Holistic Combination of Structural and Textual Code Information for Context based API Recommendation

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Abstract—Context based API recommendation is an important way to help developers find the needed APIs effectively and efficiently. For effective API recommendation, we need not only a joint view of both structural and textual code information, but also a holistic view of correlated API usage in control and data flow graph as a whole. Unfortunately, existing API recommendation methods exploit structural or textual code information separately. In this work, we propose a novel API recommendation approach called APIRec-CST (API Recommendation by Combining Structural and Textual code information). APIRec-CST is a deep learning model that combines the API usage with the text information in the source code based on an API Context Graph Network and a Code Token Network that simultaneously learn structural and textual features for API recommendation. We apply APIRec-CST to train a model for JDK library based on 1,914 open-source Java projects and evaluate the accuracy and MRR (Mean Reciprocal Rank) of API recommendation with another 6 open-source projects. The results show that our approach achieves respectively a top-1, top-5, top-10 accuracy and MRR of 60.3%, 81.5%, 87.7% and 69.4%, and significantly outperforms an existing graph-based statistical approach and a tree-based deep learning approach for API recommendation. A further analysis shows that textual code information makes sense and improves the accuracy and MRR. We also conduct a user study in which two groups of students are asked to finish 6 programming tasks with or without our APIRec-CST plugin. The results show that APIRec-CST can help the students to finish the tasks faster and more accurately and the feedback on the usability is overwhelmingly positive.

Index Terms—API, recommendation, deep learning, data flow, control flow, text

1 INTRODUCTION

In modern software development, developers heavily rely on APIs (Application Programming Interfaces). When developers do not know which API(s) to use for a desired feature, automatic API recommendation is an important way to help developers find the needed APIs effectively and efficiently. In general, API recommendation methods learn explicit or implicit API usage patterns from a large code base and then match partially written code with the patterns to recommend APIs. Existing methods differ in the types of code information they model and how they model code information.

Source code contains two core types of information: structural and textual. Structural code information, such as control and data flow, represents program logic which can be captured using a graph representation; textual code information, such as code comments, method names, variable names, reflects the semantics of the code in natural language. Take the code snippet in Fig. 1 as an example. Note that the correct API statement at line 8 should be hashCode = str.hashCode(). The method name “computeHashCode” and the variable name “hashCode” reflect the intent of this method (assuming the proper tokenization of these names). The method body uses multiple APIs which implement three pieces of correlated program logics: 1) use a reader to read contents from a file line by line (line 3/4/5/6/11/12); 2) compute the hash code of the content (line 8); 3) add the hash value into a created list (line 2/7/9). These program logics can be modeled in a control and data flow graph as shown in Fig. 3. Note that variable names (e.g., “path”, “result”, “rd”, “br”, “str”, “hashCode”) are helpful for the understanding of relevant structural program logics.

For effective API recommendation, we need not only a joint view of both structural and textual code information, but also a holistic view of correlated API usage in control and data flow graph as a whole. Unfortunately, existing API recommendation methods exploit structural or textual code information separately. Based on the observation of linguistic naturalness of source code [1], many approaches [1], [2], [3], [4] have been proposed that rely on statistical language models for code auto-completion and API recommendation. The adopted statistical language models can be simple or enhanced n-gram model [1], [2], [3], [4] or complex deep learning models (e.g., Recurrent Neural Network (RNN)) [5], [6], [7]. No matter which types of statistical language models to use, these approaches treat code as a sequence of text tokens (which may sometimes be enriched with simple syntactic information such as program construct keywords and data types), but do not exploit structural code information of source code. As such, they cannot properly model the long-range dependencies be-

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tween correlated but far-away API usage due to the limitation of the length of a sequence.

To overcome the limitation of token-sequence-based API recommendation, another important line of API recommendation methods [8], [9] analyze control and data flow graph for recommending APIs. However, these methods usually base their recommendation on the enumeration of control and data flow subgraphs, but lack a holistic view of the overall program logic. Consider the code snippet in Fig. 1. Fig. 3 shows nine control-and-data-flow subgraphs for this code snippet. Assume developers do not know the “java.lang.String.hashCode” API to be used at line 8. Unfortunately, existing methods recommend “java.io.BufferedReader.readLine” based on the fourth subgraph in Fig. 3 or “while” based on the sixth subgraph. Different subgraphs are treated independently for recommending relevant APIs. As smaller subgraphs usually appear more frequently than larger subgraphs, APIs from smaller subgraphs that capture only a partial aspect of the overall program logic often overshadow APIs from larger subgraphs that capture more holistic view of the program logic.

In this work, we propose a novel API recommendation approach called APIRec-CST (API Recommendation by Combining Structural and Textual code information), which addresses the limitation of independent modeling of structural and textual code information and the lack of holistic reasoning of code structure in existing API recommendation approaches. APIRec-CST is a deep learning model that combines the API usage with the text information in the source code based on an API Context Graph Network and a Code Token Network. As such, it can simultaneously learn structural and textual features for API recommendation. APIRec-CST uses an API context graph to model API usage in a control and data flow graph for the entire method, rather than independent partial subgraphs as in existing methods [8]. Our API context graph contains the holistic semantics of the API usage in the source code around the location for API recommendation. From this API context graph, the API Context Graph Network learns to extract informative structural features for API recommendation. The textual code information in the source code, such as method names, parameter names and variable names, is processed as a bag of code tokens which is fed into the Code Token Network to infer the developer’s intent jointly with the API Context Graph Network.

We conduct a series of experiments to evaluate the effectiveness of APIRec-CST. Our results show that APIRec-CST significantly outperforms an existing graph-based statistical approach and a tree-based deep learning approach for API recommendation. The overall top-1 accuracy of APIRec-CST is about 60.3%, the top-5 accuracy is about 81.5%, the top-10 accuracy is about 87.7% and the MRR is about 69.4%. In addition, our analysis shows that textual code information makes sense and improves the accuracy and MRR. The results of our user study with 18 students and 6 programming tasks show that APIRec-CST can help the students finish the tasks faster and more accurately and the feedback on our tool’s usability is overwhelmingly positive.

The main contributions of this work are as follows:

1. We propose an API recommendation approach called APIRec-CST that combines structural and textual code information in the source code by jointly learning a graph-based deep learning model and a token-based deep learning model for effective API recommendation.
2. We implement APIRec-CST as a tool that supports the efficient model training and API inference with GPU acceleration.
3. We evaluate the effectiveness of APIRec-CST for recommending APIs with both automatically constructed test instances and real programming tasks.

**2 Motivation**

We use the code examples in Fig. 1 and Fig. 2 to motivate the need for holistic combination of structural and textual code information for API recommendation. The example in Fig. 1 is to implement a method to compute the hash code of the content from a file line by line and then adds the computed hash code into a list. The developer has written the code he knows and needs help to complete the remaining code. The line marked as “hole” is the location that the developer requests the recommendation of proper APIs for computing the hash code of the content of a string.

We can see that this program contains rich structural code information (i.e., multiple APIs and control and data flow among these APIs). We can get many subgraphs of different sizes according to control and data flow, such as the nine subgraphs shown in Fig. 3. Note that each subgraph is labeled with a serial number for the convenience of discussion. We do not list all the subgraphs for the
When observing these two semantics in a holistic view, we can find that the declared String variable “str” is just used to store the content from the file but not used any more in semantics-1. Furthermore, the declared int variable “hashCode” is not assigned a value in semantics-2. In addition, there lack of APIs to connect semantics-1 and semantics-2 to make the program logic complete. From this holistic view, we can infer that the semantics at the hole is to get a value of int type based on some kind of processing of a variable of String type. Note that the subgraph can be a whole graph in GraLan, but the larger a graph is, the less frequent it may occur in the training data which may cause the data sparsity issue. Our deep learning model learns a vector representation for each entire graph based on an information diffusion mechanism of all nodes and edges. In this way, each entire graph that has a distinct semantics will have a meaningful vector representation, no matter how large the graph is and how frequent the graph occurs in the code base. As such, our model does not suffer from the data sparsity issue.

However, we still cannot recommend the exact API needed at the hole in Fig. 1 if we just consider the structural code information in this example. This is because we cannot decide what kind of processing should be performed on the variable of String type. Let us see the code snippet in Fig. 2. The developer needs to implement a method to read scores stored in a file, convert each score to an integer and add it into a list for further use. We can see that the code in Fig. 2 is structurally very similar to the code in Fig. 1 because the program logics for reading file and list addition are the same. The API context graph of the code in Fig. 2 is the same as that of the code in Fig. 1 but the expected APIs at hole are different. If the developer requests API recommendation for these two code snippets, we should distinguish the different intents in the two code snippets. To that end, textual code information in code becomes very useful for inferring code intents. In Fig. 1, the method name “computeHashCode” and variable name “hashCode” imply that the processing on the variable of String type is likely relevant to hash code processing. In Fig. 2 the method name “getIntegerScore” and variable name “score” can imply that the processing on the variable of String type is likely relevant to String-Integer conversion.

To sum up, a joint view of both structural and textual code information and a holistic view of correlated API usage in control and data flow graph of the entire method is required for effective API recommendation.

### 3 Background

In this work, we adopt Graph Neural Networks (GNNs), in particular, Gated Graph Neural Networks (GG-NNs) [10], for API recommendation. An API usage can be naturally represented in the form of a graph where the nodes represent APIs and edges represent control/data flow between
nodes. Furthermore, the nodes and edges can be labeled with additional context information, e.g., the nodes can be labeled with API calls and the edge labels can be used to distinguish control flow and data flow.

GNNs are a neural network model which take graph structures as inputs. GNNs are based on an information diffusion mechanism and work effectively for a variety of graphs, e.g., directed or undirected graphs and cyclic or acyclic graphs. In GNNs, each node of the graph corresponds to a unit. The unit captures the current state of a node and is used to compute the next state of the node when activated. The units update their states and exchange information until they reach a stable equilibrium [11]. The state of a node is composed of the label of the node, the labels of its incoming and outgoing edges and the states of nodes in the neighborhood of node n. Formally, a state \( x_n(t) \) of node 1 at time \( t \) is defined as follows [11].

\[
x_n(t) = f_w(l_1, l_{co[n]}, x_{ne[n]}(t-1), l_{ne[n]}),
\]

where \( f_w \) is a parametric function, \( l_n \) is the label of node \( n \), \( l_{co[n]} \) are the labels of edges containing node \( n \), \( x_{ne[n]}(t-1) \) are the states of nodes in the neighborhood of node \( n \) at the \((t-1)\)th iteration, and \( l_{ne[n]} \) are the labels of nodes in the neighborhood of node \( n \). In this way, each node can get a node representation. Take the graph in Figure 4 as an example. The state \( x_1(t) = f_w(l_1, l_{co[1]}, l_{co[2]}, l_{co[3]}, l_{co[4]}, x_{2}(t-1), x_{3}(t-1), x_{4}(t-1)) \) where \( l_1 \) is the label of node 1, \( l_{co[1]} \), \( l_{co[2]} \), \( l_{co[3]} \), \( l_{co[4]} \), \( x_{2}(t-1) \), \( x_{3}(t-1) \), \( x_{4}(t-1) \) are the labels of nodes connected with node 1. \( x_{2}(t-1), x_{3}(t-1), x_{4}(t-1) \) are the states of the neighboring nodes (i.e., node 2, node 3 and node 4) of node 1 at time \( t-1 \) and \( l_{co[1]}, l_{co[2]}, l_{co[3]}, l_{co[4]} \) are the labels of these neighbors of node 1. The state of a node is connected with other nodes in the graph as nodes can communicate with each other based on the information diffusion mechanism. Through training, GNNs can be applied for subgraph matching, mutagenesis, and web page ranking [11].

GG-NNs [10] are based on GNN. The difference is that GNNs apply Almeida-Pineda algorithm [12], [13] for computing gradients, whereas GG-NNs apply back-propagation through time with Gated Recurrent Units [14] for computing gradients. GG-NNs use a soft attention mechanism to decide which nodes are more relevant to compute the final vector representation of the graph. The graph level representation vector \( x_g \) is computed as follows [10].

\[
x_g = tanh \left( \sum_{n \in N} \sigma(i(x_n(t), I_n)) \odot tanh \left( j(x_n(t), I_n) \right) \right),
\]

where \( \sigma(i(x_n(t), I_n)) \) works as a soft attention mechanism, \( i \) and \( j \) are neural networks taking as input the concatenation of \( x_n(t) \) and \( I_n \) and output real-valued vectors [10], and \( \odot \) is element-wise multiplication.

To get a graph representation, GNNs require creating a dummy super node which is connected to all other nodes by a special type of edge [10]. Doing so in our context may destroy the structural code information of the source code itself. In addition, the soft attention mechanism of GG-NNs can help us to identify which nodes (i.e., APIs) in the API context graph are more important for API recommendation. In GG-NNs, the final representation of a graph is the accumulated information of each node with its importance computed through the soft attention mechanism. In this way, the final representation of a graph is a holistic representation of all nodes. Therefore, we choose GG-NNs as our deep neural networks to learn the features of API context graphs from a holistic view. More details of GNNs and GG-NNs can be referred to [10], [11].

4 Approach

In this section, we present the detailed design of APIRec-CST. It takes a program with a hole as input, and outputs a ranked list of API recommendations for filling the hole.

4.1 Program Representation

Given a program with a hole, APIRec-CST first constructs an API context graph and a bag of code tokens. The API context graph is a graph representation of structural code information of the user-provided program, whereas the code tokens (including the method name, parameter names and variable names) capture the textual code information. An API context graph is a directed graph \((N, E)\) where \( N \) is a set of nodes and \( E \subseteq N \times N \) is a set of edges. Each node in \( N \) represents an API method call, an API field access, a variable declaration, an assignment, a control unit or a hole. Furthermore, each node is labeled differently according to its type. Table 2 shows how each type of node is labeled. We use a special node labeled with \( \text{Hole} \) (called hole node hereafter) to represent the hole. There is an edge \((n, n') \in E\) if and only if one of the following conditions is satisfied.

- There is a direct control flow from \( n \) to \( n' \);
- There is a direct data flow from \( n \) to \( n' \);
- \( n' \) is the hole node and \( n \) is a node representing the preceding statement in the program or \( n \) is the hole node and \( n' \) is a node representing the subsequent statement in the program.

Given an edge \((n, n')\), we say that \( n \) is the parent node of \( n' \) and \( n' \) is the child node of \( n \). In APIRec-CST, the edges in an API context graph are distinguished by labeling them with different types, i.e., an edge is labeled control flow (Type c) is there is direct control flow and no direct data flow; an edge is labeled data flow (Type d) is there is direct data flow
and no direct control flow; an edge is labeled control and data flow (Type cd) if there are both direct control flow and direct data flow; and an edge is labeled special flow (Type s) if its source node or target node is the hole. Note that the special flow edge makes sure that the hole node is connected to its context.

Given a program, APIRec-CST systematically builds the API context graph statically. First, APIRec-CST builds the AST (i.e., Abstract Syntax Tree) of the program. Then it creates nodes and edges in the API context graph for each statement in the program based on the AST in the following way.

- If the statement is an API method call, an API field access, a variable declaration or an assignment, a node is created according to the corresponding node type in Table 2. Note that if the parameter of an API method call is also an API method call or an API field access, APIRec-CST first creates a node for the parameter.
- If the current statement is an expression that includes several API method calls or API field accesses, APIRec-CST creates a node for each API method call or API field access one by one.
- If the current statement is a control statement, APIRec-CST creates a node for the control unit according to its type and several other nodes together with edges connecting them as shown in Table 2. For example, if the current statement is a while statement, APIRec-CST first creates a While node, a Condition node, and a Body node. Two Type c edges are introduced, one from the While node to the Condition node and the other from the While node to the Body node.

Next, we systematically analyze the control and data dependencies between the nodes (i.e., between the corresponding statements) and introduce the edges accordingly. Take the while statement as an example. A Type c edge is added from the Condition node to the first node created for the condition expression and a Type c edge is added from the Body node to the first node created for the loop body. In addition, a Type c edge is added from the While node to the first node representing the statement following the loop. If the program contains a hole, a Type s edge is added from the node representing the statement preceding the hole to the hole node and a Type s edge is added from the hole node to the node representing the statement succeeding the hole. Since the control and data dependency analysis is performed statically in APIRec-CST, we acknowledge that it might not be fully accurate. This is however the standard approach in existing state-of-the-art approaches [8], [9], since obtaining control/data dependency through dynamic analysis has its limitations as well. Furthermore, since APIRec-CST is based on big data, the inaccuracies in individual graph (due to problems like program specific aliasing) are likely filtered out as noises.

For instance, the API context graph for the program shown in Fig. 1 is shown in Fig. 5, where solid lined triangle arrows represent edges labeled with control flow; dashed lined triangle arrows represent edges labeled with data flow; solid lined diamond arrows represent edges labeled with control and data flow; and dotted lined triangle arrows represent edges labeled with special flow. We can see that different from the graph used in GraLan, each edge is given a type in our API context graph and the structure of our API context graph is closely related to the program structure. In addition, although the program contains a hole, our API context graph is still a connected graph that contains all related structure information, but in GraLan, a graph is not a connected graph but consists of several context subgraphs around the hole.

The bag of code tokens consists of tokens of the method name, parameter names and variable names. As mentioned before, it captures the textual code information, which is useful for API recommendation. The bag of code tokens is collected as follows. First, APIRec-CST systematically extracts the method name, parameter names and variable names based on the AST of the program. Note that APIRec-CST only extracts the names of parameters and variables whose types are included in the target library (e.g., JDK). Second, because developers often use compound or nonstandard word as names, the extracted names are split as tokens.

APIRec-CST adopts a simple and efficient rule-based method for splitting names into atomic tokens. First, the numbers in a name are pruned. For example, “file2” becomes “file” afterwards. Second, the name is split into multiple tokens using the two special characters “” and “” that are often used in naming. For example, “file_name” is split into “file” and “name”. Third, each token is further split according to camel case [15]. For example, “fileName” is split into “file” and “name”. Next, each token is processed by lemmatization. For example, “files” is converted to “file”. Lastly, APIRec-CST post-processes the tokens by removing duplicated tokens as well as tokens which are meaningless, e.g., one character such as “i” and “j”. In general, only those tokens which are in the GloVe vocabulary are deemed meaningful. The GloVe vocabulary contains 400K unique tokens obtained from Wikipedia and Gigaword.

For instance, the bag of code tokens obtained from the program shown in Fig. 1 includes “compute”, “hash”, “code”, “path”, “result”, “rd”, “br” and “str”. 
TABLE 2
Labels of Different Types of Nodes in API Context Graphs

| Node Type                       | Label                                           | Example                                                                 |
|---------------------------------|------------------------------------------------|------------------------------------------------------------------------|
| Vari. Decl. with Constant Assignment | [Full Class Name].Declaration                   | String str; → java.lang.String.Declaration                              |
| Vari. Decl. with Null Assignment  | [Full Class Name].Null                          | String str = null; → java.lang.String.Null                              |
| Try                             | File file = new File(path); → java.io.File$new(java.lang.String) |                                                        |
| Switch                          | System.out.println("str");                    |                                                                       |
| Nested API Method Call          | builder.append("str"); → java.lang.StringBuilder.append(java.lang.String) |                                      |
| API Field Access                | System.out.println();                          |                                                                       |
| Cascading API Method Call       | builder.append("str").toString(); → java.lang.StringBuilder.append(java.lang.String).toString() |                                         |
| Vari. Decl.                     | label.setForeground(Color.blue)                |                                                                       |

4.2 Architecture

Given a program with a hole represented in the form of an API context graph and a bag of code tokens, the task of APIRec-CST is to predict what should be for filling the hole. APIRec-CST is designed to solve the task based on deep learning techniques. Fig. 6 shows the overall architecture of APIRec-CST, which consists of two main components i.e., the API Context Graph Network and the Code Token Network, as well as a joint layer. The API Context Graph Network learns an API context graph vector based on a given API context graph. It consists of an embedding layer and GG-NNs. The Code Token Network learns a token vector based on a given bag of code tokens. It consists of an embedding layer, multiple hidden layers and a sum operation. The joint layer is designed to combine the API context graph vector and token vector and output a joint vector. The softmax function is then used to compute the probabilities of each candidate APIs based on the joint vector. We introduce each component and the joint layer in the following.

API Context Graph Network

The API Context Graph Network takes as input an API context graph (with a hole to be filled) and outputs a vector. The API context graph is processed as a set of nodes and edges and fed into the network. An embedding layer is first used to embed the node label of each node into an individual vector which is then used as the initial vector of the node annotation in GG-NNs. Then the nodes and edges are passed into GG-NNs to get an API context graph vector.

In order to get the API context graph vector, GG-NNs first compute the state of each node and the state from the last time step is used as the node representation. The overall process of computing the state of each node is introduced in Section 3 and the details can be referred to [10], [11]. Afterwards the API context graph vector is computed based on the node representations with a soft attention mechanism to decide which nodes are relevant to the current API context graph. The detailed equation of

Fig. 6. The Overall Architecture of APIRec-CST
computing the API context graph vector can be found in Section 3 and Section 10.

**Code Token Network** The Code Token Network takes as input the bag of code tokens and outputs a vector. To obtain the output token vector, an embedding layer is first used to embed each of the code tokens into an individual vector. Subsequently, the information of each token is encoded in the form of a vector which can be learnt during training optimized by trainable parameters. We consider the code tokens as a bag of words, because we need to avoid the influence of ordering among them. For example, the embedding of “read” and “file” and that of “file” and “read” should be the same. Thus, we use multiple fully connected layers as hidden layers to capture higher-level semantic information among the code tokens. Then we sum all the vector representation of each token output by the last hidden layer as the final embedding of all the code tokens named token vector.

**Joint Layer** The joint layer takes as input the API context graph vector and the token vector and outputs a joint vector. Suppose that the API context graph vector is a \(d^A\)-dimensional vector and the token vector is a \(d^T\)-dimensional vector. The joint layer first combines the \(d^A\)-dimensional vector and the \(d^T\)-dimensional vector as a \(d^{A+T}\)-dimensional concat vector. Then the \(d^{A+T}\)-dimensional concat vector is used to compute the final joint vector through a fully connected layer using \(tanh\) as the activation function. The fully connected layer is designed to further learn the joint semantics of the structural code information (in the form of the API context graph vector) and textual code information (in the form of the token vector) in a holistic way. The joint vector output by the joint layer is used as the final vector for the softmax function.

**Softmax Function** In deep neural networks, the softmax function is usually used to map a vector to a normalized probability distribution over fixed size classes that needed to be predicted. The classes are then ranked based on their probabilities. If we consider each API as a class, the API recommendation task can be considered as a classification task. What we need to do is to compute the probability of each API and then get the top \(N\) APIs as the recommendations. Thus, the softmax function is a natural choice. It takes as input the joint vector, and outputs a normalized probability over all APIs.

### 4.3 Training Corpus Construction

To train the models in APIRec-CST, we require a large set of training instances. A training instance is a triple consisting of an API context graph (with a hole), a corresponding bag of code tokens and the expected label of the hole node (i.e., an API call). To construct training instances, we first collect a large code base and then parse the methods one by one. For each method, we construct its corresponding API context graph (without a hole) and obtain the bag of code tokens. Afterwards, we systematically replace a set of nodes from the API context graph with a hole node. The resultant API context graph (with a hole), the remaining code tokens and the label of the first removed node form a training instance.

The details of the algorithm for constructing a training instance is shown in Algorithm 1. The inputs are an API context graph without a hole, the corresponding bag of code tokens, a node \(node\) in the graph and a constant \(hole\_size\). Intuitively, \(node\) is the starting node to be removed and the label of \(node\) is used as the label for the training instance, and \(hole\_size\) is the number of nodes to be removed (including \(node\)) from the API context graph.

Algorithm 1 uses a variable \(count\) to count the number of nodes that have been removed. Whenever \(count\) reaches \(hole\_size\) or there are no more nodes to be removed, the algorithm terminates. Initially, we set \(curr\) (which is the current node to be removed) to be \(node\). If \(curr\) is not a control node (like if or while), we identify its (unique) child node \(child\) through an edge of Type \(c\) or Type \(cd\), remove the current node \(curr\) from the graph and set \(curr\) to be \(child\). Note that whenever a node is removed, so are its incoming and outgoing edges. The reason why we choose the child node following edges of Type \(c\) or Type \(cd\) is that we remove nodes according to the control flow in the source code. As a result, the remaining context graph is still well-formed from a control flow point of view. If \(curr\) is a control node, all of its subgraphs in its control scope are removed, i.e., we remove all its subsequent nodes through control flow representing a statement in the control scope (e.g., all statements in the loop body if \(curr\) is a while node). For instance, if we remove the control node labeled with While in Fig. 1, all nodes representing the API call at line 6/7/8/9 are also removed, which are the ones labeled with Condition, java.io.BufferedReader.readLine(), Body, int Declaration, java.lang.String.hashCode() and java.util.ArrayList.add(java.lang.Object). Then, we set \(curr\) to be the first subsequent node outside of the control scope.

For example, Fig. 5 is an API context graph with a hole that is produced from the code in Fig. 1. In this example, the input of node \(node\) is the node with label java.lang.String.hashCode() representing the statement of \(hashCode = str.hashCode()\); at line 8. The input of

```
Algorithm 1 Training Instance Construction
Input: API context graph without a hole, node, hole_size, code_tokens
Output: API context graph with a hole, remaining code tokens, label
1: count = 0, curr = node
2: while count is less than hole_size and curr is not Null do
3: let old be curr
4: if curr is If, While, Do, For, Foreach, Switch, or Try then
5: for each child with edge type of Type c or Type cd of curr do
6: if child represents the statement outside the control scope then
7: count = count + 1
8: curr = child
9: else
10: remove child and its subgraph
11: remove all edges connected to child and nodes in its subgraph
12: end if
13: end for
14: else
15: set curr to be child with edge type of Type c or Type cd of curr
16: count = count + 1
17: end if
18: remove old and all edges connected to old
19: end while
20: replace node with Hole
21: get remaining code tokens related to the API context graph with a hole
22: set label to be the label of node
```
hole size $hole \_size$ is set to be 1. The input of code tokens $code \_tokens$ are all the tokens extracted in the original complete code. The remaining code tokens are those tokens in the remaining source code, which are “compute”, “hash”, “code”, “path”, “result”, “rd”, “br” and “str”. For another instance, if all but line 2 and 3 are removed in Fig. 1, the remaining code tokens become “compute”, “hash”, “code”, “path”, “result”, and “rd”. The label of this training instance is $java.lang.String.hashCode()$.

To systematically construct a set of training instances, for each API context graph and code tokens constructed from a method in the code base, the above algorithm is applied with each node in the graph as the starting node to be removed and different hole sizes. Note that the hole size can range from 1 to $Max - 1$ where $Max$ is the total number of nodes in the API context graph.

5 Evaluation

The purpose of APIRec-CST is recommending APIs based on given code context by combining structural and textual code information. We develop an implementation of APIRec-CST for JDK 1.8, which has 17,173 API classes and 137,134 API methods/fields. The implementation uses JavaParser [17] to parse source code into ASTs and Java reflection mechanism to recognize API invocations in source code. The lemmatization of code tokens is implemented using Stanford CoreNLP [18]. The deep learning architecture is implemented using TensorFlow 1.14 [19] and GG-NNs reference implementation [20]. Based on the implementation, we conduct a series of experimental studies to answer the following research questions.

RQ1 (API Prediction Accuracy): How accurate is APIRec-CST in predicting the next API compared with state-of-the-art approaches for context-based API recommendation?

RQ2 (Contribution of Textual Code Information): How much does textual code information contribute to the API recommendation?

RQ3 (Effectiveness in Real Tasks): How effective is APIRec-CST in helping developers accomplish programming tasks?

All the data of the experimental studies can be found in our replication package [21].

5.1 Training Details

We create a large corpus from GitHub by crawling all the Java projects that have 1000 stars or more. In this way we obtain 1,914 Java projects, which include 944,783 source files, 7,279,321 methods, and 68,319,916 lines of code.

We randomly select 90% of the Java projects as training set and the remaining 10% projects as validation set. For methods in the files of each project in the training or validation set, we apply Algorithm 1 to create a set of training instances or validation instances. To ensure efficiency we filter out the files that are larger than 200 KB and the methods that have no JDK API invocations. The reason for filtering files that are larger than 200 KB is that parsing large files using JavaParser [17] is quite time consuming. Note that most of files (i.e., 99.9993% of them) have a size smaller than 200KB and we expect filtering those large files has minimum effect. The reason for filtering methods that have no JDK API invocations is that we focus on JDK library. When creating training/validation instances containing only preceding context, we do not limit the hole size (i.e., $hole \_size$); when creating training/validation instances containing both preceding and succeeding contexts, we limit the hole size to 5 or less to avoid data explosion. We also filter out training/validation instances that have no API invocation in the context. Finally we obtain 6,627,591 training instances and 482,186 validation instances.

Based on the training data and validation data, we train an API recommendation model using a server with Intel Xeon E5-2620 2.1GHz (16 threads and 128GB RAM) and two Nvidia 1080Ti GPUs running on Ubuntu 16.04. We set embedding size of each embedding layer to 300, the number of hidden layers to 3, hidden size of each hidden layer to 300, dropout to 0.75, learning rate to 0.005, and batch size to 256. We conduct several trial experiments with different hyper parameters and the above hyper parameters achieve the best performance. After each epoch in the training, APIRec-CST evaluates the current model using the validation instances. If the prediction accuracy does not increase in five successive epochs, the training process ends and the last best model is used as the result.

5.2 API Prediction Accuracy (RQ1)

We compare APIRec-CST with existing approaches for solving the same problem. We adopt two approaches that are most related to ours as baseline approaches in this evaluation. One is GraLan [8], which is a state-of-the-art graph-based statistical model for API recommendation and the other is Tree-LSTM [22], which is a state-of-the-art deep learning model using tree-based structure for API recommendation. We reimplement GraLan based on the description of the approach in [8] and the extraction of graph representation from code in [23]. The implementation of Tree-LSTM is directly obtained from the authors of [22]. APIRec-CST, GraLan and Tree-LSTM are trained with the same training data. We choose six open-source Java projects as the test data: Galaxy [24], Log4j [25], JGit [26], Froyo-Email [27], Grid-Sphere [28], and Itext [29]. These projects are chosen based on the following criteria: widely used as the test data; Galaxy [24], Log4j [25], JGit [26], Froyo-Email [27], Grid-Sphere [28], and Itext [29]. These projects are chosen based on the following criteria: widely used as test data in previous researches on API recommendation (e.g., [9], [30]); not included in the training data or validation data. Following the same procedure of training/validation instance construction, we create 14,986 test instances from the test data.

To confirm the effect of our GraLan implementation, we compare the API recommendation accuracy of our implementation on the six projects with that of the GraLan implementation by Liu et al. [9] based on the results they report in [9]. The comparison shows that: our implementation achieves a top-1 (top-10) accuracy of 19.6-41.6% (73.4-80.9%), while their implementation achieves a top-1 (top-10) accuracy of 22.4-33.6% (73.9-80.6%); in terms of top-1 accuracy, our implementation is better than theirs on 4 projects and worse than theirs on 2 projects; in terms of top-10 accuracy, our implementation is better than theirs on 4 projects and worse than theirs on 2 projects. The results
show that the performance of these two implementations is comparable. Note that the performance of GraLAN is sensitive to the number of subgraphs appeared in the training data. Our training data is different from the training data used in [9], which explains why the performance of our implementation of GraLAN is different from their original.

We compare the top-K accuracies and MRR (Mean Reciprocal Rank) of APIRec-CST, GraLAN and Tree-LSTM for predicting the next API. MRR is a summary metric for top-K accuracies that averages the inverse of the ranks of each recommendation, which ranges from 0 to 1 [31]. For example, a MRR of 0.25 means that the correct recommendation is to appear at the fourth position on average. The results are shown in Table 4. In the table, the number of test instances of each project is shown after the project name and the best accuracy and MRR values are in boldface. We can see that APIRec-CST achieves much higher top-1, top-5, and top-10 accuracy than GraLAN and Tree-LSTM. For the six projects, APIRec-CST’s top-1, top-5, and top-10 accuracy is 56.4-66.4% (58.6% on average), 77.9-87.1% (81.4% on average), and 79.2-92.5% (87.9% on average), respectively; GraLAN’s top-1, top-5, and top-10 accuracy is 19.6-41.6% (31.5% on average), 60.5-71.4% (64.5% on average), and 73.4-80.9% (77.6% on average), respectively; Tree-LSTM’s top-1, top-5, and top-10 accuracy is 39.3-52.6% (46.7% on average), 62.9-75.6% (70.4% on average), and 75.6-82.6% (79.3% on average), respectively. We can see that APIRec-CST also achieves much higher MRR than GraLAN and Tree-LSTM. APIRec-CST’s MRR is 58.4-74.2% (68.4% on average), GraLAN’s MRR is 37.4-53.8% (45.3% on average) and Tree-LSTM’s MRR is 51.4-61.7% (56.7% on average). Furthermore, we conduct Mann-Whitney U test to determine whether the improvements in top-1, top-5, top-10 accuracy and MRR between APIRec-CST and the other two approaches are statistically significant. If the p-value is less than 0.05, the improvement is considered to be significant. The p-value of top-1, top-5 and top-10 accuracy between APIRec-CST and GraLAN are 0.003, 0.004 and 0.004 respectively. The p-value of top-1, top-5 and top-10 accuracy between APIRec-CST and Tree-LSTM are 0.015, 0.023 and 0.010 respectively. The p-value of MRR between APIRec-CST and GraLAN is 0.003 and the p-value of MRR between APIRec-CST and Tree-LSTM is 0.007. We can see that all the improvements are significant.

5.3 Contribution of Textual Code Information (RQ2)
APIRec-CST mainly relies on the structural code information embedded in the API Context Graph Network and at the same time leverages the textual code information embedded in the Code Token Network. To evaluate the contribution of textual code information, we derive a variant of APIRec-CST that uses structural code information only (called APIRec-SO), which only includes one network (i.e., API Context Graph Network). We use APIRec-SO to train an API recommendation model based on the same training/validation data and evaluate the model with the same test data. The results are shown in Table 5. We can see that APIRec-SO achieves good top-1, top-5, and top-10 overall accuracy (56.9%, 80.0%, and 86.7%) on the six projects, but the accuracy is lower than that of APIRec-CST (60.3%, 81.5%, and 87.7%). The top-1 overall accuracy achieves a 3.4% improvement, the top-5 overall accuracy achieves a 1.5% improvement and the top-10 overall accuracy achieves a 1.0% improvement when textual code information is added. For each test project, the top-k accuracy of adding textual code information achieves different degrees of improvement. The improvement of the top-1 accuracy ranges from 1.6% to 4.9%, the improvement of the top-5 accuracy ranges from 1.3% to 5.3%, and the improvement of the top-10 accuracy ranges from 0.9% to 6.0%. We can also see that the overall MRR is improved by 2.6% when textual code information is added. For each test project, the improvement of MRR ranges from 0.1% to 4.8%. The top-5 and top-10 accuracy of Log4j project decrease when textual code information is added. It is because that textual code information maybe contains noise that negatively influences the API recommendation results. In our future work, we will try to better process the noise in textual code information.

To further understand the contribution of textual code information, we analyze its influence with an increasing number of APIs in the context. We divide all the test data into 16 subsets according to the number of APIs in the context (1-15 and above 15). For each subset, we calculate the difference of the top-1, top-5, top-10 accuracy and MRR of APIRec-CST and APIRec-SO. The results are shown in Figure 7. The dotted lines are the zero lines and the points above the lines indicate positive contribution of textual code information, which mean that APIRec-CST achieves higher accuracy and MRR than APIRec-SO. We can see that the contribution of textual code information is positive in most cases. There is no obvious positive or negative correlation between the contribution of textual code information and the number of APIs in the context. This means that the contribution of textual code information is insensitive to the number of APIs in the context. The reason of the nine negative cases in Figure 7 is also that textual code information maybe contains noise that negatively influences the API recommendation results.
TABLE 5

| Project            | Model      | Top-1 | Difference | Top-5 | Difference | Top-10 | Difference | MRR  | Difference |
|--------------------|------------|-------|------------|-------|------------|--------|------------|------|------------|
| Galaxy             | APIRec-SO  | 46.9  | +4.1       | 76.3  | +5.3       | 82.2   | +6.0       | 58.9 | +4.7       |
|                    | APIRec-CST | 51.0  |            | 81.6  |            | 88.2   |            | 63.6 |            |
|                    | (473)      |       | (473)      |       | (473)      |        | (473)      |      | (473)      |
| JUnit              | APIRec-SO  | 61.7  | +4.7       | 83.8  | +1.3       | 88.6   | +0.9       | 71.2 | +3.0       |
|                    | APIRec-CST | 66.4  |            | 85.1  |            | 89.5   |            | 74.2 |            |
|                    | (1537)     |       | (1537)     |       | (1537)     |        | (1537)     |      | (1537)     |
| Froyo-Mail        | APIRec-SO  | 58.8  | +4.9       | 82.4  | +3.6       | 88.9   | +2.4       | 68.7 | +4.8       |
|                    | APIRec-CST | 63.7  |            | 86.0  |            | 91.3   |            | 73.5 |            |
|                    | (1537)     |       | (1537)     |       | (1537)     |        | (1537)     |      | (1537)     |
| Grid-Sphere       | APIRec-SO  | 57.7  | +4.3       | 83.1  | +4.0       | 90.6   | +1.9       | 69.0 | +3.8       |
|                    | APIRec-CST | 62.0  |            | 87.1  |            | 92.5   |            | 72.8 |            |
|                    | (1847)     |       | (1847)     |       | (1847)     |        | (1847)     |      | (1847)     |
| IText             | APIRec-SO  | 56.3  | +1.6       | 78.8  | +1.9       | 84.4   | +2.4       | 65.7 | +1.9       |
|                    | APIRec-CST | 57.9  |            | 80.7  |            | 86.8   |            | 67.6 |            |
|                    | (4444)     |       | (4444)     |       | (4444)     |        | (4444)     |      | (4444)     |
| Log4j             | APIRec-SO  | 48.5  | +2.1       | 71.4  | -3.7       | 83.7   | -4.5       | 58.4 |            |
|                    | APIRec-CST | 50.6  |            | 67.7  |            | 79.2   |            | 58.4 | +0.1       |
|                    | (2155)     |       | (2155)     |       | (2155)     |        | (2155)     |      | (2155)     |
| Overall           | APIRec-SO  | 56.9  | +3.4       | 80.0  | +1.5       | 86.7   | +1.0       | 66.8 | +2.6       |
|                    | APIRec-CST | 60.3  |            | 81.5  |            | 87.7   |            | 69.4 |            |
|                    | (14986)    |       | (14986)    |       | (14986)    |        | (14986)    |      | (14986)    |

5.4 Effectiveness in Real Tasks (RQ3)

We develop an IntelliJ IDEA plugin for APIRec-CST and conduct a user study in which two groups of participants are asked to complete a set of programming tasks with and without the plugin respectively. Note that the purpose of the user study is not to compare APIRec-CST with other approaches, since we have already answered RQ1. The objective is rather to evaluate whether APIRec-CST can indeed help developers during coding. So, two groups of participants are asked to complete a set of programming tasks with and without using the APIRec-CST’s plugin respectively. We derive a set of programming tasks from Stack Overflow (SO) in the following way. We find the 500 most voted SO questions with the tag “Java” and identify those that can be used as programming tasks. For example, questions about concept explanation such as “Is Java pass-by-reference or pass-by-value?” are eliminated. Then choose those questions that have code snippets in the answers or question bodies that can be used to implement the desired functionalities. We further filter out the questions that have less than four lines of code or are not API intensive. We obtain 44 SO questions as candidates and randomly select the following six as the tasks. For each task we prepare a description based on the corresponding question title and body and design a set of test cases (2-9, 6 on average).

T1: How do I create a Java string from the contents of a file

T2: Iterating through a Collection, avoiding ConcurrentModificationException when removing objects in a loop

T3: How can I generate an MD5 hash

T4: How do I invoke a Java method when given the method name as a string

T5: How to read all files in a folder from Java

T6: How can I increment a date by one day in Java

We recruit 18 master students from our school and all of them major in software engineering. Based on a pre-experiment survey on their experience with Java programming, we divide them into two groups whose overall abilities are at an equivalent level. We respectively assign G1 to use standard IntelliJ IDEA and G2 to use IntelliJ IDEA with the APIRec-CST plugin. The participants are asked to complete the six tasks from T1 to T6. They are not allowed to
search Internet, but can look up the JDK reference documentation and use the code recommendation feature and other facilities provided by IntelliJ IDEA. The participants in G2 can request the help of the APIRec-CST plugin, which can provide a list of top 10 API recommendations for the current cursor position. For each task the participants are given 20 minutes and if they cannot finish it in time they have to stop and submit their implementation. We record the completion time of the participants and test their implementations for each task.

We use task completion time and test pass rate as two metrics for evaluation. Task completion time is the time that a participant used to complete a task. Given a submitted implementation of a task, test pass rate is the percentage of test cases passed in the total number of test cases. The results of descriptive statistics analysis of task completion time and test pass rate are shown in Table 6 and Table 7 respectively. On average, the participants in G1 use 665.7-1,173.3 seconds to finish a task, while the participants in G2 use 441.3-708.1 seconds to finish a task; the participants in G1 pass 44-47% test cases, while the participants in G2 pass 68-89% test cases. We can see that APIRec-CST helps the participants finish the tasks faster and more accurately. Furthermore, we evaluate whether the improvements are significant or not. We make a significance test using the Mann-Whitney U test where a difference is thought to be significant if the p-value is less than 0.05. We can see that APIRec-CST helps the participants finish the tasks faster and more accurately.

We have an interview with each of the participants in G2 to get their feedback on APIRec-CST. Most of them agree that APIRec-CST provides accurate recommendations which are quite helpful especially when they do not know how to proceed. In most cases, the right API is included in the top 5 recommendations. In extreme cases, APIRec-CST can even provide right APIs when the participants only declare a method (including method name and parameters). This indicates that APIRec-CST can provide useful recommendations by only using textual code information. They also provide suggestions for further improvement. Two common suggestions are recommending arguments for API invocation and providing explanations for the recommended APIs.

| Task | Group | avg | min | max | median | std. dev. | p-value |
|------|-------|-----|-----|-----|--------|-----------|---------|
| T1   | G1    | 888.0 | 485 | 1200 | 900    | 299.85    | 0.0094  |
| T2   | G1    | 671.4 | 232 | 1200 | 480    | 367.91    | 0.2677  |
| T3   | G1    | 1173.3| 960 | 1200 | 1200   | 75.42     | 0.0001  |
| T4   | G1    | 441.3 | 160 | 703  | 405    | 190.04    | 0.0003  |
| T5   | G1    | 1139.6| 836 | 1200 | 1200   | 144.39    | 0.0924  |
| T6   | G1    | 708.1 | 431 | 1154 | 697    | 211.97    | 0.0013  |

5.5 Qualitative Analysis

In RQ1 and RQ2, we perform quantitative analysis on APIRec-CST, thus we list some examples to qualitatively illustrate the advantages of APIRec-CST. In Figure 8, we list five examples.

The first example is to read contents from a reader of a file line by line. As we can see that GraLan recommends the correct API in the third place, Tree-LSTM recommends the correct API in the second place, and both APIRec-SO and APIRec-CST recommend the correct API in the first place. The first two recommendations of GraLan are due to the irrelevant subgraphs that capture the semantics of list operation. This suggests that though subgraphs in GraLan may capture the semantics at a hole, the recommendations may be over-shadowed by other irrelevant subgraphs. Tree-LSTM is a deep learning model using tree-based structure which includes control flow among APIs but lack of data flow. Tree-LSTM treats source code as code tree, and feed the code tree into the deep learning model. Compared to GraLan, Tree-LSTM also considers the structure information but lack of data flow. Thus, Tree-LSTM performs better than GraLan, although worse than APIRec-SO and APIRec-CST. APIRec-SO and APIRec-CST treat source code as an API context graph which contains the structure information, and apply GG-NNs to learn the semantic in an API context graph using a holistic view. Due to the information diffusion mechanism in GG-NNs, each node itself and its relations of other nodes in the API context graph are integrated and added to the final vector representation of the API context graph. As a result, APIRec-SO and APIRec-CST successfully recommend that the API of the hole should be used to read the next line. From this example, we can see that a holistic view of correlated API usage in control and data flow graph of an entire method can help to improve the ranking of the correct API.

The second example is to draw a BufferedImage given a RenderedImage. As we can see that GraLan and Tree-LSTM fail to recommend the correct API in the top 5 recommendations, whereas APIRec-SO and APIRec-CST successfully recommend the correct API in the first place. In this example, none of the subgraphs in GraLan can capture the real semantics at the hole. Most of GraLan’s recommendations are the APIs in java.util.Hashtable because APIs in java.util.Hashtable are closest to the hole and are used as context in subgraphs. Due to the lack of data flow among APIs, Tree-LSTM cannot recommend the correct API. Only with a holistic view of a control and

| Task | Group | avg | min | max | median | std. dev. | p-value |
|------|-------|-----|-----|-----|--------|-----------|---------|
| T1   | G1    | 0.26 | 0.00 | 1.00 | 0.00   | 0.41      | 0.0073  |
| T2   | G1    | 0.47 | 0.00 | 1.00 | 1.00   | 0.33      | 0.1461  |
| T3   | G1    | 0.58 | 0.00 | 1.00 | 1.00   | 0.33      | 0.0008  |
| T4   | G1    | 0.11 | 0.00 | 1.00 | 0.00   | 0.31      | 0.0012  |
| T5   | G1    | 0.56 | 0.00 | 1.00 | 1.00   | 0.37      | 0.0030  |
| T6   | G1    | 0.04 | 0.00 | 1.00 | 0.00   | 0.33      | 0.0013  |
Fig. 8. Qualitative Analysis Examples
data flow graph of an entire method, can APIRec-SO and APIRec-CST find that all the APIs in the method are prepared to be used as the parameters of the correct API `java.awt.image.BufferedImage.new(java.awt.image.ColorModel, java.awt.image.WriteableRaster, boolean, java.util.Hashtable)` to create a BufferedImage object. From this example, we can see that in some situations, a holistic view of correlated API usage in control and data flow graph of an entire method can help to recommend the correct API.

The third example is to remove an old database file. As we can see that GraLan fails to recommend the correct API in the top 5 recommendations, Tree-LSTM recommends the correct API in the fifth place, whereas APIRec-SO recommends the correct API in the second and APIRec-CST recommends the correct API in the first place. All of the approaches capture the semantics at the hole is to apply an operation to a File object. However, the first three approaches fail to identify which operation should be applied to the File object. APIRec-CST leverages the method name as textual information in which “remove” indicates that the operation is to delete a file. APIRec-CST applies a Code Token Network to embed the textual information to capture the semantics in the textual information and combined (joint) with the structure information. From this example, we can see that the method name is indeed helpful to clarify the semantics.

The fourth example is to set the time in millisecond of a given value. As we can see that GraLan and Tree-LSTM fail to recommend the correct API in the top 5 recommendations, APIRec-SO recommends the correct API in the third place and APIRec-CST recommends the correct API in the first place. Since there is only one JDK API (Calendar) in the method, recommendations of all the approaches are related to the Calendar object. However, the first three approaches cannot recommend the correct API in first place because they are not certain which operation should be applied on the Calendar object. APIRec-CST leverages the parameter name as textual information in which “time”, “in” and “millis” (“in” and “millis” are also in the method name) indicate that the operation is to process time in millisecond. Combined with the semantics in the API context graph, APIRec-CST successfully identifies that the operation is to set the time in millisecond. From this example, we can see that the parameter name is helpful to clarify the semantics.

The last example is to create a new directory (delete the original directory if the directory exists). As we can see that GraLan fail to recommend the correct API in the top 5 recommendations, Tree-LSTM recommends the correct API in the third place, APIRec-SO recommends the correct API in the fifth place, APIRec-CST recommends the correct API in the first place. All of the approaches capture the semantics at the hole is to apply an operation to a File object. However, the first three approaches fail to identify which operation should be applied to the File object, and thus fail to recommend the correct API in the first place. APIRec-CST leverages the variable names as textual information in which “dir” and “folder” indicate that the operation should applied on a directory not a file. Combined with the semantics in the API context graph, APIRec-CST successfully identifies that there lacks a new directory and thus the operation is to create a new directory. From this example, we can see that the variable names are helpful to clarify the semantics.

### 5.6 Threats to Validity

The threats to the internal validity of our studies lie in two aspects. First, the GraLan implementation may not be exactly consistent with the approach. Second, the test cases developed for each task may not be complete.

The threats to the external validity of our studies lie in two aspects. First, we only implement our approach for Java and evaluate it with JDK. It is not clear how well the approach can support other languages and API libraries. Second, as adopted in [8], [9], [22], the test cases used in RQ1 are constructed automatically which may not reflect the scenarios in the real world. Different from existing approaches, we additionally conduct a user study to simulate the scenarios in the real world to evaluate the effectiveness of APIRec-CST. Third, we only evaluate the approach with a group of master students and a set of tasks from SO in the user study. It is not clear how effectively the approach can support industrial developers to accomplish more complex programming tasks.

### 6 Related Work

This work is closely related to various research on code recommendation. In modern IDE (Integrated Development Environment), type information is often used to recommend API method calls when classes or objects are typed. To enhance the performance of the code recommendation in IDEs, several approaches have been proposed to sort, filter and group API methods for better recommendation [38], [39], [40]. In comparison, APIRec-CST does not require a developer to write a receiver expression. Heinemann et al. [41] propose an API method recommendation algorithm based on the extracted identifiers (such as variable and type names) in the development context. In comparison, in addition to the textual information (including identifiers), APIRec-CST also takes structural information into consideration. Besides, APIRec-CST uses a deep neural network to learn the semantics of the textual information instead of simply using Jaccard similarity. Several approaches [42], [43] compute the similarity between the current code context and previous code examples based on a set of API calls or other additional information (such as method names, Java keywords, class or interface names). In comparison, APIRec-CST considers the complete API usage modeled in an API context graph, which contains API calls, Java keywords, and control and data flow among them. Furthermore, APIRec-CST combines textual information which includes method names, parameter names, and variable names.

This work is also related to work on mining usage patterns from source code, such as [44], [45], [46], [47], [48]. These approaches often apply deterministic mining algorithms to mine usage patterns for code recommendation. Zhong et al. [46] propose MAPO to cluster code snippets and mine usage patterns by frequent subsequence mining. Nguyen et al. [47] propose GrouMiner to mine usage patterns by representing source code as grouns. Nguyen et al. propose Grapacc [48], which first mines usage patterns...
based on graphs and then matches these patterns with the code fragment under editing based on graph-based features and token-based features. Wang et al. [45] apply a two-step clustering strategy to cluster call sequences and mine usage patterns for each cluster using a frequent closed sequence mining algorithm. Fowkes et al. [44] propose a near parameter-free probabilistic algorithm to infer the most interesting usage patterns. In comparison, APIRec-CST learn regularity of the API usage based on deep learning techniques instead of mining usage patterns explicitly.

Based on the conjecture that source code is naturally repetitive and predictable [1], many approaches have been proposed to learn statistical language models from source code for code recommendation. Hindle et al. [1] train an n-gram model based on the tokens of the source code to recommend the next token. Allamanis et al. [2] use a large corpus of source code from various domains to train an n-gram model. Nguyen et al. [3] enhance the n-gram model with roles and data types of code tokens and global technical concerns/functionality. Tu et al. [4] enhance the n-gram model with a cache to capture the localized regularities in the source code to improve the accuracy. Nguyen et al. [8] propose a graph-based statistical language model by using Bayesian statistical inference to compute the probabilities of API recommendations based on graphs. Liu et al. [9] propose a re-ranking approach based on the top-10 recommendations of GraLan to improve the top-1 accuracy using API usage paths as features. Nguyen et al. [50] propose APIRec that learns from fine-grained code changes by developing an association-based change inference model to recommend API calls. In comparison, APIRec-CST learns from the control and data flow in the source code instead of treating the source code as tokens as in the above-mentioned proposals. Furthermore, APIRec-CST takes a holistic approach to learn from both structural and textual code information.

There are also approaches which apply deep learning techniques for code recommendation. Raychev et al. [5] treat the source code as sentences and combine the n-gram model with RNN for recommending sentences. Dam et al. [6] train an LSTM (Long Short-Term Memory) neural network based on code tokens. Nguyen et al. [7] train a deep neural network called Dnn4C, which not only leverages the local context of lexical code elements, but also syntactic and type contexts. In comparison, APIRec-CST combines a graph-based deep neural network and a token-based deep neural network to capture both structural and textual code information.

This work is broadly related to other applications of deep learning techniques on source code for various objectives including code summarization [49], code generation [50], [51], [52], [53], [54], code search [55], [56], comment generation [57], [58], [59], [60], [61] or defect prediction [62], [63]. For example, Allamanis et al. [49] propose an attentional neural network to give an extreme summary of a sequence of code tokens. Mou et al. [54] apply a sequence-to-sequence recurrent neural network to generate code when given a user intention. Gu et al. [55] propose a deep neural network called CODEnn to jointly embed code snippets and natural language descriptions. Hu et al. [57] propose DeepCom which takes AST sequences of source code as input and generates the corresponding comments based on an attentional Seq2Seq model. Wang et al. [63] apply Deep Learning techniques on learned features of tokens extracted from source code for defect prediction. These approaches apply different deep learning models to learn program semantics for different objectives. In comparison, APIRec-CST represents program as an API context graph and a bag of code tokens and designs a novel deep neural network for API recommendation.

7 Conclusion

In this paper, we propose a deep learning-based API recommendation approach that combines the API usage with the text information in the source code to simultaneously learn structural and textual features. Our evaluation shows that our approach significantly outperforms an existing graph-based statistical model and a tree-based deep learning model for API recommendation and can effectively help students to finish programming tasks faster and more accurately. Our future work will improve the approach from several aspects. First, we will improve the utilization of textual code information, for example, by using better data preprocessing methods and model architectures or introducing user interactions. Second, we will incorporate argument recommendation and API explanation into the approach. Third, we will apply our approach for other API libraries and try to extend the approach to support API recommendation of multiple libraries.

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