Searching for Replacement Classes

Malavika Samak malavika@csail.mit.edu CSAIL, MIT USA Jose Pablo Cambronero jcasman@csail.mit.edu CSAIL, MIT USA Martin C. Rinard rinard@csail.mit.edu CSAIL, MIT USA

ABSTRACT

Software developers must often replace existing components in their systems to adapt to evolving environments or tooling. While traditional code search systems are effective at retrieving components with related functionality, it is much more challenging to retrieve components that can be used to directly replace existing functionality, as replacements must account for more fundamental program properties such as type compatibility. To address this problem, we introduce ClassFinder, a system which given a query class Q, and a search corpus S, returns a ranked subset of classes that can replace O and its functionality. ClassFinder produces a field and method mapping between the classes that can provide useful hints to a developer and can be used to effectively refine the ranking of candidate replacement classes. Our technique leverages the complementary strengths of a distributed embeddingsbased search and type-based analysis, using the former to prune down candidates for an optimization-based approach based on the latter. ClassFinder retrieves replacement classes, along with a type-aware field/method mapping between classes. We evaluate ClassFinder on a search space of ≈ 600 thousand open source Java classes. Querying ClassFinder with 24 known Java classes provided meaningful replacement classes and mappings, in many cases producing complete mappings with functionally-identical replacement classes.

1 INTRODUCTION

Developers maintaining software systems often need to replace one of the classes in the source code base with a functionally equivalent class. Potential motivations include deprecation of deployed classes [1–3], the need to change vendors to satisfy organizational needs or intellectual property constraints [4, 5], improved performance and/or memory usage [6, 7], or the desire to identify and use better versions that may contain fewer defects [8–10]. While large software repositories often contain suitable class replacements, finding such replacements can be a challenging task given the enormous size of extant code bases (billions of lines of code) [11, 12].

We present a new technique and implemented system, Class-Finder, for automatically finding replacement classes. Given a query class, Class-Finder automatically searches large code bases to identify and rank potential replacement classes. Class-Finder combines two complementary techniques: embedding-based class ranking and method compatability matching. Treating the method names of each class as a bag of words, embedding-based class ranking maps the names to a high-dimensional vector, with the cosine similarity metric over the resulting vector space measuring the distance between classes. We find that, in practice, this metric provides a reasonably accurate proxy for the intended semantic similarity between the query class and candidate replacement classes. However,

because it ignores method type and implementation information, it fails to adequately capture aspects relevant to class replacement[13].

ClassFinder therefore next deploys a compatability matching algorithm that operates at the level of individual methods. Working with the tokens in each method as a bag of words, the matching computes an embedding for each method, with the cosine metric used as a proxy for semantic method similarity. Matching methods in the original and candidate replacement classes according to this metric, ClassFinder computes a type-similarity metric between matched methods (Section 3.5). ClassFinder also matches fields in the original and candidate classes to compute a field mapping metric (Section 3.4). Aggregating these metrics enables ClassFinder to effectively identify and rank candidate replacement classes. In particular, we find that compatability matching is effective at deranking candidate replacement classes that 1) operate with incompatible or overly specific types, 2) contain empty or placeholder methods, or 3) implement a subset of the required methods.

We evaluate ClassFinder on 24 open source Java query classes. These classes contained deprecated classes, classes used by Samak et al[13] and classes from popular packages[14]. Working with a corpus of ≈ 600 thousand open-source candidate replacement classes, our results indicate that ClassFinder can effectively find suitable replacement classes for our set of query classes within this large candidate replacement class search space. Specifically, ClassFinder found replacement classes that provide complete replacement to the query class as the top candidate for 12 of the query classes and partial replacements ranging between 30% to 95% replacement for the rest (Section 4). The results also indicate that the embedding-based search used in the first phase of our approach identifies classes that were good replacements as the top candidate in some cases, but identifies type incompatible or otherwise unsuitable replacements in others, with the combination of embedding-based search and compatability matching significantly outperforms embedding-based search alone.

This paper makes the following contributions:

- Problem and Technique: It identifies the replacement class search problem and presents a technique and system for solving this problem. The technique uses *embedding-based class ranking* to efficiently identify candidate replacement classes with good semantic similarity to the query class. It then uses method-based compatibility matching to identify candidate replacement classes whose methods exhibit good type and semantic compatibility with the query class.
- **System**: It presents the design and implementation of Class-Finder, a system that implements our class search technique.
- **Results:** It presents results that characterize the effectiveness of ClassFinder in finding replacement classes for 24 query classes

```
public class ArrayList<E> {
                                    public class ImmutableList<E> {
                                                                       public class BooleanList {
                                                                                                            public class Vector<E> {
                                      final E[] arr:
                                                                         boolean[] elementData:
                                                                                                             transient Object[] elementdata:
  transient Object[] elementdata:
 int size;
                                                                         int size = 0;
                                                                                                             int elementCount;
                                      boolean contains(Object o) {
 boolean contains(Object o) {
                                        return indexOf(o) != -1;
                                                                         boolean contains(boolean e) {
                                                                                                             boolean contains(Object o) {
    return indexOf(o) >= 0;
                                                                           return indexOf(e) >= 0;
                                                                                                                return indexOf(o) >= 0;
                                                                         }
                                                                                                             }
                                      E set(int i, E e) {
 E set(int i. E element) {
                                                                         boolean set(int i. boolean e) {
                                                                                                             E set(int i. E element) {
                                        throw new UOE():
    Objects.checkIndex(i, size);
                                                                           rangeCheck(i);
                                                                                                               if (i >= elementCount)
    E old = elementData(i);
                                                                           boolean old = elementData[i];
                                                                                                                  throw new OOBF(i):
    elementData[i] = element:
                                                                           elementData[i] = e:
                                                                                                               E old = elementData(i):
    return old;
                                                                           return old;
                                                                                                                elementData[i] = element;
                                                                         }
                                                                                                                return old;
}
                                                                       }
                                                                                                             }
                                                                                                            }
                (a)
                                                                                       (c)
                                                   (b)
                                                                                                                           (d)
```

Figure 1: The ArrayList implementation from java.util package and its potential replacement candidates: ImmutableList from jadax.core, BooleanList from abacus.util and Vector from java.util.

within a corpus of ≈ 600 thousand candidate open-source replacement classes. These results characterize the synergistic combination of embedding-based class ranking and method-based compatability matching, both of which are required for Class-Finder to effectively identify appropriate replacement classes for our benchmark query classes.

2 CLASS REPLACEMENT EXAMPLE

In this section, we explain the working of CLASSFINDER with an example. Consider the ArrayList class from java.util package shown in Figure 1. The class provides a resizable implementation of a list and it can be parameterized to create and operate on a list of any reference type E. We search for replacements to this class within a search space of over 600 thousand classes. Among many other classes, this search space contains ImmutableList from jadax.core, BooleanList from abacus.util and Vector from java.util package shown in Figure 1.

The goal of the search is to deliver a ranked list of classes that offer a complete or partial replacement to ArrayList, where the rank is determined based on the number of drop-in replacements to ArrayList methods. A class that offers partial replacement may still be useful if the developer is either willing to write adapter methods for the unmapped methods or plans to use a subset of the methods offered by the query class. All three classes from Figure 1 can provide *at-least* a partial replacement to ArrayList, therefore are relevant to the search.

To identify these classes from our corpus of classes, Class-FINDER initiates a search for classes similar to ArrayList. Class-FINDER bases this search on the assumption: *method names are good descriptor of the functionality*. It extracts the method names defined by the class, creates a bag of words containing the method names, then maps the bag of words into a high dimensional vector space [15]. It then queries the set of corresponding vectors from all of the classes in the search space to find the closest classes to the query class as measured by the cosine distance between vectors [16]. Reflecting the fact that they implement similar functionality as ArrayList, in our example the vector embeddings of ImmutableList, BooleanList, and Vector all exhibit small cosine

distances from the vector embedding of ArrayList and these three classes appear at the top of the embedding ranking.

If the embedding based rank was used as the final result, all three classes would be identified as equally good replacements to ArrayList. But a closer examination of the classes reveals important differences. The Vector class offers a complete replacement to ArrayList, whereas ImmutableList offers a partial replacement because it can not replace set and other methods that modify the list. Similarly BooleanList can not offer complete replacement either, as it narrows the underlying type of the list to boolean and therefore supports only boolean lists.

CLASSFINDER next matches methods defined by ArrayList to those defined by each of the candidate classes. The match is based on the type signature and the implementation of each method. The result of these method matches determines the rank of each candidate class. The functional equivalence of two methods is measured by creating an embedding based on their implementation and computing the cosine similarity between them. CLASSFINDER computes the similarity between all pairs of methods from ArrayList and candidate class. It also evaluates the type compatibility between all pairs of methods.

Given a method from ArrayList, CLASSFINDER matches it to the method in each candidate class that is type compatible and is most similar to the ArrayList method. If no such candidate can be found, the method will be matched to ⊥. ClassFinder also ensures the similarity score for a pair of matched methods is above a threshold set by the user. Otherwise the query class method will be matched to ⊥. In our example, the set method in ArrayList will be matched to the set method in Vector, but will be matched to \bot for other two classes — there are no type compatible methods in BooleanList and no high similarity methods in ImmutableList. The contains method in the ArrayList is similarly matched. Finally, we see that the method matches for Vector contain drop-in replacements for both methods, whereas ImmutableList contains a match for the contains method only and BooleanList does not contain any matches because of type incompatibility. The resulting ranking correctly ranks Vector as the top candidate, followed by ImmutableList and finally BooleanList.

All through this section we have assumed that, the type compatibility and functional equivalence are equally important to the user. We recognize this need not always be the case. ClassFinder allows the user to set a higher weight to type compatibility or functional similarity with a configuration variable. Setting a higher weight for one of them can change the final rank. For example, if zero weight was set for type compatibility, BooleanList would rank above ImmutableList.

3 DESIGN

Figure 2 presents the overall design of ClassFinder. ClassFinder pre-processes every class in its search space and creates a class search database. Each class available to the tool is first tokenized by extracting the field and method names in its implementation. The tokens extracted from the class are input to an embedding function, which computes a corresponding vector. This vector is then stored in our database. When queried with a class Q, ClassFinder similarly computes a vector for the query class and retrieves a list of the most similar candidate classes N, based on the cosine similarity of their vectors. This step is designed to identify a smaller set of candidate classes before moving on to more expensive analyses.

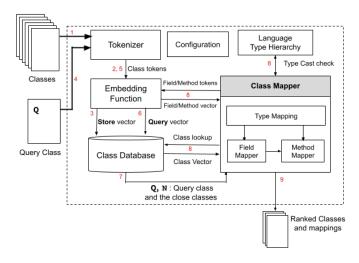


Figure 2: The ClassFinder architecture

Every class R in the set N is analyzed by the Class Mapper, which constructs a field map σ and a method map α between Q and R. All classes in N are re-ranked based on these newly constructed maps. The field map is constructed by assigning a score to every pair of fields in Q and R. The score is based on the type compatibility between fields and the vector distance between their embeddings. Depending on the data types, the compatibility is inferred either by using the language's Type Hierarchy (which handles primitive data types, classes offered by the language, etc) or based on their type similarity computed based on the cosine similarity between the corresponding vectors stored in the database. Similarly, the method map α is constructed based on the type signatures of the methods and the vector embedding of the method body. The list of re-ranked classes and their method maps is output to the user.

3.1 ClassFinder: Top-level algorithm

Algorithm 1 CLASSFINDER main algorithm

```
Require: Q \leftarrow \text{Query class}
1: Initialize DB with embeddings of all available classes}
2: tokens \leftarrow \text{ClassTokenizer}(Q); \text{vec} \leftarrow \text{embedding}(\text{queryTokens})
3: N \leftarrow \text{lookup}(\text{DB}, \text{vec})
4: for every R \in N do \rightarrow \text{Class mapping}
5: TS \leftarrow \text{TypeSimilarity}(Q, R)
6: \sigma \leftarrow \text{FieldMapper}(Q, R, TS);
7: \alpha \leftarrow \text{MethodMapper}(Q, R, \sigma, TS)
8: result [R] \leftarrow (\sigma, \alpha)
9: end for
10: return rank(result)
```

Algorithm 1 presents the top-level algorithm of ClassFinder. Initially, every class in the search corpus is tokenized, the extracted tokens are embedded into vectors, and which are then stored in the database. After initializing the database, the ClassFinder can be queried with a class Q. The input query class Q is tokenized and embedded into a vector at line 2. The resulting vector is used to search the class database DB for N, a list of classes in the database close to the query class, sorted based on their vector similarity.

The algorithm iterates over every class R contained in N (line 4-9). For a given (Q, R) pair, the algorithm creates a type similarity matrix TS, with the help of TypeSimilarity procedure. The matrix captures the similarity between a pair of data types (Ti, Ti), where type T_i is used by class Q and type T_i is used by class R. The TS matrix assigns a score to each pair (T_i, T_j) , which indicates if type T_i can be mapped to type T_i. The FieldMapper creates embeddings for all fields in class Q and R. The embedding based similarity between a pair of fields and the type similarity score in TS guide the creation of field map σ which is used by the MethodMapper to rewrite the class R. In particular, fields are renamed based on σ to account for possible naming differences between methods. The MethodMapper then creates embedding for all methods defined by class Q and R and computes the vector similarity for all pairs of methods. This vector similarity and the type similarity from TS are used to create a method map α . The constructed σ , α pair is added to the result map. Finally, the entries in result are ranked and output to user.

3.2 Continuous Representations of Code

The ClassTokenizer receives a class C as input and returns a bag of words containing the name of the class, names of all the fields defined by the class, the name of every method defined by the class and their formal parameter names. The names of methods invoked by the class are also added to this list. Camel cases and underscores are processed to split combined words. The resulting sequence is returned to the caller. For the ArrayList code shown in Figure 1 the ClassTokenizer returns the following: array, list, element, data, size, contains, o, index, of, set, i and check.

Then, to identify candidate replacement classes, ClassFinder makes use of an *embedding* function that can compute a vector representation for a given class. This embedding function, $F: T \to \mathbb{R}^d$, takes a sequence of tokens (T) extracted from a code snippet and computes a corresponding real-valued vector of dimension d. The goal of this embedding is to capture semantic properties of the code fragment. Given two sequence of tokens, ClassFinder applies

F to each sequence, and then computes a similarity score between the two resulting vectors. ClassFinder, like related code search systems [17–19], uses cosine similarity (which ranges between -1 and 1) as the similarity function over two vectors, such that vectors that are similar have a score closer to 1.

In our implementation, we instantiate F by training a continuousbag-of-words (CBOW) [16] model using FastText [15]. In a CBOW model, we take a sequence of tokens $t_1, ..., t_n$ and learn representations such that we can predict the presence of a token t_i given a representation for the context (i.e. the remaining tokens in the sequence). In practice, CBOW models take the context to be the tokens that occur within a (potentially randomly sampled-sized) window of the target token t_i . In FastText, a vector representation for the context is computed by first extracting n-gram subwords (subsequences at the character level) from the corresponding sequence of tokens, mapping each such subword to its own vector, and then averaging the subword vectors (i.e. mean-pooling). Critically, the use of subwords allows this CBOW model to produce vectors even for tokens that are otherwise out-of-vocabulary with respect to the set of tokens observed during training. When training, standard backpropagation is used to update the subword embeddings used in the model. We train the CBOW model, with embeddings of dimension 150, on a corpus of 600K classes. For more details on CBOW models, we refer the reader to Mikolov et al [16].

3.3 Type Similarity Matrix

Determining whether type T_i in class Q can be mapped to a value of type T_j in class R is crucial for the overall success of ClassFinder. This knowledge guides the creation of field and method mappings, which are used to assess if class R is a good replacement for Q. The language's type hierarchy provides a definite yes/no answer to this question for primitive types and classes that inherit from one another. However, if the types compared are unrelated, ClassFinder checks if T_i is similar to T_j based on their embedding similarity. If they have a high similarity, ClassFinder determines that the types can be mapped.

CLASSFINDER uses the TypeSimilarity procedure presented in Algorithm 2 to assign a similarity score for all type pairs and stores the scores in matrix *TS*. The algorithm takes a query class Q and

Algorithm 2 TypeSimilarity algorithm

```
Require:
     Q ← Query class; R ← Replacement class;
     tt ← Type similarity threshold
                                                                                   ▶ Configuration variable
 1: TS \leftarrow \hat{INIT}(Q,R); \hat{TS}[Q,R] \leftarrow 1
 2: for every (T_i, T_j) \in \mathsf{Types}(Q) \times \mathsf{Types}(R) do
          \textbf{if} \ \mathsf{typeCastCheck}(\mathsf{T}_i,\mathsf{T}_j) \ \textbf{then} \ \mathit{TS}[\mathsf{T}_i,\mathsf{T}_j] \leftarrow 1
                                                                    ▶ Embedding based type similarity
          else if T_i, T_j are classes then
 5:
                vec_1 \leftarrow lookup(DB, T_i); vec_2 \leftarrow lookup(DB, T_i)
                \texttt{score} \leftarrow \texttt{similarity}(\texttt{vec}_1, \texttt{vec}_2)
               if score > tt then TS[T_i, T_j] \leftarrow score
                end if
          end if
 Q.
10: end for
11: return TS
```

a replacement class R as inputs and assigns a score to every type pair (T_i, T_j) used by Q and R. The scores range between -1 to +1. +1 indicates that T_i can be mapped to type T_j and -1 indicates mapping is not permitted. The algorithm initializes all entries to

-1 with the INIT function. ClassFinder sets +1 as the similarity score for the (Q,R) pair. This allows mapping instances of type Q to instances of type R as a starting point. For every other pair of types (T_i, T_j), the type score is calculated (lines 2–10). If type T_i can be cast to T_j , a maximum replacement score 1 is set for (T_i, T_j). Otherwise, if both are non-primitive types, the embedding based similarity score is computed for the pair (lines 4–9). The class vectors for T_i, T_j is and their cosine similarity score is computed by the similarity. If the score is above a user defined threshold tt, the score is added to the matrix (line 7). Otherwise, the original –1 score is maintained.

3.4 Field Mapper

FieldMapper attempts to map every field f in class Q, to a field g in class R, by considering type similarity and the field uses within Q and R. It identifies the set of methods in the class that read or write a given field. The fields that are read and written by a similar set of methods are given a higher similarity score. This score along with the type similarity scores is used to create the field mapping, σ . Algorithm 3 presents the overall working of FieldMapper.

Algorithm 3 Field — Mapper algorithm

```
Require:
    Q \leftarrow Query class; R \leftarrow Replacement class; TS \leftarrow Type similarity matrix
    ft ← Field similarity threshold
                                                                     ▶ Configuration variables
    fw ← Field embedding weight
 1: FS \leftarrow INIT(0,R)
 2: for every (f,g) \in Fields(Q) \times Fields(R) do
         if modifier-compatibility(f,g) = false then continue;
         \langle rToken_f, wToken_f \rangle \leftarrow fieldReadWrites(f, Q);
                                                                           ▶ Read, write tokens
         \langle \text{rTokeng}, \text{rTokeng} \rangle \leftarrow \text{fieldReadWrites(g, R)};
 6:
         rScore ← similarity(rToken<sub>f</sub>, rToken<sub>g</sub>) ➤ Read, write similarity score
         wScore ← similarity(wToken<sub>f</sub>, wToken<sub>g</sub>)
         escore \leftarrow (rScore + wScore)/2
        FS[f,g] \leftarrow fw * escore + (1 - fw) * TS[f,g] \rightarrow Similarity score for f,g
10:
11: end for
12: field-map \leftarrow OPTIMIZE(FS)
13: \sigma \leftarrow \text{filter(field-map,ft)}
14: return \sigma
```

Initially, FS is initialized by assigning a -1 score for all field pairs. The algorithm iterates over every combination of fields (f,g) defined by Q and R. The modifiers attached to the fields f,g are first checked for compatibility with modifier-compatibility check. If the field modifiers are compatible, then the check returns true. If the check returns false, the pair is discarded and the next pair is processed (line 3). This check helps to eliminate erroneous maps, where a non-static field is mapped to a static field or a mutable field is mapped to an immutable field, etc.

For every compatible field pair (f,g), the similarity between their read and write uses is computed. To compute the read/write similarity, the set of methods that read and write to f,g are identified. The fieldReadWrites procedure identifies these methods for a given field. The procedure receives a field and a class as input. It returns a list of methods in the class that read the field and a list of methods that write to it.

For the ArrayList example in Figure 1, invoking the procedure with the field elementData as an input will return the following lists: {set,contains,indexOf}, {set}. The indexOf, set methods are

added to the read list, as they both read elementData. ¹. The contains method is added to the list, because it indirectly reads elementData by invoking indexOf method. A similar analogy is applied to identify the set of methods that write to elementData.

Once the read and write list for fields f,g is identified, the similarity between the corresponding lists is computed using the similarity function. The function creates vector embeddings for input lists and computes their cosine similarity score. FieldMapper computes the similarity score for both field reads and writes (lines 7–8). The average of these scores is stored in escore. The weighted sum of escore and the type similarity score for f,g (stored in TS) is added to matrix FS. The weight of the scores is determined by the value of fw, set by the user.

After all the field pairs are processed, the matrix FS contains the similarity scores for all field pairs. OPTIMIZE uses FS to compute the best match between the fields that maximizes the overall score. We used the Hungarian Algorithm[20] to instantiate OPTIMIZE function in our implementation, but any algorithm that finds an optimal match for a weighted bipartite graph can be used. The returned map is filtered by the FieldMapper to eliminate pairs with low scores. The ft value set by the user determines the minimum score for a field pair. The filtered map, σ , is returned to the main ClassFinder algorithm, which is subsequently used by the MethodMapper.

3.5 Method Mapper

The MethodMapper receives classes Q, R, the field map σ and the type similarity matrix TS as input. It creates a method map α based on the functional and type similarity between methods. Algorithm 4 presents the overall working of MethodMapper.

Algorithm 4 MethodMapper algorithm

```
Q ← Query class; R ← Replacement class
     \sigma \leftarrow \widetilde{\mathsf{Field}} \, \mathsf{Map}; \, TS \leftarrow \widehat{\mathsf{Type}} \, \mathsf{similarity} \, \mathsf{matrix}
     id ← Maximum in-line depths
                                                                          ▶ Configuration variables
     mt \leftarrow Method similarity thresholds; mw \leftarrow Method embedding weight
 1: MS \leftarrow INIT(0,R)
 2: R' \leftarrow rewrite(R, \sigma)
 3: for every (m_i, m_j) \in methods(Q) \times methods(R') do
         Tokens_i \leftarrow MethodTokenizer(m_i, id);
         Tokens_i \leftarrow MethodTokenizer(m_i, id)
         emb-score \leftarrow similarity(Tokens_i, Tokens_i)
 6:
         PS \leftarrow INIT(m_i, m_j)
         for every (p,q) \in Parameter(m_i) \times Parameter(m_i) do
 8:
 9.
              PS[p,q] \leftarrow TS[type(p), type(q)]
10:
         end for
         \texttt{parameter-map} \leftarrow \texttt{OPTIMIZE}(PS);
11:
12:
         par-score \leftarrow normalize(parameter-map, PS)
          MS[m_i, m_j] \leftarrow mw * emb-score + (1 - mw) * par-score
14: end for
15: \alpha \leftarrow \mathsf{best\text{-}match}(\mathit{MS},\mathsf{mt})
16: return α
```

The algorithm begins by creating a matrix MS, that will store the similarity score for every method pair (m_i, m_j) , where m_i is defined by Q and m_j is defined by R. The matrix is initialized with -1 score for all pairs using the INIT procedure. Next, the algorithm rewrites the class R by renaming fields based on the input field map, σ . For the ArrayList and Vector classes given in Figure 1, σ mapped size

field in ArrayList to elementCount field in Vector. Therefore, MethodMapper renamed the elementCount field as size.

After the rewrite, the algorithm iterates over all pairs of public methods (m_i, m_j) in Q, R'. Given a pair of methods (m_i, m_j) , the algorithm extracts tokens that capture the functionality of m_i, m_j , using MethodTokenizer function. Before extracting the tokens, the procedure inlines every method invocation within the input method. This is carried out upto a specific depth specified by the id value provided by the user. We implemented MethodTokenizer to extract the list of variable names and method names accessed by the method. This included the names of the invoked methods, the parameter names, field names and the local variables defined by a method. However, MethodTokenizer can be replaced with any function that can extract a list of tokens that represents the method functionality. The tokens for the methods are embedded into vectors and similarity between the vectors is computed by the similarity function (line 6).

Next, the algorithm creates a map between the parameters received by m_i, m_j , based on their type similarity. MethodMapper frames parameter mapping as an assignment problem[21]. It creates a matrix, PS, that stores type similarity score for every pair (p, q), where p, q are parameters to m_i , m_j respectively (lines 8–10). This matrix is input to the OPTIMIZE function, which returns an optimal map that maximizes the overall score. We instantiated OPTIMIZE with the Hungarian algorithm[20], but it can be replaced with any algorithm that solves the assignment problem. The overall score of the match returned by the OPTIMIZE function is normalized to fit within a range -1 to +1. The normalized score is used as the parameter mapping score (line 12). The final score assigned for the pair m_i , m_j is the weighted sum of the parameter mapping score and the method embedding score, which will be stored in MS. The weight for each score is determined by the mw value, specified by the user.

Once all pairs are processed, the algorithm scans the MS matrix to identify the required α . Each method m_i in Q is mapped to a method m_j with the highest score. If the highest ranking candidate is below a threshold mt set by the user, the method will be mapped to \bot .

The newly constructed α is returned to the ClassFinder top-level algorithm, which ranks the classes based on the number of mappings in their α . Ties are broken based on the aggregate method scores in α . If ties persist, they are resolved based on the field mapping σ . The top-level algorithm returns the ranked classes and the mappings to the user.

4 EXPERIMENTAL RESULTS

To evaluate ClassFinder, we formulated the following research questions:

- RQ1: Is ClassFinder able to highly rank appropriate replacement classes?
- RQ2: Is ClassFinder able to appropriately map methods in the original class to methods in the replacement class?
- RQ3: Does ClassFinder's hybrid methodology, which blends type analyses and embeddings-based search, improve on the class replacement task over just using embeddings?

¹index0f not shown for brevity

To investigate these research questions, we carried out three different experiments. We now outline the corresponding methodology.

4.1 Methodology

Table 1: Benchmark Information. |LOC| is the lines of code. |I| is the number of classes explicitly imported by the class. |F| and |M| are field and method counts respectively. |P| is the maximum parameters received by any method in the class.

ID	Class name	Package	L0C	1	F	M	P
1	ArrayList	:1	1731	6	15	32	3
2	Vector	java.util	1482	7	5	50	3
3	FastArray	groovy.util	144	5	4	14	4
4	FastVector	weka.core	216	3	4	47	3
5	Box2	jmist.math	773	1	8	39	3
6	Rectangle	eclipse.draw2d	1414	1	6	88	5
7	MutablePair		172	1	4	9	2
8	ImmutableTriple	apache.commons	204	0	6	5	3
9	MutableTriple		172	0	5	9	3
10	Point3DImpl	openimaj.math	293	6	3	26	4
11	CircularFifoQueue		432	12	6	23	1
12	TreeList	apache.commons	1132	11	3	19	3
13	FileEntry		276	5	10	17	2
14	CacheStats	google.common	304	8	6	17	2
15	IntMath	googie.common	1350	18	0	24	3
16	XYDataItem	jfree.data	240	3	3	11	2
17	BufferedReader	java.io	593	7	12	10	4
18	IndexedElement	dom4j.util	334	12	6	41	4
19	RequestUtil	apache.sling	104	3	0	4	4
20	ResponseUtil	apaciie.siiiig	131	1	0	2	1
21	TreeBagMultimap	eclipse.collections	215	25	2	20	2
22	SlowFuzzyQuery	apache.lucene	201	10	7	6	2
23	Matrix	weka.core	558	3	2	27	4
24	ManagedLinkedList	groovy.util	147	3	7	4	2

4.1.1 Search Corpus and Query Classes. To find replacement classes ClassFinder relies on having access to a large corpus of existing classes, from which it can draw candidate replacements. We constructed such a corpus for our experiments. The corpus consists of the Java classes previously used by Aroma [22], Java classes identified as popular [14] and the classes used by prior work on synthesizing class replacements [13]. This corresponds to ≈ 600 thousand classes in the search database.

Given a search corpus, ClassFinder finds a replacement class for the user's original *query* class. We collected a total of 24 classes for our queries. Table 1 provides an overview of these 24 query classes. The first three columns correspond to a numeric identifier for the class (for brevity of discussion), the class name, and the package from which it is sourced. The fourth column presents the number of lines of code in the class. The fifth column presents the number of classes explicitly imported by the class. The sixth and seventh columns give the count of fields and public methods in the class respectively. The maximum number of parameters received by any public method in the class is given in the ninth column.

Classes 1–10 are the set of classes used in prior work for synthesizing replacement classes [13]. This represent classes for which we know there exists potential replacement class in our search corpus. We refer to these classes as *group 1*. Classes 11–18 are additional classes that we found by inspecting libraries identified as popular [14]. We refined this to the set of classes that we could manually

inspect and determine whether replacement classes would be appropriate. This group of classes effectively represent queries where we do not know if an appropriate replacement class exists in our search corpus. We refer to these classes as *group 2*. Finally, classes 19–24 consists of classes that have been deprecated by software developers and for which we have a ground truth on the class that was used to replace the original. The packages containing the deprecated class and the replacement were part of the search corpus. We refer to these classes as *group 3*.

4.1.2 Configuration. We set the type similarity threshold (tt) to +0.8, field similarity threshold (ft) to +0.5 and method similarity threshold (mt) to +0.5 in our experiments. These thresholds eliminate poor mappings and also speed up the optimization function: OPTIMIZE. We set the field weight fw and method weight to mw to 0.5. These values can range between 0-1. Setting the weights to 0.5 informs ClassFinder to give equal importance to type mapping and semantic equivalence. These can be modified based on the user's requirements. Setting the value 0 will return classes that are type compatible but are semantically different. Setting it to 1 will yield results that are semantically equivalent but are not type compatible. The id variable determines maximum method inlining depth and it was set to 5. Increasing this depth can improve the precision of method embeddings but will also incur a slowdown. We considered fields and methods in classes Q and R inherited from the parent classes, if any. This depth can also be defined by the user. 4.1.3 Searching and Analysis. For each query class, we configured ClassFinder to first retrieve the top 1K classes from the search database that are nearest to the query class, with the help of embedding function. The distance between neighbors is defined to be the cosine similarity of their corresponding class vectors (see section 3.2 for details). ClassFinder analyzed all the 1k classes to establish a mapping between the methods in the classes. Each class N is assigned a rank based on the number of methods in 0 that are mapped to a method in R by ClassMapper. The classes were sorted based on this rank and returned to the user. If two classes have the same rank, we use the number of mapped fields and the average method scores as a tie-breakers.

4.1.4 Evaluation. To determine the performance of ClassFinder we consider two approaches. In settings where we have the ground truth replacement class (as determined by human developers), such as is the case for the deprecated classes (19 - 24), we use the rank assigned by ClassFinder as a metric of performance. A higher rank for the known ground truth corresponds to a better performance. For cases where we do not have a ground truth replacement class and furthermore it is not necessarily the case that our corpus contains an appropriate replacement class, we defer to manual inspection. In particular, we retrieve the top 5 classes suggested by ClassFinder and then manually inspect their source code and compare this to the original query class to determine if they constitute valid replacements. We perform a similar analysis for classes retrieved using only an embeddings-based search. We compute the fraction of methods in the original class that can be replaced by methods in the replacement class candidate in a 1-to-1 mapping. We also consider a nuanced breakdown of the correctness criteria for a mapping.

To determine the quality of the method mapping (α) between the original and replacement classes produced by ClassFinder, we assign each individual mapping to one of five possible quality categories: {C1, C2, E1, E2, E3}. We now define each of these categories.

Given a manually determined ideal field mapping (σ) between class R and Q, the automatically generated method mapping produced by ClassFinder (α) , and a particular method (m) in the query class, we define the following categories:

- C1: a mapping for *m* exists in the ideal mapping, and ClassFinder maps it to the same method as the ideal.
- C2: no mapping exists for *m* in the ideal mapping, and CLASS-FINDER maps it to empty.
- E1: a mapping for m exists in the ideal mapping, but CLASSFINDER maps it to the wrong method.
- E2: no mapping exists for the method in the ideal mapping, but ClassFinder maps it to a method.
- E3: a mapping for m exists in the ideal mapping, but ClassFinder maps it to empty.

For completeness, we often refer to the fraction of public methods in the query class that can be correctly replaced by the replacement class. This corresponds to the fraction of methods in α labeled as C1, E1, or E3. We denote this fraction of methods as \mathcal{P} . The motivation behind this metric is to draw a distinction between the quality of the mapping produced by ClassFinder and the ranking of replacement classes produced by ClassFinder. We measure the quality of method mapping with \mathcal{C} , this corresponds to the fraction of methods labeled C1 or C2.

To determine the quality of replacement classes' ranking, we compare the rank assigned by ClassFinder and the initial rank assigned by the *embedding* function in N. We denote the ranking from the embedding-only approach as ER (short for embedding rank). This method constitutes the first part of the ClassFinder pipeline, before method and field maps are created for the candidate replacement classes.

Evaluation Hardware All the experiments are run on a Ubuntu 16.04 machine, running on a 3GHz Intel(R) Xeon(R) processor with 528 GB RAM and 40 cores.

4.2 Results

Table 2 presents the results of our search experiments for classes in group 1 and group 2. The first column presents the name of the query class. The columns 2-15 present statistics on the top 5 classes returned by the intermediate embedding-based search and those returned by ClassFinder. The columns titled \mathcal{P}_e presents details about the top ranked class in the intermediate list N (ER rank 1-5). The column presents the percentage of methods that can be correctly replaced by this class and is used to measure the quality of classes if method and field mapping were skipped. The columns titled ER, \mathcal{P} and \mathcal{C} provide details about the final top ranked replacement class returned by ClassFinder. This is the class field and method mappings placed at the top. The ER presents the initial rank of this class in N and ${\mathcal P}$ provides the percentage of query class methods it can replace. For example, for Vector class, \mathcal{P}_e notes that the top replacement class produced by the embeddings-based search (i.e. the first class in N) can correctly replace 79% of Vector class's methods. In contrast, the top result for ClassFinder can

correctly replace 91% (\mathcal{P}). C presents the accuracy of method mapping generated by ClassFinder. This includes methods it identified correct replacement or correctly identified the absence of one.

On average, the top ranked classes identified by ClassFinder have a corresponding method replacement for 80% of the methods in the original class (with multiple cases of 100% coverage). In contrast, the top classes retrieved solely based on an embeddings search can replace an average 54% methods (\mathcal{P}_e). This trend continues to manifest across all top 5 rankings. Furthermore, ClassFinder's ranking provides substantial refinement over the original ranking produced by the embedding-only approach. In particular, for 6 of the query classes the top ranked class returned by ClassFinder had a rank between 78 and 979 in the embeddings-only approach.

Next we present our results on the correctness of the method mappings produced by ClassFinder. The C values in Table 2 demonstrate the average accuracy of method mappings is above 70% for top 5 ranking classes. In some cases, the accuracy is 100%. A more detailed analysis of the precision is presented in Figure 3.

Figure 3 presents a breakdown of the classification of mappings for top ranked replacement candidates. Specifically, the title of each subplot corresponds to the query class we want to replace. The x axis indicates the name of the top 5 ranked replacement classes produced by ClassFinder. The y axis denotes the fraction of methods in the query class that belong to a method mapping quality category (see Subsection 4.1.4) and the colors that constitute each bar correspond to the quality categories. Our results show that a significant fraction of method mappings produced by ClassFinder are correct (C1 + C2). As expected, this fraction is higher for classes that are more highly ranked, though we observe some variation depending on the query class. And this variation can represent a complex relationship between query class, replacement availability, and quality of the mappings produced.

Finally, we present ClassFinder's results when queried with classes in group 3, which correspond to deprecated classes where we know exactly what class the developers used as a replacement in their codebase. Given that we have the ground truth, and we know these replacement classes exist in our class corpus, we evaluate the rank assigned to that ground truth class as well as the method mapping produced. Table 3 presents the deprecated class name, information on the package and naming of the replacement class, the rank produced by ClassFinder for the ground truth replacement, the rank produced by the embeddings-only approach for the ground truth replacement, the fraction of methods in the query class that can be correctly replaced (\mathcal{P}) and a summary of the correct mappings produced by ClassFinder (C1 + C2). In all cases, Class-FINDER correctly retrieves the replacement class as the top result. In contrast, the embeddings only approach fails for the Matrix class, where it ranks the ground truth at 241. Additionally, ClassFinder does not just produce a ranking of replacement class, but also a mapping between methods. We find that a large fraction (between 74% and 100%) of ClassFinder's mappings for these classes' methods are correct. It is worth noting that the ground truth replacement classes for two of the deprecated classes (SlowFuzzyQuery and Matrix) are in fact not perfect replacements (as demonstrated by the low \mathcal{P}). However, in such cases ClassFinder's mapping still achieves a high fraction of correct mappings (C1 + C2) as it can

Table 2: Ranking results for query classes in group 1 and group 2. For each query class (Class name), we present statistics for the top 5 ClassFinder results. The \mathcal{P}_e , \mathcal{P} corresponds to the percentage of methods that can be ideally replaced by the top n^{th} replacement class returned by just the embedding-based search and the ClassFinder respectively. The |ER| is the initial rank assigned to the class by the embeddings-based search, before being re-ranked to the n^{th} position by ClassFinder's complete pipeline. C is the precision of the method map α . Time is the time taken by ClassFinder in minutes.

	Rank 1				Rank 2				Rank 3			Rank 4				Rank 5					
Class name	N	CENSOI INDER			N	N ClassFinder			N	N ClassFinder			N ClassFinder			N ClassFinder			Time		
	\mathcal{P}_e	ER	\mathcal{P}	С	\mathcal{P}_e	ER	P	С	\mathcal{P}_e	ER	P	C	\mathcal{P}_e	ER	P	C	\mathcal{P}_e	ER	\mathcal{P}	С	
ArrayList	100	366	100	100	100	462	100	100	87	959	100	100	0	675	100	100	0	124	100	84	90
Vector	79	78	91	83	79	4	83	83	0	2	87	95	69	606	73	70	0	1	79	81	100
FastArray	50	979	57	57	50	64	64	64	0	69	57	57	7	253	50	64	50	96	42	71	42
FastVector	68	104	85	91	17	194	85	91	40	70	85	91	21	43	72	79	91	6	91	85	95
Box2	76	1	76	84	0	156	29	84	0	284	30	71	33	15	30	74	33	12	33	94	91
Rectangle	100	1	100	100	42	80	46	72	34	2	42	70	0	27	37	67	34	6	37	70	61
MutablePair	62	1	62	75	75	2	75	87	0	11	75	87	50	7	75	87	50	10	62	75	13
ImmutableTriple	50	2	66	100	66	3	83	83	83	1	50	83	0	5	33	83	33	20	50	100	7
MutableTriple	0	2	50	75	50	8	87	87	62	7	75	75	50	6	75	75	25	19	50	62	14
Point3DImpl	19	5	30	69	11	3	30	69	30	1	19	57	11	2	11	57	30	4	11	53	66
CircularFifoQueue	100	1	100	100	42	51	86	65	42	119	86	73	42	106	86	86	17	133	86	73	33
TreeList	57	8	100	100	57	5	100	100	57	81	100	94	100	309	100	100	84	423	100	100	30
FileEntry	11	8	58	70	29	18	64	94	23	286	58	82	47	7	41	70	41	29	52	76	23
CacheStats	100	1	100	100	23	18	58	47	29	6	11	47	29	16	23	70	0	577	5	52	11
IntMath	100	3	100	100	100	2	100	81	100	1	100	95	45	19	36	59	18	69	59	31	23
XYDataItem	0	261	72	90	0	34	54	72	0	192	63	72	72	160	54	72	0	27	45	63	17
BufferedReader	0	7	100	100	0	65	60	60	100	239	70	70	0	33	90	90	0	6	100	90	46
IndexedElement	0	283	95	97	0	38	95	100	0	24	47	82	0	340	17	87	0	95	17	87	48
Average	54	117	80	88	41	67	72	79	38	130	64	77	32	146	55	77	28	94	56	74	45m

appropriately identify that some methods are not replaceable (C2) with the given replacement class.

Table 3: Deprecated class results. PN and CN indicate if both the original and ground-truth replacement classes are in the same package and have the same name respectively. ER indicates the initial rank assigned by the embedding based search. Final is the final rank assigned by ClassFinder. $\mathcal P$ provides the percentage of methods in the deprecated class that can be replaced by the top ClassFinder result. $\mathcal C$ is the precision of the method map α .

Deprecated class	PN	CN	R	lank	P	С
Deprecated class	FIN	CN	ER	Final	,	C
RequestUtil	No	Yes	1	1	100%	100%
ResponseUtil	No	Yes	1	1	100%	100%
TreeBagMultimap	No	Yes	1	1	100 %	100%
SlowFuzzyQuery	No	No	1	1	83%	100%
Matrix	No	Yes	241	1	37 %	74%
ManagedLinkedList	No	No	1	1	100%	100%

4.3 Research Question Discussion

We introduced this evaluation² with three key research questions, we now provide discussion of these based on our results.

4.3.1 Research Question 1. Our results show that ClassFinder is capable of ranking appropriate replacement classes highly. In particular, we found that for query classes in group 1 and group 2 the top ranked ClassFinder replacement class could be used to replace on average 80% of the methods in the original class (see Table 2). The second and third ranked results could still on average

cover 72% and 64% respectively. When we considered the case of query classes from our *group 3*, where we know the developer's ground truth replacement as the original class was deprecated, we found that ClassFinder produced the ground truth replacement as its top result in all 6 cases.

4.3.2 Research Question 2. A key contribution of CLASSFINDER is to produce not just a ranking of replacement classes but also a detailed mapping between methods and fields in the original and replacement classes. For our evaluation, we focused on the method mapping. For classes in group 1 and group 2 we found that CLASSFINDER's mapping for the top ranked result had a high fraction of correct mappings (C1 + C2) for most query classes in our evaluation. For 11 of theses classes over 75% of methods were correctly mapped. Similarly, we found that for the deprecated classes (group 3) CLASSFINDER's mappings are correct in almost all cases. The one exception was Matrix, where the replacement class does not have a lot of the necessary functionality, and CLASSFINDER incorrectly maps 26% of methods (E1 + E2 + E3).

4.3.3 Research Question 3. Our results show that the additional analyses result in better replacement rankings. In particular, for deprecated classes, we found that an embeddings-only approach failed to retrieve the ground truth for the Matrix class. Similarly, we showed that the top ranked ClassFinder results for group 1 and group 2 classes could have substantially different rank in the embeddings-only approach. On average, the top ranked result produced by ClassFinder can correctly replace 80% of public methods, while the top ranked result produced by an embeddings-only approach can correctly replace 54% of public methods. This relationship holds true for the top 5 results: ClassFinder's re-ranking yields classes that can correctly replace more public methods than

 $^{^2}$ The data used in our experiments and the search results are available for download. The data will be publicly available upon acceptance.

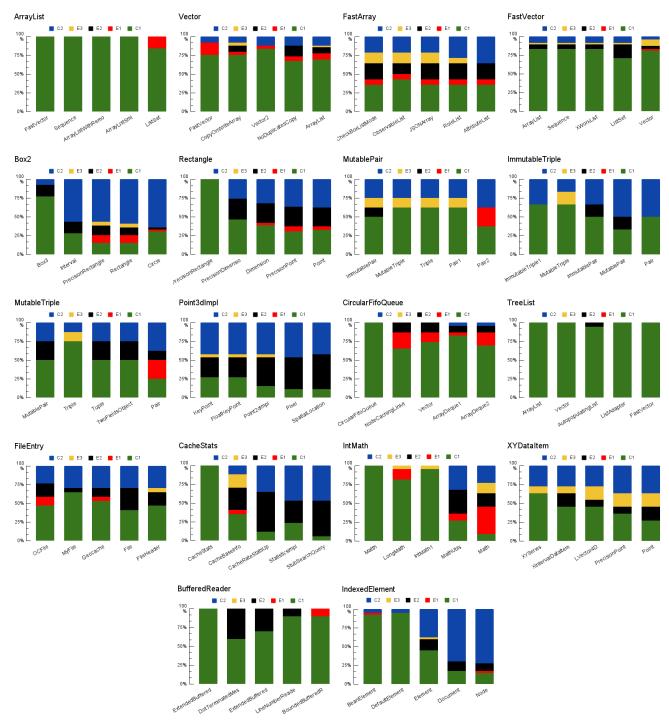


Figure 3: The quality classification of methods for the α constructed by the ClassFinder. Subplot titles correspond to query classes. X-axis labels correspond to the top 5 ClassFinder results. The y-axis corresponds to the fraction of methods in the original class, and the colors denote the fraction of such methods that are associated with a given method mapping quality classification. C1 + C2 constitute correct mappings.

the result in the same position produced by an embeddings-only approach. Additionally, in contrast to an embeddings-only approach

ClassFinder can produce not just a ranking but also a field and method mapping between the original and replacement class.

5 LIMITATIONS AND THREATS TO VALIDITY

The quality and the number of replacement classes identified by CLASSFINDER depends on the query class and the search database. For example, in our evaluation, CLASSFINDER did not identify a complete replacement for FastArray. This is a result of the unique implementation of FastArray, as it assumes the user will perform safety checks (e.g. bound checking arrays). In contrast, most classes in the search database include classes that already incorporate such checks. This mismatch in functionality, results in few classes that can correctly (and directly) replace FastArray. To mitigate this limitation, a user should aim to collect a large enough corpus of classes to populate CLASSFINDER's search database.

A key contribution in ClassFinder is the combination of an embeddings-based search and a type-aware mapping of candidate replacement classes. While type information can improve Class-Finder's ability to retrieve appropriate candidates, it may also lead to over constraining results. For example, in our evaluation the Box2 class uses a double type to store rectangle coordinates. In contrast, most rectangle class implementations in our search space use less precise datatypes such as float to represent these coordinates. Since a double cannot be represented safely as float in all cases (without additional, and potentially incomplete, analysis), ClassFinder found few candidate replacements for Box2. To mitigate this limitation, a user may consider adjusting the types in their query class, based on their knowledge of their application, to increase the possible types that can safely represent their values.

CLASSFINDER, and our evaluation, are focused on identifying drop-in replacement classes. This can be a restrictive condition, and there may exist other classes that can replace the original class' functionality, but require the user to implement adapter code. Indeed, prior work [13] showed that given an original and a replacement class, automatically synthesizing adapter code is feasible. To cover such cases, a user could consider lower ranked ClassFinder results as possible adapter-based replacement classes, where possible.

Different query classes may be more amenable to replacement and may produce different candidate replacements when queried through ClassFinder. To mitigate this risk in our evaluation, we considered a total of 24 classes, drawn from various sources.

ClassFinder uses embeddings to perform an initial search for candidate replacement classes and to compute scores for possible field/method mappings during later phases. Different ways of computing embeddings may produce different results. To mitigate this risk, we chose to implement ClassFinder in a modular fashion, where different embedding functions can be used. We evaluated a version of ClassFinder that uses FastText [15] to compute embeddings for replacement classes, and their methods/fields. FastText is a popular system and has previously been used within the context of code search [19]. Users could consider trying alternative versions of ClassFinder where the embedding function is instantiated differently, as a way of diversifying the resulting candidate replacement classes.

6 RELATED WORK

API migration and class replacement The task of automatically translating or replacing portions of an existing program to use a new API has been explored in prior research. Zhong et al [23] use a parallel corpus of projects (e.g. in two languages) to mine API

mappings by analyzing class usage in the paired examples. Samak et al [13] developed Mask, a system that combines symbolic execution and synthesis to replace a given existing class with a given target class. Nguyen et al [24]'s StaMiner mines mappings between two APIs by aligning API call sequences in parallel client code. Given paired client code, StaMiner aligns sequences of API calls, and identifies often recurring alignments as likely mappings. Ni et al [25] developed SOAR, which automatically rewrites a data science program from one API to another by combining information from the APIs' documentation, error traces from partial executions, and enumeration-based synthesis. In contrast, ClassFinder is not designed for synthesizing replacements based on two known libraries, it does not require a parallel corpus of code which can be expensive to collect, and it produces class-level mappings that associated methods and fields in the original and replacement class. Neural code representations Learning vector representations for code has become an active area of research. Different approaches vary in the way they compute embeddings and the tasks that their method is focused on solving. Alon et al [26] extracts vector representations for methods by combining embeddings produced from paths through the method's AST. Henkel et al show that these embeddings can be used for method naming, API mapping, and bug finding. Allamanis et al [27] introduced the use of Graph Neural Networks (GNN) for learning code embeddings. Wang et al [28] introduced the Graph Interval Neural Network, which learns over an abstracted representation of the program. Recently, large pretrained transformer-based language models have also been applied to code and related tasks such as program synthesis, prominent examples include CodeBERT [29] and Codex [30]. CLASSFINDER does not introduce a new way of computing vector representations for code. In particular, while ClassFinder relies on FastText [15] to compute vector representations, the system is designed such that we could replace this with the techniques presented previously. A key contribution is to show that we can combine vector representations for code with combinatorial optimization in a design guided by considering key program properties such as types.

Semantic code search and code clone detection Searching for code, given a large corpus of potential matches, has been actively explored and continues to be a source of novel techniques and systems in the software engineering community. Semantic code search in particular is meant to enable search over semantic properties of code, such as the expected behavior, in contrast to techniques that focus exclusively on the use of syntactic properties (e.g. term overlap). For example, Gu et al [18] and Cambronero et al [19] use neural networks to produce code and natural language embeddings that can be used to search a large corpus of methods given a natural language description of the desired functionality. Premtoon et al's Yogo [31] system represents a code fragment using its corresponding dataflow graph, as well as rewrites of the graph based on a set of rules, and perform queries as searches over the graphs. David and Yahav [32] also use a rewriting-based strategy to enable code search, but their system is focused on searching for function usage in a corpus of executables. Closely related to semantic code search is research focused on code clone detection. There is a large body of work on code clone detection using varied methods, including neural networks [33, 34], code rewrite rules [35], and efficient detection of term and structural overlap [36-38], among others. In

contrast, ClassFinder is designed to retrieve classes that can be used to replace any functionality exposed in the original.

CONCLUSION

We proposed a technique that receives a query class Q and a search corpus S, and a searches for classes in S that can replace Q. Class-FINDER integrates embedding based search with type awareness to refine the final search results. We demonstrate the effectiveness of ClassFinder by searching in a corpus of ≈ 600 K classes.

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