Techniques
Manual assessment	Prospector [171], Strathcona [95–97], Jsearch [251], XSnippet [236], Coogle [235], PARSEWeb [274], Contextual Search [91], McMillan et al. [183], Wang et al. [286], Selene [191, 272], PropER-Doc [173], Exemplar [77, 78, 180], Example Overflow [311], Mentor [170], Barbosa et al. [17, 18], Chan et al. [36], Yang et al. [302], PRIME [186], SCP [254], CodeHint [71], CodeGenie 2.0 [142], Tracelets [49], Keivanloo et al. [127], JECO [9], Vinayakarao [278], RACS [151], CODE-NN [115], SWIM [214], BINGO [37], QualBoa [57], FWSMF [242], Source Forager [124], LibFinder [206], Gemini [299], CoCaBu [253], FaCoY [133], SLAMPA [316], Quebio [121], GUIFetch [22], CodeNuance [162], ALICE [255], ExAssist [197, 199], BINGO-E [300], Xie et al. [297], Huang et al. [110], SoCeR [114], YOGO [212], CodeMatcher [159], CODEC [190], Extended Quebio [43], AUSearch [10]
Systematic assessment	Strathcona [95–97], XSnippet [236], PARSEWeb [274], Example Overflow [311], Chan et al. [36], Yang et al. [302], SCP [254], Keivanloo et al. [127], CODE-NN [115], LibFinder [206], Gemini [299], CoCaBu [253], FaCoY [133], SLAMPA [316], BINGO-E [300], Xie et al. [297], CodeMatcher [159], CODEC [190], Extended Quebio [43], CodeGenie [137–139, 141], SNIFF [38], S6 [223–225], MMMF [291], Hill et al. [92], Hsu et al. [100], Portfolio [45, 181, 184], Wang et al. [283], McMillan et al. [182], Satsy [260–262], Rahman and Roy [218], Lemos et al. [144], CodeHow [169], DyCLINK [265], QECK [201], QExpandator [241], ROSF [119], Extended Satsy [263], APIREC [194], Niu et al. [203], CodeLikeThis [176], NLP2CODE [34], SnippetGen [105, 294, 304], RACK [220, 221], INQRES [164], NLP2API [216, 217], QECC (InstaRec) [109], Zou et al. [318], CODEnn [80], BVAE [42], NCS [233], Lee et al. [140], Lancer [315], Aroma [166], Cosoch [150], NQE [160], SENSORY [2], QESR [122], GKSR [107], QESC [108, 317], CodeKernel [81], SCOR [3], UNIF [33], MMAN [280], CoaCor [305], Yin et al. [309], CodeMF [102], CSDA [228], CARLCS-CNN [246], AdaCS [154], Ye et al. [307], TranS^3 [285], CDRL [104], HECS [146], MSR [59], PSCS [267], COIL [149], COSEA [281], DGMS [155], APIRec-CST [40], Zhao et al. [314], CRaDLe [79], NJACS [103], CodeGenie 2.0 [142], RACS [151], Source Forager [124], ALICE [255], Sourcerer [12], Durão et al. [61], APPROX [20], Lemos et al. [143], Rendezvous [130], Extended Conquer [93], ANNE [279], Nguyen et al. [200], DeepAPIRec [39], Li et al. [152], PCR [196], MP-CAT [86], Schumacher et al. [243], Heyman et al. [89], CoNCRA [52]
Controlled user study/interview	XSnippet [236], LibFinder [206], CoCaBu [253], CodeGenie [137–139, 141], Portfolio [45, 181, 184], McMillan et al. [182], CodeHow [169], QECK [201], QExpandator [241], Niu et al. [203], CodeLikeThis [176], NLP2CODE [34], INQRES [164], CodeKernel [81], Exemplar [77, 78, 180], GUIFetch [22], CodeNuance [162], ALICE [255], SnipMatch [292], Wang et al. [284], Test Recommender [209], CodeExchange [177], MUSE [188], AutoQuery [282], HUNTER [287]
Live study	CoCaBu [253], SnipMatch [292], CodeExchange [177], TranS^3 [285]

Table 9. Relevancy metrics used for evaluating code search techniques.

Metric	Techniques
Precision	Durão et al. [61], MMMF [291], Hill et al. [92], Portfolio [45, 181, 184], Exemplar [77, 78, 180], Mentor [170], Chan et al. [36], McMillan et al. [182], Yang et al. [302], Satsy [260–262], Rendezvous [130], Keivanloo et al. [127], Rahman and Roy [218], JECO [9], Vinayakarao [278], AutoQuery [282], FWSMF [242], Zou et al. [318], SLAMPA [316], ALICE [255], CodeKernel [81], SoCeR [114], AUSearch [10]
Precision@k	Satsy [260–262], SCP [254], QECK [201], QExpandator [241], ROSF [119], Extended Satsy [263], BINGO [37], SnippetGen [105, 294, 304], LibFinder [206], CoCaBu [253], FaCoY [133], QECC (InstaRec) [109], CODEnn [80], Lee et al. [140], SENSORY [2], SCOR [3], CodeMatcher [159], CODEC [190], CDRL [104], HECS [146], MSR [59], COSEA [281]
MAP	SCP [254], Extended Satsy [263], QualBoa [57], Source Forager [124], SCOR [3], Zhao et al. [314]
MAP@k	Rahman and Roy [218], RACK [220, 221], NLP2API [216, 217], QESR [122], GKSR [107], QESC [108, 317], COIL [149]
Recall	Strathcona [95–97], Sourcerer [12], Durão et al. [61], MMMF [291], Hill et al. [92], Selene [191, 272], Mentor [170], Chan et al. [36], Yang et al. [302], Satsy [260–262], Rendezvous [130], CodeGenie 2.0 [142], Rahman and Roy [218], JECO [9], Vinayakarao [278], Lemos et al. [144], AutoQuery [282], FWSMF [242], FaCoY [133], Zou et al. [318], SLAMPA [316], ALICE [255], CodeKernel [81]
Recall@k	SCP [254], LibFinder [206], NLP2API [216, 217], QECC (InstaRec) [109], CODEnn [80], Aroma [166], SCOR [3], CodeMatcher [159], CodeMF [102], MP-CAT [86], CARLCS-CNN [246], HECS [146], Heyman et al. [89], CRaDLe [79], NJACS [103]
Accuracy	Tracelets [49], Rahman and Roy [218], DeepAPIRec [39], NQE [160], Schumacher et al. [243]
Accuracy@k	SWIM [214], APIREC [194], Nguyen et al. [200], LibFinder [206], INQRES [164], Yin et al. [309], PCR [196], CoNCRA [52], APIRec-CST [40]
SuccessRate	Jsearch [251], HUNTER [287], CodeNuance [162], PSCS [267]
SuccessRate@k	RACS [151], RACK [220, 221], NLP2API [216, 217], CODEnn [80], SLAMPA [316], Lancer [315], MMAN [280], Li et al. [152], CODEC [190], CSDA [228], AdaCS [154], TranS^3 [285], CDRL [104], COIL [149], DGMS [155]
NDCG	Exemplar [77, 78, 180], Wang et al. [284], Extended Satsy [263], SnippetGen [105, 294, 304], Ye et al. [307], TranS^3 [285], COSEA [281], Zhao et al. [314]
NDCG@k	Wang et al. [284], QECK [201], ROSF [119], Niu et al. [203], RACK [220, 221], QECC (InstaRec) [109], Cosoch [150], SENSORY [2], QESR [122], GKSR [107], QESC [108, 317], Li et al. [152], MSR [59]
F-Measure	Durão et al. [61], Contextual Search [91], MMMF [291], Hill et al. [92], Chan et al. [36], Rendezvous [130], AutoQuery [282], ALICE [255], CodeKernel [81]
ROC Curve	Tracelets [49], Gemini [299], Quebio [121]
Sensitivity	EQMINER [120], Extended Satsy [263]

Table 10. Ranking metrics used for evaluating code search techniques.

Metric	Techniques
MRR	Strathcona [95–97], CodeHow [169], CODE-NN [115], Extended Satsy [263], CoCaBu [253], Zou et al. [318], CODEnn [80], BVAE [42], SLAMPA [316], Lancer [315], Cosoch [150], NQE [160], UNIF [33], MMAN [280], CoaCor [305], Yin et al. [309], CodeMatcher [159], CODEC [190], CodeMF [102], MP-CAT [86], CARLCS-CNN [246], AdaCS [154], Ye et al. [307], TranS^3 [285], CDRL [104], HECS [146], PSCS [267], Heyman et al. [89], CoNCRA [52], COSEA [281], DGMS [155], APIRec-CST [40], CRaDLe [79], NJACS [103]
MRR@k	RACK [220, 221]NLP2API [216, 217], CSDA [228], COIL [149]
FRank	PARSEWeb [274], XSnippet [236], SNIFF [38], McMillan et al. [183], Example Overflow [311], SWIM [214],BINGO [37], Quebio [121], CODEC [190], CodeMF [102], CSDA [228], HECS [146]
FRank@k	UNIF [33]
Simple Rank	Prospector [171], PRIME [186], BINGO [37], Huang et al. [110]
ERR	Niu et al. [203]
Significance & cohesiveness	PropER-Doc [173], GUIFetch [22]

Table 11. Supplementary metrics used for evaluating code search techniques.

Metric type	Metric	Approach
Statistical test	Correlation analysis	GUIFetch [22], SCOR [3], Xie et al. [297]
	Mean Squared Error	Xie et al. [297]
	Hypothesis test	Contextual Search [91], Portfolio [45, 181, 184], Exemplar [77, 78, 180], McMillan et al. [182], Lemos et al. [143], SCP [254], Wang et al. [284], CodeGenie 2.0 [142], Lemos et al. [144], CodeExchange [177], MUSE [188], CODE-NN [115], Niu et al. [203], ANNE [279], CodeLikeThis [176], LibFinder [206], QESC [108, 317]
User satisfaction	Experience score	CodeHint [71], Extended Conquer [93], Test Recommender [209], CodeExchange [177], CodeHow [169], MUSE [188], ANNE [279], CodeLikeThis [176], NLP2CODE [34]
	Mouse click	Example Overflow [311]
Counting	Absolute matching	Code Conjurer [111, 117], PRIME [186], Lemos et al. [144], DyCLINK [265], Quebio [121], GUIFetch [22], YOGO [212], Schumacher et al. [243]
	Top k recommendation	INQRES [164], NCS [233], NQE [160], ExAssist [197, 199], BINGO-E [300], Extended Quebio [43]
Time	Retrieval/implementation time	Prospector [171], Jsearch [251], XSnippet [236], CodeGenie [137–139, 141], Code Conjurer [111, 117], S6 [223–225], Wang et al. [286], APPROX [20], Wang et al. [283], SnipMatch [292], Chan et al. [36], Satsy [260–262], Rendezvous [130], CodeHint [71], Tracelets [49], CodeExchange [177], AutoQuery [282], HUNTER [287], DyCLINK [265], Extended Satsy [263], SWIM [214], APIREC [194], ANNE [279], Source Forager [124], LibFinder [206], Gemini [299], Quebio [121], CodeNuance [162], Lancer [315], Aroma [166], DeepAPIRec [39], BINGO-E [300], Li et al. [152], CodeMatcher [159], CODEC [190], MP-CAT [86], AdaCS [154], PSCS [267], APIRec-CST [40], Extended Quebio [43]
Other metrics	External library	Coogle [235]
	Rate of passing test cases	S6 [223–225], APIRec-CST [40]
	BLEU	BVAE [42], CoaCor [305]
	METEOR	BVAE [42]
	QC (Query Coverage)	CodeGenie 2.0 [142], Keivanloo et al. [127]