Source Forager: A Search Engine for Similar Source Code

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Abstract—Developers spend a significant amount of time searching for code—e.g., to understand how to complete, correct, or adapt their own code for a new context. Unfortunately, the state of the art in code search has not evolved much beyond text search over tokenized source. Code has much richer structure and semantics than normal text, and this property can be exploited to specialize the code-search process for better querying, searching, and ranking of code-search results.

We present a new code-search engine named Source Forager. Given a query in the form of a C/C++ function, Source Forager searches a pre-populated code database for similar C/C++ functions. Source Forager preprocesses the database to extract a variety of simple code features that capture different aspects of code. A search returns the k functions in the database that are most similar to the query, based on the various extracted code features.

We tested the usefulness of Source Forager using a variety of code-search queries from two domains. Our experiments show that the ranked results returned by Source Forager are accurate, and that query-relevant functions can be reliably retrieved even when searching through a large code database that contains very few query-relevant functions.

We believe that Source Forager is a first step towards much-needed tools that provide a better code-search experience.

Index Terms—code search, similar code, program features.

I. INTRODUCTION

In this age of software proliferation, it is useful to be able to search large source-code corpora effectively for code with desired properties.1 Developers routinely use code search as a learning and debugging tool for tasks such as looking for existing functionality in a code base, determining how to use an API or library, gathering information about what code is intended to do, etc. [11].

Text-based search techniques are not always precise enough for code because they focus purely on strings in the code: comments, complete or partial names of functions and variables, and so on. Text search largely ignores code structure and semantics (i.e., what the code does and how it does it). A text-based approach can cause searching to be imprecise: relevant code fragments may be missed, while many spurious matches may be returned. Recent search techniques allow users to specify certain aspects of code semantics in addition to the textual query [2]–[8]. Some techniques allow users to specify structural requirements, such as that the search target should have nested loops. Others specify context, such as that the search target should implement a particular interface. Yet others specify sets of input/output pairs.

Additional semantic information can improve search accuracy. However, existing techniques share the following shortcomings:

• The techniques do not provide a unified way of specifying semantics for the search query. Each technique has its own ad-hoc specification of the semantic aspects of the code that it uses.

• Each technique is closely married to its chosen semantic aspect, which is deeply ingrained into the implementation of the search technique. This tight coupling makes it hard to extend these techniques to model additional semantic aspects.

We propose a search technique for finding similar source code that addresses these shortcomings:

• **Unified Query Specification.** Our code-search mechanism takes code fragments as queries. Various kinds of semantic information can be extracted from the query and used by the search. This approach provides a unified mechanism for code search: searching code using code fragments. Moreover, the same techniques for extracting semantic information are used on both queries and elements of the corpus being searched, leading to greater consistency.

• **Extensibility.** Our code-search technique uses a vector of feature-observations extracted from elements in the corpus. Feature-observations capture various aspects of the syntax and semantics of a program (each such aspect is called a feature-class), and provide a unified interface for querying. This approach also makes our search technique extensible: it is easy to introduce more feature-classes that model additional aspects of the code.

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1 In this paper, the term “search” is used in the sense of Google search—namely, to retrieve documents that are related to a specified query. The term is not used in the sense of finding an occurrence of a user-specified string or pattern in a given document.
The ability to find other code similar to a query can help which Source Forager can reason about are called program code database, and an online query-search phase. Source Forager has two stages: an offline phase to populate its functions. C/C++ functions; that is, both queries and results are C/C++ elements

A code-search architecture that uses multiple code feature-classes to be employed in code search of a given query, given no a priori domain information about the query.

The main contributions of Source Forager are:
- The ability to perform C/C++ code searches using code fragments as queries. The searches and answers of Source Forager are both based on a query formalism that is close to the concepts that developers are already familiar with.
- A code-search architecture that uses multiple code feature-classes simultaneously. The architecture is extensible, allowing easy addition of new code feature-classes, which enhances the dimensions along which code is searched.
- A mechanism for automatically selecting useful code feature-classes to be employed in code search of a given query, given no a priori domain information about the query.
- A supervised-learning technique to pre-compute the relative importance of different feature-classes, when it is known that a query belongs to a specific domain for which suitable training data is available.

Organization: The remainder of the paper is organized into four sections: §II gives an overview of our approach and algorithms. §III describes our different feature-classes in detail. A feature-observation is some specific value observed for a given feature-class. Thus, each function has one feature-observation for each feature-class. For example, one of our feature-classes is Numeric Literals. The corresponding feature-observation is the set of all the numeric constants used in the function. For the binary-search implementation code given in Fig. 2, the Numeric Literals feature-observation is the set \{-1, 0, 1, 2\}.

A feature extraction engine consists of several feature extractors, which collect a given function’s feature-observations into a feature-vector. Note that the elements of the feature-vector can be non-numeric, such as sets, multisets, trees, maps, etc. The number of feature-classes determines the length of the feature-vector.

The feature extractors operate on a code corpus, and populate a code database. Each element of the code database consists of a C/C++ function from the corpus along with its extracted feature-vector. If Numeric Literals is employed as one of the feature-classes, then one element of a function’s feature-vector is the set of numeric constants.

The code database also has access to several similarity functions, one for each feature-class. The similarity function for a given feature-class takes any two feature-observations belonging to that feature-class and returns a value between 0.0 and 1.0. A higher value indicates greater similarity between two feature-observations. For example, the similarity function for Numeric Literals is the Jaccard index. Given two sets $S_1$ and $S_2$, the Jaccard index is given by:

$$sim_{jaccard}(S_1, S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|}. \quad (1)$$

Fig. 1 provides an architectural overview of Source Forager. Source Forager has two stages: an offline phase to populate its code database, and an online query-search phase.

In addition to being useful on its own right as a developer tool, similar-code search can serve as an important building block for automated program repair and program synthesis. The ability to find other code similar to a query can help automated tools learn from the similar code, and fix bugs or perform code completion tasks on the query.

Fig. 2. Example program that implements a binary search over a sorted integer array

```c
int binsearch(int x, int v[], int n) {
    int low, high, mid;
    low = 0;
    high = n - 1;
    while (low <= high) {
        mid = (low + high) / 2;
        if (x < v[mid]) {
            high = mid - 1;
        } else if (x > v[mid]) {
            low = mid + 1;
        } else {
            /* found match */
            return mid;
        }
    }
    return -1; /* no match */
}
```
int bins(int key, int array[], int min, int max) {
    if (max < min) {
        return KEY_NOT_FOUND;
    }
    else {
        int midpoint = (int)floor((min+max)/2);
        if(array[midpoint] < key) {
            return bins(key, array, midpoint+1, max);
        } else if(array[midpoint] > key) {
            return bins(key, array, min, midpoint-1);
        } else {
            return midpoint;
        }
    }
}

Fig. 3. Example Source Forager code-search result for the query in Fig. 2. This result is a recursive implementation of binary search.

B. Online Phase: Search for Similar Code

In the online search phase, Source Forager takes a query and uses the same feature-extraction infrastructure to obtain the feature-vector that corresponds to the query. This infrastructure re-use creates a consistent representation and view of code throughout the code-search infrastructure. For each feature-class in the feature-vector, a weight is assigned to determine the importance of that feature-class. This feature-class weight determination is based on which configuration Source Forager is run with; sections III-B, III-C and IV-B provide an overview of the different configurations.

A combined similarity function is defined on any two feature-vectors by combining the per-feature-class similarity functions with the per-feature-class weight assignment using a weighted average. That is,

$$sim_{combined}(\vec{A}, \vec{B}) = \frac{\sum_{c=1}^{n_c} sim_c(\vec{A}_c, \vec{B}_c) \cdot w_c}{\sum_{c=1}^{n_c} w_c},$$

(2)

where $\vec{A}$ and $\vec{B}$ are two feature-vectors; $n_c$ is the total number of feature-classes (i.e., the length of each feature-vector); $sim_c$ is the similarity function for feature-class $c$; $\vec{A}_c$ and $\vec{B}_c$ are the feature-observations for feature-class $c$ in $\vec{A}$ and $\vec{B}$, respectively; and $w_c$ is the weight assigned to feature-class $c$.

The feature-vector of the query is compared with each of the feature-vectors in the code database using this combined similarity function, and the $k$ most-similar results (for some configurable limit $k$) are returned as results. Fig. 3 shows an example Source Forager code-search result when the code in Fig. 2 is used as query.

We have two implementations of Source Forager. The first one is a slower-performing version, in which the code database is implemented as a large, in-memory JSON object, and the various similarity functions and the algorithm for $k$-most-similar function-search are implemented in Python. This implementation allows for easier and quicker experimentation with new ideas. We use this version for the experiments reported in IV.

The second implementation integrates our infrastructure with Pliny-DB [10], which is an in-memory object-store database implemented in C++. The feature-observations in feature-vectors are serialized into efficient in-memory data structures by Pliny-DB. Pliny-DB has access to similarity functions implemented in C++ for all feature-classes. It implements the search for the $k$ most similar to the query by (1) scanning all the feature-vectors in the database, (2) comparing each of them to the query feature-vector, and (3) maintaining a priority queue of size $k$ that keeps track of the $k$ most-similar feature-vectors. Given a query feature-vector and relative weights for different feature-classes, Pliny-DB can find the 10 most-similar functions in a code database containing 500,000 functions in under 2 seconds on a single machine with 8 Intel i7 3.6 GHz cores and 16 GB RAM. Effort is underway by the developers of Pliny-DB to make a distributed version, which would allow Source Forager to search large code databases without taking a big performance hit: a large code database can be split into $p$ smaller units that can each be searched in parallel, and the sorted $k$ most-similar results from each of the $p$ units can be merged using a multi-way merge algorithm.

C. Extensible Architecture

Source Forager’s architecture allows for easy extension. To add a new feature-class, one implements (1) a feature extractor that determines the feature-observation for any given function, and (2) a corresponding similarity function. We currently implement our feature extractors using CodeSonar®. However, Source Forager is not tightly coupled with CodeSonar: any C/C++ processing tool can be used to implement a feature extractor. The feature-observations for all existing feature-classes are represented with well-known container data structures, such as lists, maps, and trees; all similarity functions work at the level of container data structures, and thus are available to be reused with any additional user-supplied feature extractors. Furthermore, Source Forager is not tied to having functions as the only kind of program element. The underlying architecture is also not limited to C/C++, and thus Source Forager can be re-targeted to perform code searches of programs written in other languages.

III. Code Search

In this section, we first describe the different feature-classes and the accompanying similarity functions that are employed in Source Forager. We then describe two configurations of Source Forager. The first configuration (dyn-select) selects a subset of the feature-classes on a per-query basis for performing code search: this configuration is useful when no additional information is available regarding a code query. The second configuration (svm-weights) pre-computes the relative importance of feature-classes for a specific domain ahead of time using supervised-learning techniques. This configuration is useful when the domain of the code query is known.
TABLE I

A brief overview of the different feature-classes employed in Source Forager. The marked* feature-classes all use Jaccard Index (Eq. 1) as the similarity function. The similarity functions used for the remaining feature-classes accompany their descriptions in III-A.

| Feature-Class         | Brief Description                                      |
|-----------------------|--------------------------------------------------------|
| Type-Operation Coupling* | types used and operations performed on the types       |
| Skeleton Tree          | structure of loops and conditionals                    |
| Decorated Skeleton Tree | structure of loops, conditionals, and operations       |
| Weighted NL Terms      | processed natural language terms in code               |
| 3 Graph CFG BFS       | CFG subgraphs of size 3, BFS used for generating subgraphs |
| 4 Graph CFG BFS       | CFG subgraphs of size 4, BFS used for generating subgraphs |
| 3 Graph CFG DFS       | CFG subgraphs of size 3, DFS used for generating subgraphs |
| 4 Graph CFG DFS       | CFG subgraphs of size 4, DFS used for generating subgraphs |
| Modeled Library Calls* | calls made to modeled libraries                       |
| Unmodeled Library Calls* | calls made to unmodeled libraries                     |
| User-Defined Library Calls* | calls made to user-defined libraries                 |
| Type Signature         | input types and the return type                        |
| Local Types*           | types of local variables                               |
| Numeric Literals*      | numeric data constants used                            |
| String Literals*       | string data constants used                             |
| Comments*              | associated comment words                               |

A. Feature-Classes and Similarity Functions

Table I summarizes Source Forager’s feature-classes. Below, we further describe these feature-classes and their associated similarity functions.

Type-Operation Coupling: The feature-observation for this feature-class consists of the types of variables operated on in the function, coupled with the operations performed on those types. The feature-observation is a set of (type, operation) pairs. Primitive types are paired with the built-in arithmetic, logical, and relational operations, for example, (int, >=). User-defined types such as C++ classes are paired with the user-defined operations on them, including direct and indirect field accesses and method calls. For example, the pair (Bar, .foo) indicates that the field foo of an aggregate data type Bar is accessed. The intuition behind including this feature-class is that similar functions tend to use similar type-operation pairs. For the example in Fig. 2, the Type-Operation Coupling feature-observation extracted is the set {(int, unary-), (int, /), (int*, +), (int, >), (int, +), (int, <=), (int, -), (int, <)}.

Skeleton Tree: The feature-observation for this feature-class is based on the abstract syntax tree (AST) of a function.

The AST is further abstracted by retaining only the loops (for, while, do...while) and conditionals (if...else, switch). Operationally, the feature extractor can be realized as a tree transducer that drops all AST nodes that are not loops or conditionals. Sequences of loops or conditionals are encapsulated within a sequence node, and empty sequences are dropped from the feature-observation. The intuition behind using this feature-class for code search is that similar functions tend to have similar loop and conditional structures.

Fig. 4a shows the Skeleton Tree feature-observation for the example program in Fig. 2.

The similarity function used for Skeleton Tree feature-observations is based on tree edit distances. Let \( d_r \) be a rough approximation of the distance between two trees, only based on their sizes:

\[
d_r(T_1, T_2) = \frac{|size(T_1) - size(T_2)|}{\max(size(T_1), size(T_2))}
\]

Further, let \( D_T \) be a fixed distance threshold (which we set to 0.5). We obtain an approximate distance between two trees, \( d_r \), as follows:

\[
d_r(T_1, T_2) = \begin{cases} 
\frac{\max(\text{ed(pre}(T_1), \text{pre}(T_2)), \text{ed}(\text{post}(T_1), \text{post}(T_2))}{\max(size(T_1), size(T_2))} & \text{if } d_r(T_1, T_2) \geq D_T \\
\end{cases}
\]

Here \( \text{pre}(T) \) is the sequence obtained by performing a pre-order traversal of the tree \( T \), \( \text{post}(T) \) is the sequence obtained by performing a post-order traversal of the tree \( T \), and \( \text{ed}(S_1, S_2) \) is the word edit distance between the sequences \( S_1 \) and \( S_2 \). The similarity function used for Skeleton Tree feature-observations is then computed as:

\[
sim_{tree}(T_1, T_2) = 1 - d_r(T_1, T_2)
\]
An exact tree-edit-distance computation [11] has quartic-time complexity in the size of the trees being compared. We instead use a fast under-approximation of edit distance [12] that gives our similarity function quadratic-time complexity overall. Note that we also use a further rough approximation based on just the size of the trees, if one of the two trees being compared is at least twice as large as the other. We found that using these approximations as opposed to the exact tree-edit-distance based similarity made no discernible difference in the quality of the final search results obtained, but made a big difference in performance: more than $6 \times$ faster in our tests.

**Decorated Skeleton Tree:** This feature-class is similar to the Skeleton Tree, except that instead of retaining just the loop and conditional structure in the feature-observations, most operations (e.g., `+`, `-`, and `<`) are also retained from the AST. We discard some common operations, such as assignment (`=`) and address-of (`&`), because they cause excessive bloat. The intuition behind including this feature-class is that similar functions use similar operations in structurally similar locations.

Fig. 4b shows the Decorated Skeleton Tree feature-observation for the example code in Fig. 2. The similarity function used is $\text{sim}_{\text{tree}}$ from Eq. (3).

**Weighted NL Terms:** The feature-observations for this feature-class consist of various natural-language (NL) terms in source code, such as function name, comments, local variable names, and parameter names of a function. Such NL terms, after extraction, are subjected to a series of standard NL pre-processing steps, such as splitting words with under_scores or CamelCase, stemming, lemmatization, and removing single-character strings and stop-words. Stop-word removal discards both typical English stop words such as “the”, “and”, and “is” [13], as well as stop words specialized for code, such as “fixme”, “todo”, and “xxx”. Additionally, we use a greedy algorithm [14] for splitting terms into multiple words based on dictionary lookup. This splitting is to handle the case where programmers choose identifiers that combine multiple words without under_scores or CamelCase.

After NL pre-processing, we compute a term frequency-inverse document frequency (TF-IDF) score for each NL term. We consider each function as a document, and compute the TF-IDF per C/C++ project. We give function-name terms an TF-IDF value for the $(\text{TF-IDF})$ score for each NL term. Functions tend to have similar natural-language vocabulary. The intuition behind including this feature-class is that similar functions tend to have similar natural-language vocabulary. The feature-observation for the example in Fig. 2 is `{“bin”: 0.65, “search”: 0.65, “high”: 0.13, “low”: 0.13, “found”: 0.13, “mid”: 0.13, “match”: 0.13}.

The similarity function for two observations of Weighted NL Terms uses cosine similarity:

$$\text{sim}_{\text{nl}}(A, B) = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$

Here $n$ is the total number of words in the universe, $A$ and $B$ are vectors with TF-IDF scores, and the $i$th index $A_i$ is the TF-IDF value for the $i$th word.

![Fig. 5. An example 4-graph and its corresponding adjacency matrix. Serializing the adjacency matrix entries yields binary digits “0100 0011 0000 0000”, or 17,152 in decimal. Node ordering in the adjacency matrix is the traversal order.](image)

**K-Subgraphs of CFG:** We implement multiple feature-classes based on $k$-sized subgraphs of the control flow graph (CFG) of a function. Given the CFG of a function, we begin either a breadth-first-search (BFS) traversal or a depth-first search (DFS) traversal at a node until $k$ nodes are traversed; a subgraph of the CFG involving these $k$ nodes is extracted. If fewer than $k$ nodes are reachable from a node (including itself), then such a sub-graph is thrown away. We repeat this process for every node in the CFG, extracting at most $n$ subgraphs of size $k$, where $n$ is the size of the CFG. We represent a graph of size $k$ as a $k^2$-bit integer, which is a 1-D representation of a 2-D adjacency-matrix representation of the graph, obtained by concatenating each of the matrix rows in order. Thus, from each function’s CFG, we extract a multiset of $k$-graph shapes.

Fig. 5 shows an example of converting a 4-graph into a 16-bit integer in this manner.

We implement the following four feature-classes based on the value of $k$ and the traversal strategy chosen:

- **3 Graph CFG BFS:** $k = 3$, traversal strategy is BFS.
- **4 Graph CFG BFS:** $k = 4$, traversal strategy is BFS.
- **3 Graph CFG DFS:** $k = 3$, traversal strategy is DFS.
- **4 Graph CFG DFS:** $k = 4$, traversal strategy is DFS.

For the example in Fig. 2 the feature-observation extracted for the feature-class “4 Graph CFG BFS” is the multiset $\{134, 134, 134, 194, 194, 194, 2114, 2114, 2114\}$. The intuition behind including these feature-classes is that similar functions tend to have similar control-flow structures [15].

The similarity function used for these feature-class is based on the generalized Jaccard index between two multisets $O_1$ and $O_2$:

$$\text{sim}_{\text{Gen-Jacc}}(O_1, O_2) = \frac{\sum_i \min(O_{1i}, O_{2i})}{\sum_i \max(O_{1i}, O_{2i})}$$

Here, $i$ iterates over all the unique elements in $O_1 \cup O_2$, and $O_{1i}$ is the number of times $i$ appeared in the multiset $O_1$.

**Calls to Library Functions:** We implement three feature-classes that extract calls to various kinds of library functions:

- **Modeled Library Calls:** CodeSonar models a large range of library functions for performing static analysis on C/C++ code. For this feature-class, calls made to any of these modeled library functions are extracted.
- **Unmodeled Library Calls:** Calls made to any unmodeled library functions are extracted for this feature-class—that is, calls to a function not modeled by CodeSonar, and whose definition is not available in the source code.
User-Defined Library Calls: For this feature-class, calls to functions whose definitions are available in a directory different from the caller function are extracted. We use such functions as a heuristic for identifying user-defined libraries.

The intuition behind including the above three feature-classes is that similar code tends to call the same library functions. For each of these three feature-classes, the feature-values are sets of library functions called. A library function is represented as a tuple: it includes the name of the function together with the filename containing the function’s declaration. For example, if a function calls `strcpy` and `strncpy`, then the feature-observation corresponding to Modeled Library Calls for that function is `{(strcpy, string.h), (strncpy, string.h)}`.

Type Signature: For this feature-class, the feature-observations consist of the name signature of the function: i.e., the argument types and the return type form a multiset of types. For the example code in Fig. 2 the feature-observation corresponding to Type Signatures is `{int, int, int*, int}`. Type signatures define a function’s interface for interaction with the rest of the code. Similar code tends to have similar interfaces, and therefore type signatures could help with code search.

The generalised Jaccard index (Eq. (4)) is used as the similarity function for this feature-class.

Local Types: For this feature-class, the feature-observations consist of the set of types of all the local variables. The intuition behind using local variable types in code search is that similar code creates and operates on variables of similar types. For the example code in Fig. 2 the Local Types feature-observation is `{int}`.

Constants: We implement two feature-classes that extract constants from a function:

Numeric Literals: This feature-class is described in §II-A

String Literals: For this feature-class, a feature-observation is the set of all the literal strings used in a function. The intuition behind using sets of constants in code search is that similar code typically uses similar constants.

Comments: For this feature-class, the feature-observations consist of the comments associated with a function. The comments are represented as a set of words. The intuition behind using comments in code search is that comments in similar pieces of code are likely to use a similar vocabulary. For the example code in Fig. 2 the Comments feature-observation is `{“found”, “match”, “no”}`.

Combining Feature-Classes: Using several feature-classes in combination allows Source Forager to obtain good code-search results in a fairly robust manner by using different dimensions of the code. For example, consider the binary-search implementation in Fig. 2. We see that variables named `mid`, `low`, `high` are used; that there are two conditionals nested inside a single loop; and that an integer division and integer less-than-or-equal-to operation is performed. When put together, these observations are hallmarks of a binary-search implementation.

B. Dynamic Feature-Class Selection

Combining feature-classes can be beneficial for code search, however, the feature-classes that are useful for performing a code search may vary from one query to another. For example, consider a query function containing of just straight-line code. A significant number of functions in our code-database are devoid of loops and conditionals and all such functions look identical to the query function with respect to the Skeleton Tree feature-class. Thus, performing a code search with this query by including the Skeleton Tree feature-class can lead to lower-quality results. On the other hand, if a query function has an unusual loop and conditional structure that is idiomatic to the computation being performed, then the Skeleton Tree feature-class would be useful in code search: other instances of the same distinctive structure from the code database would have high similarity scores to the query function.

Thus, it is useful to select feature-classes automatically on a per-query basis for code search. This configuration of Source Forager is called dyn-select. Intuitively, a feature-class for a given query is selected for code search if the corresponding feature-observation is sufficiently discriminatory/unique with respect to the overall feature-observation distribution for that feature-class.

To prepare for the dynamic feature-class selection on a per-query basis, we take following steps offline:

- From the code database, we retrieve a random sample $S$ of feature-vectors. Random sampling gives an inexpensive estimate of feature-observation distributions across the entire code database.
- We calculate a similarity threshold for each feature-class $c$ by (1) computing pairwise similarity scores on the feature-observations for $c$ in $S$ and (2) taking the sum of means and standard deviations of the similarity scores. Two feature-observations for $c$ are considered similar if their similarity score is above the similarity threshold for $c$.

Online, when a query is posed, we take the following steps for each feature-class $c$ (which can be performed in parallel):

- We compare the query’s feature-observation for $c$ with all other feature-observations for $c$ in sample $S$ (of size $n_{samp}$), and count the number of similar feature-observations $n_{sim-c}$.
- We select the feature-class $c$ for code search if it is not too common, that is, if $\frac{n_{uniq}}{n_{samp}} < t_{uniq}$. Here $t_{uniq}$ is a threshold that indicates a feature-observation is sufficiently unique in the sample. For example, $t_{uniq} = 0.15$ indicates that any feature-observation that is similar to less than 15% of the sample feature-observations is considered distinctive enough to warrant inclusion.

Each feature-class is assigned a weight of exactly 1.0 or exactly 0.0, based on whether the feature-class is selected in the above process. These weights are used for combining feature-class similarities for code search (Eq. (2)), and the $k$-most-similar-function search is carried out between the query

\[ \text{weight} = \begin{cases} 1.0 & \text{if } \frac{n_{uniq}}{n_{samp}} < t_{uniq} \\ 0.0 & \text{otherwise} \end{cases} \]

\[ \text{score} = \sum_{c} \text{weight}(c) \cdot \text{score}(c) \]

\[ k = \text{argmax}_{f \in \text{results}} \text{score}(f) \]
function and the functions in the code database as described in §IV-B to obtain the $k$ functions most similar to the query.

### C. SVM-Guided Feature-Class Weight Generation

Note that dyn-select does not need any additional knowledge about the query. However, if we know ahead of time that a query belongs to a specific domain, and we have ground-truth information available regarding what constitutes similar code in that domain, then we can use supervised-learning techniques to learn good feature-class weights (for Eq. (2)) for that domain ahead of time, and use these weights for code search with all future queries in that domain.

Given a particular ground-truth data set with labeled similar code, we generate fine-tuned weights by training a binary-classification support vector machine (SVM). We do not train using raw code text, or even raw sets of feature-observations. Because we use the SVM training process to generate relative weights for feature-class similarity scores in Eq. (2), we train the SVM on these similarity scores directly. The similarity scores for all feature-classes between two functions are assembled into a similarity vector. The SVM is then trained on examples of similarity vectors for both similar and dissimilar functions, each labeled accordingly. This technique allows us to optimize ahead of time how these feature-classes are relatively weighted in a code search, by using the same similarity functions that are employed in code search of a query.

Our SVM uses a linear classifier, which allows a convenient interpretation of internal weights [16]. The final pre-processing step is to extract these internal weights and normalize them relative to the sum of their magnitudes, truncating negative weights. These normalized weights are then used directly as feature-class weights in Eq. (2). §IV-B provides more details about the corpus and training process. Of course, it is not obvious that weights obtained by training for classification purposes are useful in ranking results for code-search queries. §IV-C measures the effectiveness of this strategy in practice.

### IV. Experimental Evaluation

This section outlines the research questions we seek to answer through experiments (§IV-A); describes the setup and methodology used in the experiments (§IV-B); and presents the results of the experiments (§IV-C).

#### A. Research Questions

Our experiments were designed to answer the following research questions:

**RQ1** How do the individual feature-classes described in §III perform in code-search tasks relative to each other?

**RQ2** Does combining feature-classes using per-query dynamic feature-class selection (§III-B) improve Source Forager’s performance?

**RQ3** Does combining feature-classes using supervised learning (§III-C) further improve Source Forager’s performance, when the query domain is known?

A code-search task involves searching for relevant documents from a group of documents that include both relevant and non-relevant documents. (In the case of Source Forager, “documents” are C/C++ functions.) Non-relevant documents are also known as distractors, which leads naturally to the following question:

**RQ4** How much does Source Forager’s code-search performance degrade as we increase the number of distractors in the code base being searched?

#### B. Experimental Setup and Methodology

Source Forager uses CodeSonar, an industrial-strength C/C++ static-analysis engine, to analyze C/C++ corpora and implement feature extractors. CodeSonar handles real-world C/C++ projects with tens of millions of lines of code. CodeSonar also exposes a wealth of information about a program through well-defined APIs. Source Forager’s feature extractors are implemented as CodeSonar plugins that use these APIs. Consequently, Source Forager inherits CodeSonar’s requirement that programs must be compilable to be analyzable.

**Code-Search Tasks:** Our experiments assess Source Forager’s performance under various configurations. Code-search tasks are set up as follows. For each query function, there is a set of known relevant functions that are similar to the query. The relevant functions are treated as ground truth. The relevant functions are then mixed with many non-relevant functions as distractors, and together they form the code database used in the experiment. Source Forager then searches the code database for similar functions. We compute information-retrieval statistics based on the ranking of the known-relevant functions in the returned results.

**Queries:** We use two query ground-truth sets for the code-search tasks, representing two domains. One, called algo-qs, represents “algorithmic” code queries. For algo-qs, we created seven tasks, outlined in Table III and manually curated a total of thirty-eight functions that each accomplish one of the seven tasks. The functions were mostly obtained from GitHub and were written by a variety of programmers, none of whom are authors of this paper. The functions that accomplish a specific task have been manually vetted to be
similar to each other. We thus have a total of thirty-eight base queries.

We use these sets of real-world functions as queries (and the desired search results), and consider them to be an appropriate proxy for the code-search queries performed (and search results expected) by users in the algorithm domain. We have made the labeled queries available for inspection.

To make sure that the similar functions we found were not all clones of each other, we ran them through the MOSS software-plagiarism detector [17]. Given a group of programs, MOSS reports program pairs that may be clones, along with an overlap percentage. Table I reports MOSS’s findings, run using default settings. In this table, partial overlap represents any pair that MOSS reports as possible clones, while significant overlap counts only possible clones with at least 50% overlap. Observe that many function pairs marked manually as being similar are not just MOSS-detectable clones of each other. Thus, recognizing similar function pairs in this corpus is a nontrivial challenge.

The second query ground-truth set we use is called libc-qs, and represents code queries from systems programming. We looked at three implementations of the standard C library: musl libc [18], diet libc [19], and uClibc [20]. From these we define 88 function categories corresponding to 88 functions that all three implementations provide. We assume that within the same function category, the three libc implementations are “similar.” For this domain, we have 88 × 3 queries. For example, musl libc’s `sprintf` and uClibc’s `sprintf`, and dissimilar to everything else.

Distractor Functions: The distractor functions have been taken from the openly available MUSE corpus [21], and mainly consist of code from Fedora source packages (SRPMs). Our feature extractors currently require compilable code, which Fedora SRPMs provide. Due to the large size of the distractor-function corpus (over 200,000), we have not manually vetted all of the distractor functions to be sure that they are irrelevant to the queries issued. It is possible that some distractor functions are indeed relevant to some queries, so our retrieval statistics are under-approximations. With the exception of the experiments reported in Fig. 7, all experiments use 10,000 distractors.

Retrieval Statistics: We compute Mean Average Precision (MAP) as the retrieval statistic, as is common in information retrieval. MAP is typically used to measure the quality of ranked retrieval results, because MAP takes into account the rank of the relevant documents in the retrieved results. MAP provides a measure of quality across all recall levels. MAP is the mean of the average precision computed for each query. The average precision (AP) for each query is given by \( \frac{\sum_{k=1}^{n} P(k) \cdot r(k)}{R} \), where \( n \) is the total number of documents searched; \( R \) is the number of documents marked relevant to the query; \( P(k) \) is the precision when \( k \) documents are requested; and \( r(k) = 1 \) when the \( k^{th} \) retrieved document is relevant, and 0 otherwise. That is, AP is the average precision at all the points when a new relevant document is retrieved in a ranked result list. The best MAP score that can be achieved is 1.0, when for each query, the \( R \) relevant documents appear as the top \( R \) search results.

**SVM-Guided Weights:** We applied the techniques discussed in §III-C on algo-qs and libc-qs to provide labeled data-sets on which to train an SVM. Each instance in our training set is generated by comparing two functions \( a \) and \( b \), yielding a single similarity vector that consists of similarity scores for each feature-class. The binary classification for each training instance is 1.0 if \( a \) and \( b \) are implementations of the same function, 0.0 otherwise.

We use LIBLINEAR [22] to train the SVM to classify these function comparisons; this process takes roughly twenty milliseconds. Using this technique, we are able to achieve over 98% accuracy under ten-fold cross-validation.

Once the SVM is trained, we extract and normalize its internal weights for use in code search. For the svm-weights configuration described below, within each domain, the data-set is divided into multiple folds of training-set and test-set pairs. The weights extracted from the training set are used to obtain MAP scores on the test set. That is, weights are trained on a subset of a given domain (algo-qs or libc-qs) and tested using queries from a different subset of the same domain. For the cross-weights configuration described below, algo-qs is used to train weights for queries from libc-qs, and vice-versa.

**Source Forager Configurations:** Our experiments run Source Forager under many configurations. Each configuration is defined by the weight \( w_c \) assigned to each of the feature-classes \( c \) given in Table I. These weights are used in Eq. (2) for performing the code search.

- **solo-c:** For each query, the weight \( w_c \) corresponding to feature-class \( c \) is 1.0. Weights corresponding to all other feature-classes are set to 0.0.
- **equal-all:** For each query, for all feature-classes \( c \), \( w_c = 1.0 \), giving equal importance to all feature-classes for all queries.
- **dyn-select:** For each query, a subset of feature-classes are selected and given equal weights, as described in §III-B. The dynamic selection of feature-classes adds a small run-time overhead to each query.
- **rand-select:** For each query, a new random configuration is used as follows: a random subset of the feature-classes is selected, and the selected feature-classes are given equal weights. Repeat this process 10 times with different random selections, and report mean results over these 10 trials.
- **svm-weights:** For each query, use weights learned for the domain that the query belongs to, as described in §III-C and above.
- **cross-weights:** For each query, use weights learned for the domain that the query does not belong to.

\(^{3}\)Available at the URL: http://tinyurl.com/source-forager-algo-benchmarks.
Note that, unlike the other configurations, the \textit{svm-weights} and \textit{cross-weights} configurations permit weights to give different (non-zero) importance levels to different feature-classes.

\textbf{C. Results and Discussion}

The left side of Fig. 6 shows how each individual feature-class performs on the code-search tasks in isolation. This experiment addresses \textbf{RQ1}. The solo feature-class Weighted NL Terms \(0.70, 0.86\) performs the best individually on both \textit{algo-qs} and \textit{libc-qs}. Thus:

\textbf{RQ1 Finding:} If we were to drive Source Forager using only one feature-class, Weighted NL Terms is the best option. However, Fig. 6 shows that the performance of the different feature-classes varies considerably depending on the query ground-truth set. This variance suggests that different feature-classes are important for different kinds of queries.

\textbf{RQ2} asks whether multiple feature-classes can be usefully combined, and whether \textit{dyn-select} is a good way to do such a combination. A straightforward manner in which feature-classes can be combined is the \textit{equal-all} configuration, which represents a baseline to compare against other configurations. The \textit{dyn-select} configuration selects different subsets of the feature-classes on a per-query basis (§III-B). As a sanity check for the selections performed by \textit{dyn-select}, we also compare it with the \textit{rand-select} configuration, which randomly selects feature-class subsets for every query. The right side of Fig. 6 shows that \textit{dyn-select} \(0.84, 0.89\) performs better on both \textit{algo-qs} and \textit{libc-qs} when compared to \textit{equal-all} \(0.67, 0.73\) and \textit{rand-select} \(0.57, 0.63\).\textit{dyn-select} also outperforms each of the solo configurations from the left side of Fig. 6.

\textbf{RQ2 Finding:} In the absence of any additional information about the query, combining multiple feature-classes and dynamically selecting feature-classes on a per-query basis (§III-B) is the most effective strategy for code search.

\textbf{RQ3} addresses the scenario where the domain of a query is known, and additional information is available regarding that domain (as described in §III-C). The \textit{svm-weights} configuration tests Source Forager under this scenario. Pre-learning the relative importance of feature-classes for a given domain (in the form of weights \(w_c\) for each feature-class) also makes code search more efficient by eliminating any run-time overhead in feature-class selection. The right side of Fig. 6 shows that \textit{svm-weights} \(0.86, 0.95\) outperforms all other configurations.

\textbf{RQ3 Finding:} When the domain of a query is known, and training data is available, combining multiple feature-classes using weights derived from supervised learning (§III-C) is the most effective strategy for code search.

The \textit{cross-weights} \(0.74, 0.85\) configuration tests whether the weights learned from one domain are useful in a different domain. The rightmost two bars in Fig. 6 show that it is hard to derive a single set of relative feature-class weights that work well for queries in both domains. Thus, in the absence of domain information about the query, \textit{dyn-select} is preferred.

Fig. 6 shows how Source Forager’s result quality scales with increasing distractor-set sizes. This experiment addresses \textbf{RQ4}. Source Forager is used in the \textit{dyn-select} and \textit{svm-weights} configurations for this experiment. As one would expect, MAP scores decline as distractors proliferate. However, consider that relevant sets contain just 2 to 6 items competing against distractor sets that are up to five orders of magnitude larger.

\textbf{RQ4 Finding:} Resilient MAP scores indicate that Source Forager returns high-quality results even when distractors outnumber relevant items by several orders of magnitude.

\textbf{D. Threats to Validity}

The issue of whether evaluation benchmarks are appropriate is a potential threat to the validity of any information retrieval system. We mitigate this threat for Source Forager in several ways. First, we use benchmark queries from two different domains, \textit{algo-qs} and \textit{libc-qs}. Second, we use the MOSS plagiarism detector to show that our manually labeled set of relevant functions in \textit{algo-qs} are not trivial clones of each other. Third, we draw the \textit{algo-qs} and \textit{libc-qs} data sets from real-world code written by arbitrary programmers, not artificial programs written by us.

Feature-classes can be combined in various ways to perform code searches. We have explored part of the vast space of all such combinations, and our results speak only to those we have tried. We find that the MAP scores of the configuration \textit{dyn-select} on both \textit{algo-qs} and \textit{libc-qs} are good. We designed the experiments with \textit{equal-all} and \textit{rand-select} configurations to test whether the selections made by \textit{dyn-select} are indeed necessary and useful, and find that they are.

\textbf{V. RELATED WORK}

\textit{Code-search engines:} Several popular text-based code-search tools “grep” over tokenized source code: GitHub, SearchCode, Open HUB, etc. While these tools are useful, they fall short in many use cases, as they do not exploit the rich semantics of code. For example, the top search results for the term “dfs” on C code projects in GitHub yields function declarations, macro names, and \#include directives that mention “dfs”, but that are not actually useful.

The Sourcerer code-search engine\cite{Sourcerer} combines text-based search techniques with information about relations among programming “entities” like packages, classes, methods, and fields.
Sourcerer also uses fingerprints that capture some light-weight structural information about the code, such as depth of loop nesting and presence or absence of certain language constructs. Queries in Sourcerer are text-based and are powered by Lucene [http://lucene.apache.org], as opposed to the code-based search by Source Forager.

Strathcona [8] returns relevant Java code examples to developers learning to use complex object-oriented frameworks. It uses several heuristics based on class-inheritance hierarchies, method calls, and type uses. Source Forager could also use the applicable heuristics from Sourcerer and Strathcona as feature-classes, but additionally demonstrates how to search using more complex structures, such as decorated skeleton trees and CFG-subgraphs.

CodeGenie [7], [23] proposes test-driven code search, in which the user supplies a set of unit tests for the code component they want to find. CodeGenie leverages Sourcerer [2] to perform keyword-based search; test cases refine these results. Source Forager could be used as a replacement for Sourcerer to perform similar code search in CodeGenie.

Stollee et al. [4], [24] perform code search based on logical characterizations of programs’ I/O behaviors, obtained via symbolic execution. A query consists of concrete I/O pairs for the desired code fragment. While this approach precisely captures the semantics of the corpus elements, it does not immediately handle some common programming constructs, such as loops and global variables. It also restricts the size of the program elements in the corpus, because symbolic execution of larger elements may lead to path explosion. Source Forager can easily be extended to use I/O pairs as an additional feature-class in scenarios where the above restrictions are acceptable.

XSnippet [5] and ParseWeb [25] are specialized code-search engines: XSnippet looks specifically for code that instantiates objects of given type in a given context, ParseWeb has a similar focus on code sequences that instantiate objects. Codify [6] extracts and stores a large amount of metadata for each symbol in a program, and provides a user interface for querying that...
metadata. Codify aids in understanding and browsing code. The goal of Source Forager’s code search is different from the above, i.e., to find source code similar to a query.

**Code-clone detection:** Source Forager’s code searches differ from the typical clone detection problem in that we are interested in finding code that has both semantic and syntactic similarity. Therefore, we use a range of feature-classes that span from syntactic to semantic. Source Forager’s notion of similarity does not neatly fall into any of the definitions of standard clone types 1–4 [26].

**Similar-machine-code search:** Finding similar machine code [15], [27], [29] is useful in finding known vulnerabilities in third-party code for which source code is not available. The primary difference in code search at the source-level and machine-level is that machine code has poorer syntactic, semantic, and structural information available compared to source code. As a result, while there is some overlap between techniques, research on machine-code search is focused on tackling different problems, such as how to do similar-machine-code search across different CPU architectures, compiler optimizations, compilers, operating systems, etc.

**SVM-based code-classification:** Rosenblum et al. [30] train SVMs with features extracted from source code in the attempt to classify programs by author. Source Forager builds on this idea by training an SVM with similarity scores derived from feature-observations, and then extracting internal weights from the trained SVM to strengthen the combined similarity function used for code search.

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