Simplifying Deep-Learning-Based Model for Code Search

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Abstract—To accelerate software development, developers frequently search and reuse existing code snippets from a large-scale codebase, e.g., GitHub. Over the years, researchers proposed many information retrieval (IR) based models for code search, which match keywords in query with code text. But they fail to connect the semantic gap between query and code. To conquer this challenge, Gu et al. proposed a deep-learning-based model named DeepCS. It jointly embeds method code and natural language description into a shared vector space, where methods related to a natural language query are retrieved according to their vector similarities. However, DeepCS’ working process is complicated and time-consuming. To overcome this issue, we proposed a simplified model CodeMatcher that leverages the IR technique but maintains many features in DeepCS. Generally, CodeMatcher combines query keywords with the original order, performs a fuzzy search on name and body strings of methods, and returned the best-matched methods with the longer sequence of used keywords. We verified its effectiveness on a large-scale codebase with ‘41k repositories. Experimental results showed the simplified model CodeMatcher outperforms DeepCS by 97% in terms of MRR (a widely used accuracy measure for code search), and it is over 66 times faster than DeepCS. Besides, comparing with the state-of-the-art IR-based model CodeHow, CodeMatcher also improves the MRR by 73%. We also observed that: fusing the advantages of IR-based and deep-learning-based models is promising because they compensate with each other by nature; improving the quality of method naming helps code search, since method name plays an important role in connecting query and code.

Index Terms—code search, code indexing, mining software repositories.

1 INTRODUCTION

Code search is the most frequent activity in software development [1], [2], [3] as developers favor searching existing code and learning from them just-in-time when meeting a programming issue [4], [5]. Reusing existing diverse technologies and complex frameworks from millions of open-source repositories (e.g., in GitHub) can maximize developers’ productivity [6], [7], [8], [9], [10]. During software development, it was observed that more than 90% of developers’ code search efforts are used to find code snippet [11], thus this study focuses on searching code methods following previous studies [12], [13], [14] instead of searching repositories [15], [16].

Existing Challenges. Prior works on code search start with leveraging information retrieval (IR) techniques (e.g., Koders and Krugle), which regard method code as text and match keywords in query with indexed methods [14], [17]. But their performance is poor due to two reasons: (1) short and diverse queries, keywords matching can hardly represent the search requirement due to insufficient context; (2) representation of method as text, method has a structure that carries specialized semantics [11]. To address these issues, many past studies focus on query expansion and reformulation [9], [18], [19], [20], [21]. For example, the Sourcerer model [14] extended the textual content of a method with structural information; the model proposed by Lu et al. [20] expanded a query with synonyms generated from WordNet and matched keywords to method signatures; the CodeHow model [13] extended query with related APIs, and searched code methods with matched APIs and query keywords through an extended Boolean model.

Recently, Gu et al. [12] observed that IR-based models have two problems: (1) semantic gap, keywords cannot adequately represent high-level intent implied in the query, and they also cannot reflect low-level implementation details in code; (2) representation gap, query and code are semantically related, but they may not share common lexical tokens, synonyms, or language structures. To connect the gaps between query and code, Gu et al. [12] proposed a deep-learning-based model named DeepCS. It jointly embeds method code and natural language description into a high-dimensional vector space, where the methods with high similarities to a query are retrieved. Their experiments on a large-scale codebase collected from GitHub verified the model validity, showing substantial advantages over two representative IR-based models Sourcerer [14] and CodeHow [13]. However, the working process of DeepCS is complex and time-consuming. It requires more than 50 hours for model training on a machine with an Nvidia K40 GPU,
and developers need to wait for about 14s on a code search. Thus, it is necessary to explore the possibility to simplify DeepCS in a controllable way for a practical appliance.

The Proposed Model. We observed that DeepCS succeeded because it can correctly match query tokens with code method string. Inspired by this observation, we proposed a simplified IR-based model named CodeMatcher. Generally, it combines query keywords with the original order, performs a fuzzy search on name and body strings of methods, and returned the best-matched methods with a longer sequence of used keywords. Our study investigated the following research questions:

**RQ1**: Can CodeMatcher outperform DeepCS? We tested CodeMatcher and DeepCS on a large-scale testing data with ~41k repositories. Experimental results showed that CodeMatcher substantially outperforms DeepCS, where its MRR is higher than the MRR of DeepCS by 97%—i.e., 0.71 vs. 0.36.

**RQ2**: Is CodeMatcher faster than DeepCS? CodeMatcher needs no model training like DeepCS, and it only takes 0.21s for code search per query, which is 66 times faster than DeepCS.

**RQ3**: What is the advantage of CodeMatcher over the IR-based model CodeHow? CodeHow is a state-of-the-art IR-based model proposed by Lv et al. [13] CodeMatcher outperforms CodeHow by 73.17% from an MRR of 0.41, because CodeHow ignores the importance of programming words (e.g., int and string) and their sequence.

**RQ4**: Why does CodeMatcher work well? The major reason is that CodeMatcher can return expected methods by precisely matching their names with a given query.

We offer these results to the software analytics community and suggest that sophisticated techniques like deep learning worth a try for innovation, but simple methods should be considered first. Meanwhile, although the IR-based model performs better than deep learning models in terms of accuracy and time-efficiency in our experiment, the IR-based model cannot address queries with complex syntax and tolerate errors as the deep learning model. Thus, it is recommended to fuse their advantages in the future. Besides, the high performance of CodeMatcher indicates that the method name is significant for code search, because it usually shares similar syntactic and semantic format as the query. Thus, improving the quality of developers’ method naming also helps code search.

Paper Organization. The remainder of this paper is organized as follows. Section 2 describes the background of the DeepCS model. Section 3 provides the proposed model CodeMatcher. Section 4 and 5 respectively presents the experiment setup and results, followed by the discussion in Section 6 and the implication in Section 7. Section 8 describes related work, and Section 9 summarizes this study and presents future work.

2 Background

In the section, we present a brief background of the state-of-the-art model DeepCS proposed by Gu et al. [12]

Queries and Codebase. To simulate a real-world code search scenario, Gu et al. [12] manually collected 50 queries from Stack Overflow, as shown in Table 1. These queries are top-50 voted Java programming questions following three criteria: (1) concrete, a question should be a specific programming task, such as “How can I concatenate two arrays in Java?”; (2) well-answered, the accepted answers corresponding to the question should contain at least one code snippet; (3) non-duplicated, the question is not a duplicate of another question in the same collection.

Moreover, Gu et al [12] extracted all methods from 10k GitHub repositories as the codebase for testing code search. To perform code search, each method is represented by a (method name, API sequence, token) tuple. In the tuple, method name is a sequence of camel split tokens derived from the name of the method, e.g., we split 'getFile' into 'get file'; Also, API sequence is a sequence of constructor invocation and method calls in the method body; Moreover, token is a set of camel split tokens in the method body, where duplicated tokens, stop words (e.g., ‘the’ and ‘in’) and Java keywords are removed.

DeepCS and Training Data. To obtain the semantic relationship between natural language in query and programming language in code, Gu et al.’s DeepCS [12] leverage deep learning to jointly embed the two languages in three steps:

1. **Tokenization**, a natural language is represented by a sequence of English tokens (A). Meanwhile, a code is represented by three parts as referred above: camel split token sequence of the method name (B), a sequence of APIs (C), and a set of tokens (D).

2. **Joint embedding**, To embed a method code as a characteristic vector, DeepCS uses two recurrent neural network (RNN) [22] to embed tokens in method name and API sequence in method body respectively, and it leverages a multilayer perceptron (MLP) [23] to embed tokens in method body with the bag-of-words assumption [24]. As to the natural language description d, DeepCS utilizes a RNN to embed its tokens. In this way, the similarity between method and description can be measured by \( \cos(c,d) = \frac{c^T d}{|c||d|} \).

3. **Optimization**, the parameters in DeepCS are initialized by pseudo-random generators and optimized by randomly selected methods with related Javadoc comments. Specifically, the commented methods were extracted from GitHub Java repositories created from Aug. 2008 to Jun. 2016 with at least one star. During the training time, a training instance is a triple \( \langle C,D^+,D^- \rangle \): for a code (\( e \in C \)) and the first line in related Javadoc description (\( d^+ \in D^+ \)), the model randomly chooses an incorrect description (\( d^- \in D^- \)) from the pool of all \( D^+ \)'s. Then, to optimize parameters \( \theta \) in all neural networks, DeepCS predicts the cosine similarities of both \( \langle C,D^+ \rangle \) and \( \langle C,D^- \rangle \) pairs and minimize the loss function, \( L(\theta) = \sum_{\langle C,D^+ \rangle,e} \max(0,0.05 - \cos (e,d^+) + \cos (e,d^-)) \). Intuitively, the loss function encourages the correct description to a method \( \cos(e,d^+) \) and discourage the incorrect one \( \cos(e,d^-) \). Using the optimized model, the top-10 methods mostly related to a query are returned, in terms of cosine similarities between returned methods and query calculated by DeepCS.

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4. https://stackoverflow.com/questions/tagged/java?sort=votes
5. https://en.wikipedia.org/wiki/camelcase
The key to an IR-based model is using the first correct result values, where DCS is the DeepCS model; CM is the proposed model CodeMatcher; CH is the CodeHow model by Lv et al. [19].

| No. | Query                                                                 | FRank |
|-----|----------------------------------------------------------------------|-------|
| 1   | convert an inputstream to a string                                   | DCS   |
| 2   | create arraylist from array                                         | CM    |
| 3   | iterate through a hashmap                                            | CH    |
| 4   | generating random integers in a specific range                       |       |
| 5   | converting string to int in java                                     |       |
| 6   | initialization of an array in one line                                |       |
| 7   | how can I test if an array contains a certain value                  |       |
| 8   | lookup enum by string value                                          |       |
| 9   | breaking out of nested loops in java                                  |       |
| 10  | how to declare an array                                             |       |
| 11  | how to generate a random alpha-numeric string                        |       |
| 12  | what is the simplest way to print a java array                       |       |
| 13  | sort a map by values                                                 |       |
| 14  | fastest way to determine if an integer’s square root is an integer   |       |
| 15  | how can I concatenate two arrays in a file                          |       |
| 16  | how do I create a java string from the contents of a file           |       |
| 17  | how can I convert a stack trace to a string                          |       |
| 18  | how do I compare strings in java                                     |       |
| 19  | how to split a string in java                                       |       |
| 20  | how to create a file and write to a file in java                    |       |
| 21  | how can I initialise a static map                                    |       |
| 22  | iterating through a collection, avoiding concurrent modification exception when removing in loop |       |
| 23  | how can I generate an md5 hash                                       |       |
| 24  | get current stack trace in java                                     |       |
| 25  | sort arraylist of custom objects by property                         |       |
| 26  | how to round a number to n decimal places in java                    |       |
| 27  | how can I pad an integers with zeros on the left                     |       |
| 28  | how to generate a generic array in java                              |       |
| 29  | reading a plain text file in java                                    |       |
| 30  | a for loop to iterate over enum in java                             |       |
| 31  | check if at least two out of three booleans are true                 |       |
| 32  | how do I convert from int to string                                  |       |
| 33  | how to convert a char to a string in java                           |       |
| 34  | how do I check if a file exists in java                              |       |
| 35  | java string to date conversion                                      |       |
| 36  | convert inputstream to byte array in java                            |       |
| 37  | how to check if a string is numeric in java                          |       |
| 38  | how do I copy an object in java                                      |       |
| 39  | how do I time a method’s execution in java                           |       |
| 40  | how to read a large text file in java                                |       |
| 41  | how to make a new list in java                                      |       |
| 42  | how to append text to an existing file in java                       |       |
| 43  | converting iso 8601-compliant string to date                         |       |
| 44  | what is the best way to filter a java collection                     |       |
| 45  | removing whitespace from strings in java                             |       |
| 46  | how do I split a string with any whitespace chars as delimiters      |       |
| 47  | in java, what is the best way to determine the size of an objects    |       |
| 48  | how do I invoke a java method when given the method name as a string |       |
| 49  | how do I get a platform dependent new line character                 |       |
| 50  | how to convert a map to list in java                                 |       |

3 CodeMatcher

Our proposed model CodeMatcher is a simplification of DeepCS and based on the information retrieval technique. It has two phases to perform a code search:

**Phase-I: Parsing and Indexing Code.** DeepCS represents a code as a (method name, API sequence, token) tuple, as described in Section 2. Similarly, we represented code as a (method name, token sequence) tuple: (1) Method name. We extract the string of method name without any processing, e.g., stemming. (2) Token sequence. A sequence of fully qualified tokens [13] (e.g., Java.lang.String or System.io.File.readlines()) in method parameters, method body, and returned parameter, where the token sequence can be regarded as a combination of (API sequence, token) in DeepCS. To parse a method, we developed a tool Janalyzer [25], which transforms a method into an abstract syntax tree (AST) with the Javaparser [26] library and extracts method components by traversing the AST like DeepCS [12]. Moreover, to build a method-level code search engine, we leveraged the Elasticsearch [27], a Lucene-based text search engine, to index method tuples and corresponding source code.

**Phase-II: Matching Method with Keywords.** DeepCS leveraged the joint embedding to learn the relationship between query and method represented by (method name, API sequence, token) tuple. We assume that DeepCS successively matches keywords in query with the method name and method body, and the joint embedding aims to generate correct keywords and replace keywords with synonyms at the proper time. To simulate this assumption, the proposed IR-based model CodeMatcher performs code search in three steps as follows:

**Step-1: Token metadata.** The key to an IR-based model is how to generate appropriate keywords from a query. To characterize the tokens in query, we encode each token with a metadata in a three dimensional tuple ⟨property, frequency, importance⟩: (1) property, the class of word (e.g., verb) identified by the Stanford Parser [28], [29]; (2) frequency, the occurrence number of the camel split tokens in method names in the codebase; (3) importance, the naming worth of token property, which has five levels as shown in Table 2, e.g., the representative method named with ‘getFile’ consists of a verb (get) and a JDK noun (File).

With the token metadata, we can remove the query tokens not commonly used for method naming. In specific, we filtered out the question words and related auxiliary verb (e.g., how do), and excluded the verb-object/adpositional phrase on the programming language (e.g., in Java) as it is only used for the identification of programming language while our study focuses on Java projects. Moreover, we removed the level-1 tokens because they are seldom used for method naming. If the frequency of a token is zero, therefore this token is meaningless in the search corpus, i.e., the out-of-vocabulary issue. We thus used its synonym that generated by the WordNet [10] [30] with the highest frequency as the substitution. Afterword, we stemmed[H] the rest of query tokens to improve their generalizability in code search.

**Step-2: Keywords for iterative fuzzy search.** Using the filtered query tokens in Step-1, we can generate keywords to perform a code search. Here we only match the query with indexed method names to quickly exclude irrelevant methods. We did this because we assume that if a method name matches a query, its method body is likely to have expected code implementation.

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6. https://github.com/javaparser/javaparser
7. https://www.elastic.co/cn/downloads/elasticsearch
8. https://nlp.stanford.edu/software/lex-parser.shtml
9. https://en.wikipedia.org/wiki/camelcase
10. http://www.nltk.org/howto/wordnet.html
11. https://pythonprogramming.net/stemming-nltk-tutorial/
TABLE 2

| Level | Condition               |
|-------|-------------------------|
| 5     | JDK Noun                |
| 4     | Verb or Non-JDK Noun    |
| 3     | Adjective or Adverb     |
| 2     | Preposition or Conjunction |
| 1     | Other                   |

To perform code search, we launched an iterative fuzzy match on indexed method names with a regular string. The string is formed by all remaining query tokens in order as "token1.*token2.*...*tokenn.*". We used the regular match instead of the term match because we assume that the token sequence is important. For example, "int to string" should be different from "string to int". Afterward, if the total number of returned methods is no more than 10, we removed the least important token with lower frequency one at a time according to their metadata, and performed the fuzzy search again until only two tokens left. For each search round, we filtered out the repeated method by comparing the MD5 hash values of their source code.

Step-3: Reranking on method name and body. To refine the method rankings returned from Step-2, we designed a metric \( S_{name} \) to measure the matching degree between query and method name as Eq. (1). A larger value of \( S_{name} \) indicates a higher-ranked method with more overlapped tokens between query and method name in order. Moreover, if equal \( S_{name} \) exists, we boosted the rank of a method with a higher matching score \( S_{body} \) between query and method body, as calculated in Eq. (2). Similar to \( S_{name} \), higher \( S_{body} \) value implies better token matching between query and tokens in method body orderly. However, different from \( S_{name} \), we added the last term in \( S_{body} \) to represent the ratio of JDK APIs in method, in terms of the fully qualified tokens, which assumes that developers favor a method with more JDK APIs. After the above two rounds of ranking refinement, we returned the top-10 methods in the list.

\[
S_{name} = \frac{\text{#query tokens as keywords}}{\text{#query tokens}} \times \frac{\text{#characters in name orderly matched keywords}}{\text{#characters in name}} \tag{1}
\]

\[
S_{body} = \frac{\text{#API tokens matched query tokens}}{\text{#query tokens}} \times \frac{\max[\text{#API tokens orderly matched query tokens}]}{\text{#query tokens}} \times \frac{\text{#JDKAPIs}}{\text{#APIs}} \tag{2}
\]

Example. Fig. 1 illustrated an example for the first query "convert an inputstream to a string" in Table 1. From the token metadata, we can notice that both 'inputstream' and 'string' have level-5 importance (i.e., they are JDK objects), and they are frequently used for method naming (frequency > 3442).

Fig. 1. An example for CodeMatcher.

With this metadata, CodeMatcher successively generates three candidate regular match strings on indexed method names. For the two returned methods, the first one ranked higher due to its larger matching scores on method name \( S_{name} \) and body \( S_{body} \).

4 EXPERIMENT SETUP

This section describes the investigated research questions, the collected large-scale dataset for model validation, and the widely used model evaluation criteria.

4.1 Research Questions

To investigate the performance of the proposed model CodeMatcher, this study investigated the following three research questions (RQs):

- **RQ1**: Can CodeMatcher outperform DeepCS?
- **RQ2**: Is CodeMatcher faster than DeepCS?
- **RQ3**: What is the advantage of CodeMatcher over the IR-based model CodeHow?
- **RQ4**: Why does CodeMatcher work well?

RQ1 and RQ2 aim to investigate whether the simplified model CodeMatcher outperforms DeepCS in code search.
accuracy and time-efficiency, respectively. RQ3 is to analyze the advantage of our IR-based model CodeMatcher over the state-of-the-art IR-based model CodeHow. RQ4 further investigates why CodeMatcher works well.

4.2 Dataset

Codebase. As Gu et al. [12] provide no raw project data, we cannot test our model and other baseline models on their testing data. Thus, we build a new dataset similar to Gu et al. but with a larger scale. We crawled 41,025 Java repositories from GitHub created from Jul. 2016 to Dec. 2018 with more than five stars. The time duration of our new codebase can ensure the non-overlapping with DeepCS’ training data (created from Aug. 2008 to Jun. 2016). From Table 3, we can observe that the new codebase contains 17 million methods, and 21.91% of them have Javadoc comments that describe the corresponding methods.

Queries. Following Gu et al. [12], we validated a code search model with 50 queries as model inputs as referred to in Section 2. The used queries are listed in Table 1.

4.3 Baseline Models.

To test baseline models on our codebase, we first preprocessed Java code files within all projects by our tool Janalyzer [25]. It first parses the abstract syntax tree of each Java code file by leveraging the Javaparser library, and extracts all necessary method components as the inputs of baselines, such as method name, comment, Javadoc, APIs in the method body, etc. The baseline models are described as follows.

DeepCS, the deep-learning-based model proposed by Gu et al. [12]: We trained DeepCS by re-running the source code, and training data provided by the authors. To test DeepCS on our codebase, we first did some natural language processing (e.g., stemming) following the description in Gu et al.’s paper [12], then encoded data using DeepCS’ vocabulary, and saved the encoded data into the required format by using DeepCS’ internal APIs.

CodeHow, the state-of-the-art IR-based model developed by Lv et al. [13]: It expands a query with words in related official APIs and matches it with code methods. As Lv et al. [13] provide no source code and data for replication, we reimplemented CodeHow strictly following their paper. Note that as CodeHow was used for searching C# projects while our targets are Java repositories, we thus used the JDK (Java development kit) as the source of official APIs.

CodeMatcher, the proposed model described in Section 3: It is an IR-based model but incorporated with many features from DeepCS.

CodeMatcher-\textit{S}_{body}, a special version of CodeMatcher: In the CodeMatcher, we designed two metrics to measure the matching degree between query and method name/body (\(S_{name}/\textit{S}_{body}\)) respectively, as illustrated in Eq. (1) and (2). To analyze their importance to the model performance, we set up the model CodeMatcher-\textit{S}_{body} that does not rank the returned code method with the \(S_{body}\) part in the code search.

Note that we do not test these models on original DeepCS testing data but our new data, because DeepCS provides no raw data and our larger-scale testing data has no intersection with DeepCS’ training data. Besides, we do not tune DeepCS with more training data from the new data because the scale of DeepCS’ training data is already very large. Moreover, if we train DeepCS with more labeled data from the newly collected data, the scale of new testing data will reduce substantially; the comparison with the proposed model CodeMatcher and the other baseline CodeHow would be unfair as they require no training data.

4.4 Evaluation Criteria

To measure the effectiveness of code search, we utilized four common evaluation metrics following prior code search studies [12], [13], [31], [32], [33], including FRank, Recall@k, Precision@k, and Mean Reciprocal Rank (MRR). Note that FRank is defined only for one query while other metrics are defined on all queries.

\textbf{FRank}, is the rank of the first correct result in the result list [32]. It measures users’ inspection efforts for finding a relevant method when scanning the candidate list from top to bottom. A smaller FRank value implies fewer efforts and better effectiveness of a code search tool for a particular query.

\textbf{Recall@k}, the percentage of queries for which more than one correct result exists in the top-k ranked results [31], [33], [34]. Specifically, \(\text{Recall@k} = Q^{-1} \sum_{q=1}^{Q} \delta(FRank_{q} \leq k)\), where \(Q\) is the total number of tested queries; \(\delta(\cdot)\) is an indicator function that returns 1 if the input is true and 0 otherwise. Higher Recall@k means better code search performance, and users can find desired method by inspecting fewer returned method list.

\textbf{Precision@k}, is the average percentage of relevant results in top-k returned method list for all queries. It is calculated by \(\text{Precision@k} = Q^{-1} \sum_{q=1}^{Q} r_{q}/k\), where \(Q\) is the total number of queries; \(r_{q}\) is the number of related results for a query \(q\) [12]. Precision@k is useful and important because users often check many returned results for learning different code usages [32]. Larger Precision@k indicates that a code search model returns less noisy results.

\textbf{MRR}, the average of the reciprocal ranks for all queries, where the reciprocal rank of a query is the inverse of the rank of the first relevant result (\(FRank\)) [12], [31], [33]. Thus, the formula is \(\text{MRR} = Q^{-1} \sum_{q=1}^{Q} FRank_{q}^{-1}\). Larger MRR value means a higher ranking for the first relevant methods.

Note that, following Gu et al. [12], FRank and MRR are calculated within the top-10 results, as users are likely

| #Project | #Method | #Javadoc |
|----------|---------|----------|
| 41,025   | 16,611,025 | 3,639,794 |
to check at most the top-10 results. Meanwhile, the cutoff coefficients $k$ in Recall@$k$ and Precision@$k$ are set to 1, 5, and 10 respectively, which reflect the typical number of returned methods that users are likely to inspect [31].

5 RESULTS
This section provides the experimental results to the four investigated research questions raised in Section 4.1.

5.1 Can CodeMatcher Outperform DeepCS?
Table 4 compares the experimental results between DeepCS and CodeMatcher on our large-scale testing data. We can notice that DeepCS obtains an MRR of 0.36, where Recall@1/5/10 = 0.22/0.46/0.64 and Precision@1/5/10 = 0.22/0.23/0.22. In comparison, our simplified model CodeMatcher achieves an MRR of 0.71 with Recall@1/5/10 = 0.64/0.76/0.76 and Precision@1/5/10 = 0.64/0.58/0.57. These results indicate substantial improvements over DeepCS, where MRR increased by 97.22%, Recall@1/5/10 improved by 190.91%/65.22%/18.75% respectively while Precision@1/5/10 enhanced by 100%/152.17%/171.43% separately. These results support our hypothesis about CodeMatcher raised in Section 3.

Result 1: Our CodeMatcher outperforms DeepCS significantly, indicating the simplification from DeepCS to CodeMatcher is reasonable and valuable.

| Model     | Recall@1/5/10 | Precision@1/5/10 | MRR  |
|-----------|---------------|------------------|------|
| DeepCS    | 0.22/0.46/0.64| 0.22/0.23/0.22   | 0.36 |
| CodeHow   | 0.32/0.52/0.58| 0.32/0.23/0.21   | 0.41 |
| CodeMatcher| 0.64/0.76/0.76| 0.64/0.58/0.57   | 0.71 |
| CodeMatcher-S$\text{body}$| 0.60/0.72/0.74| 0.60/0.53/0.50   | 0.68 |

5.2 Is CodeMatcher faster than DeepCS?
Table 5 compares the time efficiency between CodeMatcher and DeepCS in three different phases. The IR-based model CodeMatcher is also advantageous over the state-of-the-art IR-based model CodeHow by 73.17% in terms of MRR, where Recall@1/5/10 improved by 100%/46.15%/31% respectively while Precision@1/5/10 enhanced by 100%/152.17%/171.43% separately. These results imply that the simplified model CodeMatcher from DeepCS is also better than the state-of-the-art IR-based model CodeHow.

Result 2: The IR-based model CodeMatcher is faster than the deep-learning-based model DeepCS, because CodeMatcher requires no model training and it can process a query with 66x speedup.

5.3 What is the Advantage of CodeMatcher over the IR-based model CodeHow?
Table 4 compares the performance of CodeMatcher with CodeHow proposed by Lv et al. [13] We can observe that CodeHow obtains an MRR of 0.41 with Recall@1/5/10 = 0.32/0.52/0.58 and Precision@1/5/10 = 0.32/0.23/0.21. In contrast, CodeMatcher outperforms CodeHow by 73.17% in terms of MRR, where Recall@1/5/10 improved by 100%/46.15%/31% respectively while Precision@1/5/10 enhanced by 100%/152.17%/171.43% separately. These results imply that the simplified model CodeMatcher from DeepCS is also better than the state-of-the-art IR-based model CodeHow.

Result 3: CodeMatcher is also advantageous over the state-of-the-art IR-based model CodeHow substantially.

5.4 Why does CodeMatcher Work Well?
For CodeMatcher described in Section 3, $S_{\text{name}}$ and $S_{\text{body}}$ are two matching scores to determine the ranks of searched results, but it is unknown how much they attributed to the performance of CodeMatcher. Thus, we used CodeMatcher for code search but removing the matching score $S_{\text{body}}$. Table 4 shows that the model only using $S_{\text{name}}$ (CodeMatcher-$S_{\text{body}}$) obtains MRR=0.68, Recall@1/5/10 = 0.6/0.72/0.74, and Precision@1/5/10 = 0.6/0.53/0.5 respectively. Comparing with standard CodeMatcher, MRR is reduced by 4.23%, where Recall@1/5/10 slid by 6.25%/5.26%/2.63% separately while Precision@1/5/10 decreased by 6.5%/8.28%/11.58% respectively.

These results indicate that the score $S_{\text{name}}$ that matches query keywords with method name dominated the performance of CodeMatcher, and implies that method name is a significant bridge for the semantic gap between query

### Table 4
Performance comparison of baseline models.

| Model     | Recall@1/5/10 | Precision@1/5/10 | MRR  |
|-----------|---------------|------------------|------|
| DeepCS    | 0.22/0.46/0.64| 0.22/0.23/0.22   | 0.36 |
| CodeHow   | 0.32/0.52/0.58| 0.32/0.23/0.21   | 0.41 |
| CodeMatcher| 0.64/0.76/0.76| 0.64/0.58/0.57   | 0.71 |
| CodeMatcher-S$\text{body}$| 0.60/0.72/0.74| 0.60/0.53/0.50   | 0.68 |

### Table 5
Time efficiency comparison between CodeMatcher and DeepCS in three different phases.

| Model     | Train  | Preprocess | Search |
|-----------|--------|------------|--------|
| DeepCS    | 58.16h | 24.51h     | 695.03s|
| CodeMatcher| -      | 23.46h     | 10.50s |

Expanding code scale of GitHub as this model requires no optimization, where changed or new methods can be rapidly parsed and indexed. In contrast, the DeepCS model cannot support these features entirely because it needs to be optimized frequently for a dynamic codebase, and the optimized model should vectorize the method again, taking at least 0.5h considering the scale of the codebase that we use in our experiments.
and code. Furthermore, although the influence of $S_{body}$ that matches query keywords with method body is low, we cannot ignore its contribution, especially for recommending code methods with more JDK APIs to developers.

**Result 4:** CodeMatcher works well mainly because it can precisely match the query with relevant methods in names by considering the importance of the programming words in the query and the order of query tokens.

### 6 DISCUSSION

#### 6.1 Qualitative Analysis on CodeMatcher, DeepCS, and CodeHow

To compare three models (DeepCS, CodeMatcher, and GitHub search), we classified their 500 returned methods (50 queries × top-10 results) into seven categories in a view of code matching. Fig. 2 illustrates the definitions and real query-code examples for each category. To be specific, the categories identified whether keywords in query match a code’s method name or body; whether a code’s method body is useless, i.e., an abstract method or a getter/setter; whether a method is a duplication of previously inspected one in the top-10 code list. Table 6 lists the classification results for different models.

The reasons why DeepCS succeeded and failed. From the Table 6, we observed that the DeepCS obtained a 21% success (MM and NM), where 18.6% of success in MM was due to a correct semantic matching between query and method, as Fig. 2(1); the 2.4% of success in NM implies that DeepCS can somewhat capture the semantics in code (i.e., API sequence and tokens) although the method name does not relate to the goal of a query as Fig. 2(2).

However, there are 79% of failed results, where 0.4% of failures were caused by returning repeated methods (RM). The source code provided by Gu et al. [12] excluded the methods whose cosine similarity differences with related queries are larger than 0.01. But we observed that this judgment could not clear out repeated methods with some negligible difference, e.g., the modifier difference, as shown in Fig. 2(7). Meanwhile, 5% of failures (MN) were caused by unmatched method body, because two methods for different usages may have the same method name, as exemplified in Fig. 2(3).

For the 30% of failures (MU and NU), we found that DeepCS returned some useless methods that can be a getter/setter for a class, or contain abstract APIs with insufficient context to understand, such as the examples in Fig. 2(4-5). In this way, useless methods do not satisfy the requirement of the method-level code search since developers need to search and jump to related code. And the manual code jump will increase developers’ code inspection time, and it is also uncertain how many jumps they need. Thus, the self-contained source code is advantageous for the method-level code search.

For the most part (43%) of features (NN), DeepCS completely mismatched the code to queries, as illustrated in Fig 2(6). We attribute these failures to the insufficient model training, because (1) DeepCS was optimized by pairs of method and Javadoc comment, but 500 epochs of training with randomly selected pairs cannot guarantee its sufficiency; (2) DeepCS assumed that the first line of Javadoc comment could well describe the goal of related code, but it is uncertain whether the used line is a satisfactory label or a noise; (3) during the model training, the optimization never stop because of the convergence of its loss function values.

**CodeMatcher vs. DeepCS.** For the proposed model CodeMatcher that matches keywords in query with a method, Table 6 shows that 57% of code search succeeded due to the well-matched method name and body. However, there is no success from NM because wrongly combining keywords in the query only leads to unmatched code, i.e., MN (6.4%) and NN (25%). This is because CodeMatcher cannot handle complex queries like DeepCS via the embedding technique. The 11% of failures (MU and NU) on useless methods indicate that boosting the useful methods on a higher rank in terms of the percentage of JDK APIs is not the optimal solution, and directly removing those useless methods may be a better substitution. Same as DeepCS, CodeMatcher also returned 0.6% repeated methods. Thus, filtering redundant methods by their MD5 hash values, as described in Section 3, is not enough. A better choice would be comparing the API usages, data structure, and working flow in the method
Comparing with DeepCS, the main advantage of CodeMatcher is the correct keywords matching between query and code, i.e., a high percentage of MM. However, CodeMatcher cannot handle partial matching only on the code body (i.e., NM=0). But this is what DeepCS model is good at (12 NM for DeepCS) because it can capture high-level intent between query and method by joint embedding. But DeepCS model suffers from the out-of-vocabulary issue, where the number of NM for DeepCS drops much. Therefore, DeepCS’ advantages are good to compensate for CodeMatcher’s disadvantages.

**CodeMatcher vs. CodeHow.** By analyzing the classification of these search results in Table 6, we can observe that CodeHow is good at matching a query with the method body (14.60% for NM), because it extends query with related official APIs so that method body can be well filtered in terms of internal APIs. However, the main reason for the failures is the unmatched keywords (66.20% for NN) since CodeHow ignores the importance of programming words and their sequence. The other main reason is that it does not exclude repeated methods (11.00% for RM). However, we can observe that CodeHow can compensate for the disadvantages of CodeMatcher, i.e., the difficulty in matching a query with the method body.

**Observation 1:** DeepCS shows better ability in addressing complex queries; The IR-based models CodeMatcher and CodeHow compensate with each other as they are good at matching a query with method name and body respectively.

### 6.2 How Far is CodeMatcher from Optimum?

From Table 1, we found that CodeMatcher cannot return any correct results (i.e., NF, not-found) for 12 queries. We assumed that this is due to two reasons: (1) mislabeled metadata, we observed that 12.65% of the token property was mislabeled by the used Stanford parser, which frequently identified the ‘String’ token as a verb instead of a noun; (2) oversimple algorithm, the keywords generation algorithm and the reranking algorithm in CodeMatcher are too simple to capture the semantics of the complex query. To verify this assumption, we did the following experiments.

We manually analyzed 12 NF queries and searched function names by combining query tokens in our codebase. Results in Table 7 show that 3 NF queries can be correctly extracted, including ‘createStringFromFile’, ‘readFileLineByLine’, and ‘appendTextToFile’. These results indicate that improving our keyword generation algorithm can enhance the MRR by 7.04% from 0.71 to 0.76.

When we perform code search on GitHub with manually generated keywords in Table 7, nearly all NF queries can find correct methods, except for query 22. These results imply that extending codebase will further increase the performance of CodeMatcher in terms of MRR by 19.74% from 0.76 to 0.91.

For the query 22 “iterating through a collection, avoiding concurrent modification exception when removing in loop”, we cannot find code in GitHub with method name ‘iterateConcurrentCollection’. However, we found a class with the same name, which implemented the ‘iterate’ part with a function named ‘updateThreadList’ and implemented the ‘iterate collection’ part in a main function, respectively. Therefore, the class-level code search should be considered, and the MRR can be slightly boosted from 0.91 to 0.92 when considering this class-level search.

Besides, the above results indicate that all NF queries can be found by combining query tokens on GitHub-scale codebase. Thus, the rest of the MRR improvements from 0.92 to the optimum 1 could be gained by optimizing the CodeMatcher’s reranking algorithm.

**Observation 2:** The performance of CodeMatcher can be further improved by extending the scale of testing data, and considering the class-level code search, not just the method-level.
6.3 Why DeepCS Did Not Work Well on the New Dataset?

As DeepCS gives no raw data to run other baseline models, we collected a new larger-scale codebase as described in Section 4.2, which has no overlap with DeepCS’ training data. Table 8 compares the DeepCS optimized by its training data and tested on DeepCS’ codebase vs. ours. On Gu et al.’s dataset (DeepCSold), our replication effort shows that DeepCS can achieve similar performance (MRR = 0.59) to the one (MRR = 0.6) reported in the paper [12]. However, in the new dataset, its MRR is decreased to 0.36, which implies the overlap between its training and testing data affects the generalizability of DeepCS.

Additionally, we investigate whether the performance of DeepCS can be improved by training it with more data from the new codebase. Specifically, following the experimental approach described in Gu et al.'s work [12], we used the code methods commented with Javadoc as new training data. Due to the fixed-sized of the vocabulary of DeepCS, we excluded the methods in which no words can be covered by the vocabulary. Finally, we obtained 1,283,445 training data instances. In model optimization step, we used the pre-trained DeepCS and tuned it with the new training data with default settings, i.e., 500 epochs of total optimization iteration. Table 8 shows that the tuned DeepCS (DeepCStune) achieved a better performance with MRR 0.44 (an improvement of 22.22%). The experimental results confirm the gap between DeepCS’ training and testing data, but tuning DeepCS with data generated from the testing data can significantly mitigate the generalizability issue.

However, the tuned performance (MRR = 0.44) is still far from the result for Gu et al.’s dataset (MRR = 0.6). We observed that this case is likely attributed to the limited training data and a fixed size of vocabulary. As shown in Table 3, our new testing data contains about 16 million methods in total but only 21.91% of them have Javadoc comments. Moreover, there are only 7.73% of the total methods can finally be used to tune DeepCS due to the limited size of vocabulary. Therefore, DeepCS would have difficulty in comprehending the semantics of methods and their relationship to related Javadoc comments. To further analyze the impacts of the vocabulary, we investigate how it covers the words in the new testing data. Table 9 shows that the more than 95% of words in method components (API, name, and tokens) cannot be covered. In terms of the word frequency, there are 42.95%, 6.22%, and 12.75% of new words that appeared in method API, name, and token respectively. Because of the out-of-vocabulary issue, more than half (52.91%) of methods in testing data contain new words. Therefore, the trained DeepCS would have difficulty in understanding the semantics of methods in the new testing data.

Observation 3: DeepCS is affected by overfitting and out-of-vocabulary issues, but it could be a good code search engine for a static codebase by training with sufficient commented methods in a codebase.

6.4 What is the Advantage of CodeMatcher over the GitHub Search?

The GitHub search engine, also an IR-based model, is what developers frequently used for code search in the real world. Comparing CodeMatcher with GitHub search is helpful for understanding the usefulness of CodeMatcher. To investigate the advantages of CodeMatcher over the GitHub search, we used the 50 queries in Table 1 as their inputs. However, we need to note that GitHub search is different from CodeMatcher in three aspects: (1) Larger-scale codebase. As GitHub cannot control the search scope as our experiment setup for code snippets (only for repositories), its codebase contains more repositories. (2) Wider context. GitHub search matches keywords in a query on all text in code files (e.g., method, comment, and Javadoc) while CodeMatcher only uses texts on methods. (3) Code snippet vs. method. GitHub search returns a list of code snippets, but they would not necessarily be a method as what CodeMatcher returns.

When using the GitHub search for code search, it returns a list of code snippets with matched keywords being highlighted, and then we inspect top-10 code snippets to check whether they are relevant to the corresponding queries. However, during the code inspection, we found that many developers created methods after a tested query raised in Stack Overflow (e.g., "create an inputstream to a string"), and added a Stack Overflow link in method comments with same query words (e.g., "https://stackoverflow.com/questions/309424/how-do-i-read-convert-an-inputstream-into-a-string-in-java"). This situation indicates that the GitHub search did not work when developers perform code search in the first place, so that including these retrieved code snippets as correct results will overestimate the performance of GitHub search. Therefore, we excluded this kind of code snippets, and substituted them with the following code in the returned list.

From the results in Table 10, we can notice that the
GitHub search achieves MRR = 0.44 with Recall@1/5/10 = 0.28/0.6/0.64 and Precision@1/5/10 = 0.28/0.21/0.17. Comparing with CodeMatcher, its MRR is lower by 38.03% (0.71 vs. 0.44), where Recall@1/5/10 are lowered by 56.25%/21.05%/15.79% and Precision@1/5/10 slid by 56.25%/63.79%/70.18% respectively. These results imply the benefits of CodeMatcher’s features inherited from DeepCS.

Observation 4: The CodeMatcher is valuable in practical usages comparing with the current code search engine in GitHub.

### 6.5 What is the Advantage of CodeMatcher over the Google Search?

The Google search engine is an advanced and commonly used tool for searching GitHub code in practices. To investigate the performance of Google search, we input it 50 queries in Table 1 with the following advanced settings: “site:github.com” and “filetype:java”. Following the code inspection steps described in Section 6.4, we reviewed the top-10 returned results and checked whether the code snippets identified by the Google search are relevant to the search queries. Experimental results in Table 10 shows that Google search achieves an MRR of 0.51, 15.91% better than the GitHub search but 39.22% lower than the proposed CodeMatcher. The lower MRR of Google search is mainly caused by the low Precision@1/5/10 (no more than 0.35). In summary, these results indicate the practical merit of the CodeMatcher over the Google search.

Observation 5: The CodeMatcher shows substantial outperformance over the Google search.

### 6.6 Threats to Validity

There are some threats affecting the validity of our experimental results and conclusions as follows.

**Manual Evaluation by Developers at Baidu.** The relevancy of returned results to 50 queries was manually identified, which could suffer from subjectivity bias. To mitigate this threat, the manual analysis was performed independently by two developers from Baidu inc.; and if a confliction occurred, the developers performed an open discussion to resolve it. In the future, we will mitigate this threat by inviting more developers. Moreover, in the relevancy identification, we only consider the top-10 returned code results. Queries that fail are identically assigned with a FRank of eleven following Gu et al. [12], which could be biased from the real relevency of code methods. However, in the real-world code search, this setting is reasonable because developers would like to inspect the top-10 results and ignore the remaining due to the impacts of developers’ time and patience.

**Limited Queries and Java Codebase.** Following Gu et al. [12], we evaluated the model with popular questions from Stack Overflow, which may not be representative of all possible queries for code search engines. To mitigate this threat, the selected top-50 queries are the most frequently asked questions collected by Gu et al. [12] in a systematic procedure, as referred to in Section 2. In the future, we will extend the scale and scope of the code search queries. Furthermore, we performed the experiments with large-scale open-source Java repositories. But we have not evaluated repositories in other programming languages, though the idea of extending CodeMatcher to any language is easy and applicable.

Moreover, we collected about 41k GitHub projects with high-quality code (i.e., more than 5 stars) as the codebase. But such search space is likely to overestimate a model, because such projects are going to have more accurate Javadoc and generally cleaner, easier to understand code that is more likely to be commented. Although we extended Gu et al.’s [12] codebase (around 1k projects with at least 20 stars) on a larger scale, this situation cannot be ignored. We plan to extend our codebase more in the near future.

**Baseline Reproduction.** To estimate DeepCS on our testing data, we preprocessed the testing data according to Gu et al. [12] although the source code and training data have no difference. Meanwhile, we re-implemented the baseline CodeHow strictly following the paper because its authors provide no source code and related data.

### 7 IMPLICATION

#### 7.1 The Importance of Model Simplification

Our study shows that it is worth simplifying complex approaches or trying simple and fast methods on software engineering tasks, same as the recommendation of the well-known Occam’s razor principle [35]. Our experimental results also suggest that: although deep learning is a promising technique for modeling software engineering issues, using a simple approach well should be a better choice; moreover, a simple approach is more efficient for practical usage. Thus, it is recommended to consider a simple method first in software engineering research.

**Suggestion 1:** Considering using a simple and efficient model first.

#### 7.2 Pros and Cons of Deep-learning-based Model and IR-Based Model

The deep-learning-based model has three major advantages over the IR-based model. One is language processing ability. By leveraging the embedding technique, it can better address complex queries and tolerate errors to some extent.
According to Section 6.1. The second is the bilingual learning ability. With the joint embedding framework between a query in natural language and a code in programming language, their mapping relationship can be well learned as described in Section 6.3. At last, the deep-learning-based model may require less upfront cost than IR-based model, because the former requires much less domain knowledge and feature engineering like the IR-based model.

However, the current version of the deep learning model has a limitation on a new and dynamic codebase, because the model training suffers from overfitting and out-of-vocabulary issues as discussed in Section 6.3. But these problems do not occur for the IR-based model. Meanwhile, running the IR-based model is substantially more efficient over the deep-learning-based model, because the IR-based model requires no model training and can speedup the code search process using framework like Elasticsearch, as shown in Section 5.2. To sum up, the two kinds of code search models complement each other, therefore it is suggested to balance their pros and cons and make a fusion in the future.

**Suggestion 2:** Combine the advantages of IR-based and deep-learning-based models.

### 7.3 The Importance of Method Name

Section 5.4 indicates that CodeMatcher works well mainly because it can precisely match the query with the method name, where CodeMatcher assigns higher importance on programming words (e.g., Inputstream or String) and considers their sequence in the query. Besides, Section 6.1 also shows that if a method precisely matched keywords in query such method is likely to contain expected implementation in the method body. This is because the method name is very similar to the query: (1) writing in natural language. There is no semantic gap between query and method name; (2) short in text. They usually use the same keywords in order; (3) specific to code implementation. Their semantic relationship to code implementation is usually the same and straightforward. Therefore, a code search engine should assign higher weights on method names, no matter for the deep-learning-based or IR-based model.

Moreover, although CodeMatcher is capable of handling synonyms in a query by using the WordNet as described in Section 3, it has three limitations: (1) abbreviation. It cannot match the word 'initialize' in a query to the method named with 'ini'; (2) Acronym. The method named with 'RMSD' should be missed for a query with the keyword “root mean square deviation”; (3) low quality of method naming. The method name is not a correct abstraction on its code implementation. Meanwhile, other deep-learning-based and IR-based models also do not consider these situations. To solve these challenges, maybe the best way is to require developers strictly following a method naming standard in the beginning. For example, a developer follows the Google Java style guide and writes method name in verb (phases) with commonly used words, instead of self-defined synonym, acronym, and abbreviation. As to the existing large-scale source code in GitHub, maybe a better solution is to format their method names in a standard and unified way.

**Suggestion 3:** Method name has a significant role in code search; improving the quality of developers’ method names helps code search.

### 8 Related Work

#### Categories of Code Search.

In the software development, developers may directly search existing applications to work on [11], and many application search engines have been built [15], [16], [36], [37], [38], [39]. However, application-level search is not frequently used during the development, and more than 90% of developers’ search efforts are used for searching code snippets (e.g., code method) [11]. For this reason, method-level code search has been studied for decades [40], [41], [42], [43], and this study follows this type of code search.

The research objective of method-level code search is to investigate the mechanics of developers’ searching behaviors [2], [6], [11], [34], [44], [45], and build a model to fill the semantic gap between natural language (i.e., search query) and programming language (i.e., method source code) [12], [13], [14], [20], [46]. Better code search techniques can boost the rapid software development [3] and promote other search-based researches, such as program synthesis [47], [48], code completion [49], [50], [51], program repair [52], [53], and mining software knowledge [54].

For the setting of method-level code search, this study works on the ‘query-codebase’ search following previous studies [12], [13]. The query in natural language is commonly used as developers’ search input, although method declarations and test cases can complement and clarify developers’ specification [40], [55], [56]. But we cannot assume that developers would always provide this information. Moreover, the codebase like GitHub is usually used for code retrieval. Because the stored code are large-scale and ready-to-use [12], [13], [14], although there are some useful code provided in Stack Overflow [57] or software development tutorials [58].

#### Evolution of Method-Level Code Search.

At the beginning of this study, researchers just regarded code as plain texts, and simply applied the capabilities of web search engines into code search [17]. Google Code Search [19], Koders [20] and Kruggle [21] were few promising systems [14].

Later, many researchers attributed the challenge of code search to the understanding of query in natural language. To generate correct keywords for a search engine, many existing works focused on query expansion and reformulation [9], [18], [19], [20], [21]. For example, Hill et al. [18] rephrased queries according to the context and semantic role of query words within the method signature. Haiduc et al. [19] proposed Refoqus that reformulated query by

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18. https://google.github.io/styleguide/javaguide.html#s5-naming
19. https://code.google.com/
20. www.koders.com
21. www.kruggle.com
choice of reformulation strategies, and a machine learning model recommends which strategy to use based on query properties. Lu et al. [20] extended a query with synonyms generated from WordNet [59]. McMillan et al. [9] proposed Portfolio, which returns a chain of functions through keyword matching and speeds up search by PageRank [60]. All query processing models can outperform early search engines, such as the substantial improvements of Portfolio over Google Code Search and Koders [9].

However, source code is more than just a plain text, and it contains abundant programming knowledge. Thus, matching code text with keywords is far from enough [14]. To push the code search study forward, Bajracharya et al. [14] proposed Sourcerer, an IR-based code search engine that combines the textual content of a program with structural information. Moreover, researchers observed that the API usage is a key to understand code and its specification. Following this intuition, Li et al. [46] proposed RACS, a search framework for JavaScript that considers API relationships, including their sequencing, condition, callback relationships, etc. Meanwhile, Lv et al. [13] proposed CodeHow, a code search engine that correlates related APIs from a query and matches them with code by an extended Boolean model. Its validity and usefulness were validated by Microsoft developers. Similarly, Feng et al. [61] proposed a model to expand query with semantically related API class names and search the best-matched source code.

Recently, Gu et al. [12] proposed a deep-learning-based model DeepCS, which jointly embeds method in programming language and query in natural languages, and search methods by comparing the similarity between query and candidate methods. Their experiments show that DeepCS can significantly outperform two representative models, Sourcerer [14] and CodeHow [13]. They attributed these improvements to the successful application of a deep learning model, which considers both code property (e.g., API sequence, programming tokens) and text property (e.g., token synonymous, rephrasing, sequencing) in a unified model. As described in Section 3, our proposed CodeMatcher can be regarded as a simplified model of DeepCS that also considers code and text property in search but implemented in the way of keyword matching. Experimental results showed that CodeMatcher substantially outperforms DeepCS in searching accuracy and time efficiency. Also, CodeMatcher shows better performance over the state-of-the-art IR-based model CodeHow.

9 CONCLUSION

The challenge for code search is how to fill the semantic gap between a query in natural language and code in programming language. Recently, Gu et al. proposed a state-of-the-art model DeepCS that leverages deep learning approaches to jointly embed query and method code into a shared high-dimensional vector space, where methods related to a query are retrieved by their vector similarities. However, the working process of DeepCS is complicated and time-consuming. In this paper, we proposed a simple and faster model named CodeMatcher, which leverages information retrieval technique to simplify DeepCS but inherits many features of DeepCS. Experimental results show that CodeMatcher is over 66 times faster and it substantially outperforms DeepCS on a larger-scale codebase by 97% in terms of MRR. CodeMatcher also showed significant advantages over the state-of-the-art IR-based model CodeHow, with 71% improvement on MRR. Finally, we conducted an in-depth qualitative analysis on results of deep-learning-based and IR-based models, and provided some suggestions for the road ahead for code search.

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