Code Generation Based on Deep Learning: a Brief Review

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ABSTRACT
Automatic software development has been a research hot spot in the field of software engineering (SE) in the past decade. In particular, deep learning (DL) has been applied and achieved a lot of progress in various SE tasks. Among all approaches and techniques, automatic code generation by machines as a general concept, including code completion and code synthesis, is a common expectation in the field of SE, which may greatly reduces the development burden of the software developers and improves the efficiency and quality of the software development process to a certain extent. Code completion is an important part of modern integrated development environments (IDEs). Code completion technology effectively helps programmers complete code class names, method names and keywords, etc., which improves the efficiency of program development and reduces spelling errors in the coding process. Such tools use static analysis on the code and provide candidates for completion arranged in alphabetical order. Code synthesis is implemented from two aspects, ones based on input-output samples and the others based on functionality description. In this study, we introduce existing techniques of these two aspects and the corresponding DL techniques, and present some possible future research directions.

KEYWORDS
code generation, deep learning, code synthesis, code completion

1 INTRODUCTION
To effectively improve the efficiency and quality of software development process has always been a concern in the field of software engineering (SE). Among all approaches and techniques to improve the automation level of software development, the automatic code generation technique has caught extensive attention in the fields of academia and industry. Intuitively, as a general concept, automatic code generation refers to the utilization of techniques to automatically generate source code for software development, according to the requirements from the users. These techniques are capable to greatly reduces the coding burden of developers, so that they can focus on the design of software. There are two major tasks in code generation – code completion and code synthesis, which are the subjects of this paper.

Code completion is the most widely used code generation technology and an important part of modern integrated development environments (IDEs). Code completion significantly improves the efficiency of program development and reduces spelling errors when coding, which usually helps programmers predict the class name, method name and keywords, etc. of the code. The prediction of the next token is the most common form of code completion, and is also the current completion method used by mainstream IDEs. In the widely used IDEs, the recommended tokens are often sorted alphabetically, which increases the developer’s choice time for candidate tokens. Traditional code completion is mainly divided into two types. The first is to use static type information combined with various heuristic rules to determine the token to be predicted, while the second is to use code samples and previous semantics to complete the token. For the deep learning methods, they learn the probability distribution between code tokens from large-scale codes to improve the accuracy of token recommendations.

Code synthesis, also known as code generation in the narrow sense, is an important branch of program synthesis [18], which aims to assist or even substitute the human labor in coding. Traditional program synthesis refers to the automatic construction of computer programs according to the user requirements, including logic based formal specification, natural language description, input-output samples, and program execution path, etc. [15]. In this paper, we focus on code synthesis based on deep learning (DL) techniques, where the DL models learn the embedded knowledge from code bases with high quality and large quantity, and utilize them for program automatic development. In general, according to the different formats of user requirements, code synthesis based on DL can be divided into two major types: (1) those based on input-output samples, and (2) the others based on functionality description. Table 2 summarizes the technical characteristics of some of the previous work of DL-based automatic code generation.

Code generation has been used for several application. The most widely application is generating SQL query. The early models Yu et al. 2018 [47] also are based on the sequence-to-sequence framework, which are inspired by the technology used in code generation and adopt a context-free grammar rule to parse the SQL query sequence. Another application is automated repairing program. Automated repair indicates that generating corresponding code patches when given a buggy program with its execute traces. Tufano et al. [41] and Hata et al. [20] use sequence-to-sequence translation, where neural machine translation (NMT) with attention-based encoder and decoder are adopted. They utilize different code abstractions to generate patches with a copy mechanism.

There are at least three possible research directions in this field: 1) to encode the context-free grammars into the neural network for better syntax understanding, 2) to apply code completion for specific development tool to alleviate the burden of software development, and 3) to counter the adversarial non-robust issue caused by the nature of DL models by introducing the features of programming languages.

In the rest of this paper, we first formulate the subject code generation task in Section 2. Then we introduce the previous research lines of code completion and code synthesis in Section 3 and 4 respectively. Next, we briefly illustrate the possible research directions of our future work in Section 5. At last, we present the related work in Section 6 and summarize this paper in Section 7.
2 PROBLEM FORMULATION

Both code completion and code generation usually are able to produce tokens iteratively, yet the condition is different. From the perspective of machine learning, code completion is an unconditional generation task, which models the code distribution, while code generation is a conditional generation task, which models the distribution with the condition of the requirement. We formulate these two tasks in this section.

2.1 Code Completion

Code completion [28] requires the DL model, denoted as \( f \), to model the conditional distribution of source code. The task of code completion comes from the popular application of auto-completion in most modern integrated development environments (IDEs). The IDEs provide recommendations of the next token, which can greatly increase the efficiency of software developers. In specific, given the \( k \)-prefix \( x_{1:k} = \{ t_1, t_2, \cdots, t_k \} \) of the source code \( x = \{ t_1, t_2, \cdots, t_n \} \), a code completion model \( f \) is supposed to predict the probability of the next token, denoted as \( f(x_{1:k}) = P_f(t|x_{1:k}) \). The training process of \( f \) can be formally defined as an optimization problem as below:

\[
\min_{\Theta_f} \sum_{i=1}^{n-1} L(f(x_{1:i}), t_{i+1}) \tag{1}
\]

where \( \Theta_f \) is the set of trainable parameters in \( f \), and \( L \) is the loss function, which estimates the error of the prediction \( f(x_{1:i}) \) and the ground-truth \( (t_{i+1}) \). Usually, the cross-entropy function is employed as the loss. In addition, the input \( (x_{1:i}) \) can be token sequence prefixes, partial abstract syntax trees (ASTs), partial control flow graphs (CFGs) or partial data flow graphs (DFGs), etc., according the format requirement of the model \( f \).

Besides the traditional definition, other tasks have the same formulation, and can be viewed as variants of code completion. For instance, the completion of Application Programming Interface (API) [36] completes API sequences. In a word, code completion, along with its variant tasks, is one of the most important tasks in the SE domain.

2.2 Code Synthesis

Code synthesis [15] requires the DL model \( g \) to produce source code snippets based on the requirements provided by the user. In specific, the requirements of different forms are denoted as \( z \), and the corresponding ground-truth code snippets are denoted as \( y \). \( g \) is retrieved by optimizing the objective on every data pair in the training set:

\[
\min_{\Theta_g} \sum_{(z, y) \in \text{training set}} L(g(z), y) \tag{2}
\]

where, similarly, \( \Theta_g \) is the set of trainable parameters in \( g \), and \( L \) is the loss function, which estimates the error of the produced snippet \( g(z) \) and the ground-truth snippet \( (t_{i+1}) \). \( z \) can be different forms, such as input-output samples and natural language descriptions.

Additionally, \( g \) usually is a two-step model. It first comprehend the requirements by processing \( z \), and then produce code snippets (usually token by token). The second step is similar to code completion, hence, we can employ \( f \) in \( g \) in most cases.

3 CODE COMPLETION

In this paper, we focus on the code completion methods based deep learning. Deep learning methods learn the probability distribution between code tokens from large-scale codes to improve the accuracy of token recommendations. The features of different types of techniques introduced in this section are listed in Table 1.

| Type          | Work | Technical characteristics                                      |
|---------------|------|---------------------------------------------------------------|
| Next-token    | [24] | Applying language model to learn the distribution of code.   |
|               | [22, 40] | Considering the localness of code.                           |
|               |       | Directly processing and modeling the AST representation.    |
| API           | [13] | Employing language model to complete API calls based on context. |
|               | [14] | Applying language model to complete API sequences.           |

3.1 Next-Token Completion

Probabilistic modeling of code token sequences was first proposed by Hindle et al. 2012 [24], where they point out that the programming language is theoretically written by humans and repetitive. Therefore, the code has some statistical characteristics that can be predicted, and these statistical features can be captured by language models (LMs). This hypothesis becomes the cornerstone of learning programming languages using probabilistic models and even deep learning.

The most direct way to predict the next token is to use the token sequence of program to predict the current completion position. Recently, the main flow of using deep learning includes two parts: the training phase and the code completion phase. Researchers first obtain a large amount of data from the open source community as a corpus for learning, and process the corpus with a parser for better learning, forming representations such as ASTs. Then, the researchers design a DL architecture and use the corpus as the training set to train the network. The deep neural networks used in code completion tasks are mostly LMs, such as recurrent neural networks (RNNs). The LM can effectively learn the sequence features of the program, and use this feature for code completion tasks. Given an input code fragment, the trained deep learning model predicts the tokens or APIs that need to be completed according to the semantic or structural characteristics of the input code fragments.

Localness is an important feature of programming languages, and is supposed to be considered in code completion. In 2014, Tu et al. 2014 [40] propose on the basis of Hindle et al. 2012 [24] that the token of the code has repeatability in a partial range. The LM can learn the law of the code, but it still ignores the local features of the program. Therefore, they employ a "cache" mechanism, and experimental results show that this approach is much higher than the previous approaches (16% to 45%). Hellendoorn and Devanbu 2017 [22] found that by comparing recurrent neural networks with N-grams with a 'cache' mechanism, the local features in code are helpful in predicting tokens.
How to effectively use the structural information of the program to improve the accuracy of code completion has been the focus of attention of many researchers. When using code structure for code completion, researchers usually conduct research from two directions: 1) transforming the tree structure into a sequence, and 2) directly modeling the tree structure. Li et al. 2018 [28] and Liu et al. 2016b [30] predicted the terminal and non-terminal nodes of the program through the AST sequence. These predictions based on the AST sequence can not only predict the next terminal node (i.e., the code token), but also predict the structural information of the code (i.e., the non-terminal node). When modeling the AST sequence, the AST sequence is required to ensure both the semantic information of the program and the structural information of the program. Therefore, when researchers convert an AST into a sequence, it is necessary to ensure that the AST sequence uniquely represents a code fragment. Li et al. 2018 [28] added two extra features to indicate whether the node has child nodes and right sibling nodes when encoding the AST node. Modeling the code structure directly requires designing the network structure of the corresponding structure to model it. Raychev et al. 2016 [35] used decision trees to directly model the tree structure of the program to predict the token of the code.

### 3.2 API Completion

In addition to completing the next token, the completion of Application Programming Interface (API) has also received a lot of attentions. The use of API effectively improves the development efficiency of programmers. How to use deep learning methods to complete APIs with a high accuracy is the difficulty of API completion. API level completion usually learns API usage patterns, and uses API usage patterns to complete large-scale API completions.

Raychev et al. 2014 [36] proposed to use LMs to complete API calls based on context information. The tool SLANG they proposed can effectively complete API calls and API parameters. Gu et al. 2016 [13] used sequence-to-sequence models to train large-scale natural language descriptions and API sequence pairs, which establishes the mapping relationship between natural language and API sequences. Their model DEEPAPI effectively queries according to natural language and returns the calling sequence of API. Gu et al. 2017 [14] utilizes the API sequences as training data and generate API sequence in a similar situation. They use the API sequence and its natural language description to learn the vector representation of the API sequence. The distance between API sequences with similar functions in the vector space is also close, so the similarity of vectors can be used to generate API sequences.

From the current work, the emergence of deep learning methods has greatly promoted the development of program generation tasks and code completion tasks, but the current work is still limited to generating small-scale, single-function programs. The programs generated according to the given input and output samples are often less versatile. How to use deep learning to generate programs that can actually run is still a problem that needs to be solved.

### 4 CODE SYNTHESIS

Although there are many other formats of user requirements, DL-based code synthesis mainly generates source code from input-output samples and natural language descriptions. The features of different types of techniques introduced in this section are listed in Table 2.

| Type | Work | Technical characteristics |
|------|------|---------------------------|
| Sample | [5, 7, 37, 44] | Simulating the execution traces to generate code snippets. |
|       | [2]     | Search in the code base for the most appropriate code snippets. |
| Desc. | [3, 9, 29]     | Learning the structural rules to generate IFTTT programs. |
|       | [13, 46]     | Generating general language (eg., Java, Python) code snippets. |
|       | [8, 49]     | Applying machine translation to generate SQL queries. |

## 4.1 Input-Output Samples

The sample-based automatic code synthesis is derived from traditional inductive program synthesis (IPS) or programming by examples (PBE) by introducing DL techniques into generating code snippets to map input-output samples. To generate input-output samples for real programs is rather challenging, as the searching space is very large. Up to present, these sample-based tasks are mainly implemented on two kinds of data: (1) one utilizes a well-defined domain specific language (DSL) instead of any certain program languages, and (2) the other uses actual Microsoft Excel data.

In the tasks specific for DSL, Reed and de Freitas 2016 [37] develop NPI to interpret the execution program. They apply neural networks to generate statements and parameters required for program execution, where the code is regarded as a sequence of vectorized words. The NPI architecture is refined later [5, 7, 44]. Balog et al. 2017 [2] utilizes DL models to assist in searching codes consistent with a set of input-output samples. Although these work focus on DSL instead of general programming languages, they pointed out a research direction. Later, these techniques are utilized in AI for video games (the operations can be defined as DSL), such as PHP [10] in NanoCraft.

Besides AI for simple games defined by DSL, the character conversion function of Microsoft Excel is a more successful application in PBE tasks. Flashfill [16, 17] is an important feature of Microsoft Excel, which is based on the string samples provided by users. Shu and Zhang 2017 [38] propose NPBE to complete 45 kinds of string operations. The generated code by NPBE consists of a sequence of atomic operations. Therefore, NPBE is capable to synthesize complex programs with a few atomic operations. Parisotto et al. 2017 [33] propose R3NN, consisting of an input-output pair vectorized representation module and an tree-based code expansion module. The generated code expands while NPBE processes the vectorized input-output pairs. Devlin et al. 2017 [8] further introduce the variable length attention mechanism into the PDE models to effectively encode the input and output sample set of variable length disorder. These techniques are now adopted by Microsoft Excel in practice.
4.2 Natural Language Descriptions

Natural language is often adopted by the users, who are less familiar with coding, to describe the functionality of programs. The diversity of code and text, the ambiguity of text, and the complex logical structure of code makes the generation of source code very challenging. However, the DL models, which are capable to learn the embedding complex knowledge, can solve this problem with high effectiveness.

If-This-Then-That (IFTTT) code [34] is simpler in structure and easier to learn its structural rules, compared to the general program languages (eg., Java). Therefore, IFTTT is a suitable subject for automatic code generation. Dong and Lapata 2016 [9] propose an encoder-decoder-based model with attention mechanism. This model utilizes RNN to encode natural languages, and uses tree-based RNN to generate programs. Liu et al. 2016a [29] propose an implicit attention mechanism, which effectively learn the important words in the text description. Beltagy and Quirk 2016 [3] regard the generation of IFTTT as a semantic analysis problem, with the goal of generating derivative trees according to the text descriptions.

Automatic generation of general programming language is rather difficult than IFTTT. Gu et al. 2016 [13] propose DeepAPI, which generates API sequences based on text descriptions. DeepAPI applies the encoder-decoder architecture to establish the correlation between the semantics of text descriptions and the semantics of API sequences. Yin and Neubig 2017 [46] propose a syntax model to generate Python code from functionality descriptions, by applying the generation rules of compilation.

SQL queries are usually short code to manipulate the relational databases. Since SQL queries can be difficult for non-professionals, many researchers attempt to generate SQL from natural language descriptions. Seq2SQL [49] utilize the natural machine translation (NMT) architecture to translate text descriptions to SQL queries. Cai et al. 2018 [6] further combine traditional semantic parsing with the DL models, by introducing Backus-Naur form (BNF) to constrain the generation process.

To sum up, automatic code generation based on DL is a powerful technique to reduce the development burdens in SE community. In sample-based and description-based tasks, DL solutions provide state-of-the-art (SOTA) results, and are adopted in real-world applications, such as Microsoft Excel.

5 FUTURE WORK

This section describes the detailed possible research direction of our future work.

5.1 Grammar Information

The tree structure of code in a programming language is confined by its context-free grammar, the above representation still cannot directly tell the neural network how the tree structure is confined. For example, when the code is represented as a rule sequence, existing approaches encode the rules through one-hot encoding. The production rule \(a \rightarrow b\) may be encoded as 1 and the rule \(b \rightarrow c\) may be labeled as 2, but it is not clear whether 12 is a legal sequence or not. Since the grammar greatly confines the space of possible rule sequences or syntax trees, we conjecture that directly encoding grammar into the neural model boosts the performance of the neural model.

5.2 Code Generation Testing

We have found that there are many inconsistencies in deep learning systems.

For example, when we generate “open a file, F1” , we can get "open(F1, "r")". But when we change the translation of the original sentence from "F1" to "F2", the translation would be "open(F2)". Such an inconsistency problem can cause a team or company to suffer a great deal of damage and hence, we should try to test and solve the problem.

In the future, we hope to propose testing approach that combines variation testing and metamorphosis testing for inconsistency testing. And we can also propose a repair method that can fix inconsistency errors to some extent.

We tentatively find that the inconsistency problem can be solved well by using a strategy called "Ensemble". Thus, we expect further research on this strategy to effectively solve the inconsistency problem and bring advances to the existing neural network model to the Progress.

5.3 Application

As a powerful technical approach, code generation may apply to the several aspects in software development. This technology could be used for more convenient API suggestion. Besides, code completion also can be combined with some IDE to improve the efficiency. We leave these as the future work.

5.4 Adversarial Robustness

Adversarial non-robust issues are one of the major problems of the DL-based models. The neural networks are vulnerable to some minor adversarial perturbations, which are considered as noises from the perspective of human beings. For instance, by renaming the identifiers within the code snippet, the source code processing model would output completely erroneously [48].

Zhang et al. 2020 [48] have identified the non-robust problem of DL architectures for source code processing. We can tackle the non-robust problem by augmenting the training data with adversarial perturbations, which is known as adversarial training.

The robust models are one of the most popular research directions in the field of DL, which means it is also worth studying in the tasks of code generation.

6 RELATED WORK

Automatic code generation is a branch of program synthesis and is strongly related to code completion. In this section, we briefly introduce the concepts of traditional program synthesis and DL-based code completion, and explain their relations and differences with DL-based code generation.

6.1 Program Synthesis

Program synthesis is first proposed in constructive mathematics [27] as a mathematical problem. After the appearance of von Neumann computer, deductive program synthesis (DPS) draws much
attention [11, 31, 42], which is dependent on theoretical deduction of logics. Although DPS produces provable accurate program, it takes logical expressions as inputs, which is equally complex with the program itself. Therefore, Summers 1976 [39] propose IPS to simplify the problem. Summers 1976 [39] demonstrate that under some specific constraints, a LISP program can be generated from the input-output samples without search in the whole program space, which enables IPS. Later, Gulwani 2011 [16] apply IPS into real-world applications, and develop FlashFill [17] for Microsoft Excel, showing the capability and feasibility of program synthesis in the industry field.

Traditional program synthesis, especially IPS, adopts logical deduction or induction approaches to generate programs. The computational overhead limits the application, since the logics cannot be too complex and the program cannot be too long. The DL-based techniques studied in this paper solve this problem by using powerful DL models to internally learn the logics. Although the generated programs by the DL models may not be guaranteed to be correct, with constraints and filtering, the data-driven DL-based techniques are capable to capture the complex logic and knowledge embedded in the code base, and are much more scalable, feasible and applicable than the rule-based approaches.

### 6.2 Code Completion

Code completion is a common program automated tool in the IDEs. In the common IDEs, the recommended tokens are usually sorted alphabetically, which increases the time for programmers to select the candidate tokens. Eclipse performs code completion based on heuristic rules without considering the context. Bruch et al. 2009 [4] apply k-NN considering the previous context information to recommend identifiers (i.e., variables, method names).

Hindle et al. 2012 [24] first propose to model the sequence probability distribution of program languages with RNN models, which is conceptually the same as language modeling in the field of natural language processing (NLP). Later, memory mechanism is introduced to cope with the localness of source code [40]. In the recent year, researchers focus on tree-based representations, because the tree structure may carry more information than sequences. Li et al. 2018 [28] employ pointer mixture network to process sequentialized ASTs for code completion. Raychev et al. 2016 [35] further utilize decision tree to directly process ASTs for next-token prediction.

### 6.3 Code Retrieval

Code retrieval is an important software engineering problem, which aims to retrieve the most related code snippet among a set of code snippets by a given natural language description.

Early studies mostly focus on applying the information retrieval methods to code retrieval task [1, 12, 19, 23, 26, 32]. With the development of deep learning, more and more works try to use neural networks to code retrieval [12, 25, 45]. Gu et al. 2018 [12] first proposed an LSTM-based model for code retrieval, where they encode the input NL description and code into a vector space and compute the cosine similarity between them. Based on a code annotation work proposed by Iyer et al. 2016 [25], where they use a sequence-to-sequence model to generate the specific annotation

by a given code, Yao et al. 2019 [45] proposed CoaCor for code retrieval, where they combine the code annotation approach of Iyer et al. 2016 [25] and the code retrieval approach of Gu et al. 2018 [12] together by a reinforcement learning framework.

When it is applied to code generation, Hayati et al. 2018 [21] proposed a model combines the code retrieval with code generation model to boost code generation task.

### 7 SUMMARY

In order to reduce the development burden of programmers, increase the degree of automation of software development, and improve the efficiency and quality of software development, academia and industry are trying to research automatic code generation technology. Although code completion tools are often integrated in common integrated development environments, existing code completion tools are usually simply based on static word frequency statistics, and candidate results are arranged in lexicographic order, which leads to low-accuracy code completion tools. Instead, it may increase the development cost of the programmer. In addition, researchers are also devoted to directly generating code fragments or complete programs that perform a specific function (i.e., code generation). The development of artificial intelligence has greatly promoted the progress of automatic code generation technology, but it is still very difficult to directly generate code. The current code generation technology is limited to generating small-scale, single-function, domain-specific programs, and its technology is still very limited for complex programs.

As the deep learning technology is hot, more and more researchers begin to apply the deep neural network model to improve the performance of automatic code generation. Since the programming language is also a language created by humans, overall, researchers tend to apply the model originally used to model natural language to the programming language. However, compared with natural language, the programming language is a structural language with an unlimited large vocabulary and a fast evolution speed. This brings more challenges to researchers and also provide new possibilities. For example, the code can be transformed into its corresponding abstract syntax tree. Recently, more and more approaches has been proposed to model abstract syntax trees, which has achieved better results than the approaches of modeling word sequences only. In addition, how to better handle the excessively large vocabulary in the programming language is also an optional way to conduct research on code generation based on deep learning. With the rapid development of deep learning technology, we believe that in the future, more and more repetitive program development will be replaced by machines, and programmers will pay more attention to upper-level development and designs.

x [43]

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