CodeGRU: Context-aware Deep Learning with Gated Recurrent Unit for Source Code Modeling

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Abstract

Recently many NLP-based deep learning models have been applied to model source code for source code suggestion and recommendation tasks. A major limitation of these approaches is that they take source code as simple tokens of text and ignore its contextual, syntactical and structural dependencies. In this work, we present CodeGRU, a Gated Recurrent Unit based source code language model that is capable of capturing contextual, syntactical and structural dependencies for modeling the source code. The CodeGRU introduces the following several new components. The Code Sampler is first proposed for selecting noise-free code samples and transforms obfuscate code to its proper syntax, which helps to capture syntactical and structural dependencies. The Code Regularize is next introduced to encode source code which helps capture the contextual dependencies of the source code. Finally, we propose a novel method which can learn variable size context for modeling source code. We evaluated CodeGRU with real-world dataset and it shows that CodeGRU can effectively capture contextual, syntactical and structural dependencies which previous works fails. We also discuss and visualize two use cases of CodeGRU for source code modeling tasks (1) source code suggestion, and (2) source code generation.

Keywords: Deep Neural Networks, Source Code, Code Suggestion, Code Generation

1. Introduction

Source code suggestions, code generation, bug fixing, etc. are vital features of a modern integrated development environment (IDE). These features help
software developers to build and debug software rapidly. In the last few years, there have been massive amount of increase in code related databases over the internet. Many open source websites (i.e. w3school, GitHub, Stack Overflow, etc.) provide API libraries and code usage examples to help troubleshoot the source code, bug fixing, and much more. Software developers exceedingly rely on such resources for above-mentioned purposes.

Natural language processing (NLP) [9, 32, 39] explores, understands and manipulates natural language text or speech to do serviceable things. NLP techniques have shown its effectiveness in many fields such as speech recognition [6], information retrieval [7], text mining [38], machine translation [50], code completion [25, 41, 27, 46] code search, API usage patterns mining and code summarization. One of the most common NLP technique for source code modeling is statistical language models (SLM), which calculates the probability distribution over sequences in a corpus. Given a sequence \( S \) of length \( N \) it assigns the probability to the whole sequence \( P(b_1, \ldots, b_n) \) and then calculates the likelihood of all sub-sequences to find the most likely next sequence.

The advancement in the deep neural network (DNN) based NLP models [52] have recently shown that they can effectively overcome the context issue that cannot be effectively addressed by SLM [41, 25, 10] based models. Many deep learning based approaches have been applied for different tasks for source code modeling such as code summarization [26, 41], code generation [43], error fixing [43, 22], and code recommendation [49, 20, 14]. Applying Recurrent neural networks (RNN) models for source code modeling can help improve the performance of such SLM models. Recently some works [49, 41] directly implement RNN for code suggestion. A major limitation of these approaches is that they take source code as simple tokens of text and ignore its contextual, syntactical and structural dependencies. Another limitation is that they learn source code as a sequence to sequence problem with fixed size context where the right context may not be captured in the fixed size window, which leads to the inaccurate prediction of the next code token.

Compared with natural language text, source code tends to have richer contextual, syntactical and structural dependencies. Treating source code as a simple text cannot effectively capture these dependencies. Software developers usually choose to have different names for methods, classes, and variables, which makes it difficult to capture the right context. For example, one software developer may choose a name \texttt{num} for an \texttt{INT} data type, while another one may choose \texttt{size} for the same purpose. Consider another example where a common method \texttt{i.tostring()} converts a variable to \texttt{String} data type. A similar method \texttt{person.toString()} refers to an object of a \texttt{person} class that returns a person’s information. In addition, the source code must follow the rules defined by its grammar. For example, a \texttt{catch} block must be followed by a \texttt{try} block. Another example is that when a developer uses \texttt{do} block, the next block should be \texttt{while()} and the next token suggestion should be \texttt{;} according to the syntax of java language grammar. We argue here that these
structural, syntactical and contextual dependencies can be fruitful in source code modeling. Using them can help improve various applications including code suggestion and code generation.

In this paper we propose CodeGRU to better capture source code’s context, syntax and structure when suggesting the next source code token. This work includes several new components. First, different from previous works [42, 41, 25], we do not simply consider source code as text. To capture the structural dependencies, we propose code sampler, a novel approach to carefully sample the noise-free data. It removes all the unnecessary code and transforms obfuscate code into its proper structure. Second, we propose a novel code regularize technique, which parses the source code into an abstract syntax tree (AST) for encoding the contextual dependencies, which will be discussed in detail in section 4. The CodeGRU can effectively capture the right context even it is separated far apart in the code due to our novel code regularize technique. Finally, we introduce a novel approach for variable size source code context learning.

This work make the following unique contributions:

- A novel approach for source code modeling is proposed, which consists of the Code Sampler and the Code Regularizer. The Code Sampler selects noise-free data and transforms the source code into its proper structure and syntax. The Code Regularizer parses the source code into an abstract syntax tree (AST) and encodes its contextual information. These two components help CodeGRU to capture contextual, syntactical and structural dependencies. CodeGRU also reduces the vocabulary size up to 10%-50% and helps to overcome the out of vocabulary issue.

- A novel method which learns variable size context of the source code is also proposed. Unlike previous works, we do not use fixed size context window approach to model the source code. The CodeGRU can learn variable size context of the source code and increases its context based on source code syntax and structure.

- An extensive evaluation of the CodeGRU on the real-world data set shows improvement in accuracy. Different from previous works, CodeGRU considers a large vocabulary size which enables it to suggest the next code token that has not appeared in the training data.

- We also present two use cases of CodeGRU: (1) code suggestion, which can suggest multiple predictions for the next code token, and (2) code generation, which can generate the whole next code sequence.

The remainder of the paper is organized as follows. Section 2 discusses the related works. Section 3 covers preliminary technical details. Section 4 discusses our novel CodeGRU model in detail. Section 5 covers the empirical evaluation of CodeGRU. Then we move on to section 6 where we discuss use cases of CodeGRU. Finally, section 8 concludes this work.
2. Related Work

Most of the modern IDEs provide code completion and code suggestion features. In recent years, deep neural techniques have been successfully applied to various tasks in natural language processing, and also have shown its effectiveness to problems such as code completion, code suggestion, code generation, API mining, code migration, and code categorization.

Hindle et al. [25] have shown how natural language processing techniques can help in source code modeling. They provide a simple n-gram based model which helps predict the next code token in Eclipse IDE. Raychev et al. [41] used statistical language model for synthesizing code completions. They applied n-gram and RNN language model for the task of code completion. Tu et al. [40], proposed a cache based language model that consists of an n-gram and a cache. Hellendoorn et al. [24] further improved the cache based model by introducing nested locality. White et al. [49] applied deep learning for source code modeling purpose. Another approach for source code modeling is to use probabilistic context-free grammars (PCFGs) [8]. Allamanis et al. [2] used a PCFG based model to mine idioms from source code. Maddison et al. [31] used a structured generative model for source code. They evaluated their approach with n-gram and PCFG based language models and showed how they can help in source code generation tasks. Raychev et al. [40] applied decision trees for predicting API elements. Chan et al. [10] used a graph-based search approach to search and recommend API usages.

Recently there has been an increase in API usage mining and suggestion. Thung et al. [45] introduced a recommendation system for API methods recommendation by using feature requests. Nguyen et al. [39] proposed a methodology to learn API usages from byte code. Allamanis et al. [2] introduced a model which automatically mines source code idioms. A neural probabilistic language model introduced in [5] that can suggest names for the methods and classes. Franks et al. [17] created a tool for Eclipse named CACHECA for source code suggestion using a n-gram model. Nguyen et al. [35] introduced an Eclipse plugin which provide context-sensitive code completion based on API usage patterns mining techniques. Chen et al. [11] created a web-based tool to find analogical libraries for different languages.

Yin et al. [51] proposed a syntax-driven neural code generation approach that generate an abstract syntax tree by sequentially applying actions from a grammar model. A similar work conducted by Rabinovich et al. [37], which introduced an abstract syntax networks modeling framework for tasks like code generation and semantic parsing. Sethi et al. [44] introduced a model which automatically generate source code from deep Learning based research papers. [2]. Allamanis et al. proposed a bimodal to help suggest source code snippets with a natural language query. It is also capable of retrieving natural language descriptions with a source code query. Recently deep learning based approaches have widely been applied for source code modeling. Such as code summarization [26, 4], code mining [17], clone detection [30], API learning [20], etc.

Our work is similar to [49, 11], which applied RNN neural networks based
models to show how deep learning can help in improving source code modeling. A major limitation of their works is that they consider source code as simple tokens of text and ignores the contextual, syntactical and structural dependencies. The most similar work to ours is DNN [34], however it varies in several important ways. They apply deep neural networks for source code modeling with a fixed size of context, which can only suggest the next code token, whereas our work can generate whole sequence of source code and consider variable size context. Their work considers the context size of $n=4$, where larger size may cause scalability problem as mentioned in their work [34]. This work introduces a novel approach of variable size context learning which shows tremendous improvement in source code modeling. This work can not only predict the next code token according to the correct context and syntax of the grammar but also can predict variable types, class objects, class methods and much more. The CodeGRU is capable of suggesting multiple next code tokens with correct context, syntax, and structure. Different from the Santos et al. [16] and Gupta et al. [23], our work focuses on source code suggestion tasks, whereas their works focus on fixing syntax errors with a very limited vocabulary size of 113 and 129 code tokens respectively. Their approach only considers language defined keywords and stop words to build a limited vocabulary which is not ideal for source code suggestion purpose.

3. Preliminaries

In this section, we will discuss the preliminaries and technical overview of this work.

![Figure 1](image.png)

Figure 1: An architecture of a RNN neuron where input is a code token vector at index $i$, and the outputs are different next code tokens $y^i$ based on the context and probabilities.

*Figure 1* shows the architectural of the RNN for source code modeling, where $\tau$ is input layer, $c$ is context layer also known as hidden layer and $y$ is the output layer. The hidden state activation at a time step $i$ is computed as a function on
the previous $h_{i-1}$ along with current code token $\tau_i$.

$$h_i = f(\tau_i, h_{i-1})$$ (1)

Usually $f$ is composed of an element-wise nonlinear and affine transformation of $\tau_i$ and $h_{i-1}$.

$$h_i = \phi(W\tau_i, Uh_{i-1})$$ (2)

Here $W$ is the weight matrix for the input to hidden layer and $U$ is the weight matrix for the state to state matrix, and $\phi$ is an activation function. The RNN models \[33, 18\] tends to look back further than $n - 1$. But vanilla RNN suffers from vanishing gradient problem which can be overcome by using Gated Recurrent unit (GRU) model.

The GRU exposes \[53\] the full hidden content without any control which is ideal for source code modeling. It is composed of two gates, the rest gate $r_i$ and the update gate $z_i$. Further, it entirely exposes its memory context on each time step $i$. Exposing the entire context on each time step helps to learn contextual dependencies better which vanilla RNN fail to capture. It can be expressed as

$$h_i = (1 - z_i)h_{i-1} + z_i h_i$$ (3)

Where $h$ and $\bar{h}$ is prior context and fresh context respectively.

$$z_i = \phi(W_z \tau_i + U_z h_{i-1})$$ (4)

$$h_i = tanh(W\tau_i + r_i \otimes U h_{i-1})$$ (5)

$$r_i = \phi(W_r \tau_i + U_r h_{i-1})$$ (6)

A major difference from Eq. 2 is that the $\bar{h}$ is modulated by the reset gates $r_i$. Here $\otimes$ is element-wise multiplication and $\phi$ is the activation function. We use sigmoid $f(sig)$ activation which can be expressed as

$$f(sig) = \frac{1}{1 + e^{-sig}}$$ (7)

We use both RNN and GRU based models to show the effectiveness of our approach. Next we will discuss our proposed CodeGRU in detail.

4. The CodeGRU Model

In this section, we will introduce CodeGRU in detail. The CodeGRU is composed of several novel components. The overall workflow of CodeGRU is illustrated in Fig. 2. The first step is data collection, which we have discussed in section 6.1. Next step is Code Sampler, which helps to remove noise from raw data and capture syntactical and structural dependencies. Then, we encode the sampled data using Code Regularizer to capture the contextual dependencies. Finally, we build the language model which learns the variable size context of the source code which will be discussed later in detail.
Figure 2: The framework of CodeGRU, which is a context aware deep learning model for source code modeling.

4.1. Code Sampler

Code sampler will first take the code database and selects the language specific files such as Java, Python, c, c++, etc. Here we focus on java files. Then it compiles the sampled files using java compiler [13] to remove noise. Here noise refers to incorrect syntax, the unsuccessful compilation of code, debug issue, etc. It also removes partially compiled programs. The source code compilation process is solely done on the model training dataset and has no impact on the model testing dataset. Further, it removes all blank lines in the sampled files. Next, it removes all block level and inline level comments. Then it transforms the obfuscate source code into proper structure as shown in Fig. 3. Here structure means indentation, block leveling, and other such elements. This transformation helps CodeGRU to capture structural and syntactical dependencies for source code. Our approach is general and can be easily extended to other static type languages where a language parser is available.

4.2. Code Regularizer

Source code consists of different kinds of tokens such as classes, functions, variables, literals, language-specific keywords, data types, stop words, etc. Among all these, language dependent keywords, stop words, library functions, and data types form a shared vocabulary which can also be considered as context. To capture the context of source code tokens we encode them into their token types. Here we care about the token type rather than the token identifier. As discussed earlier code token identifiers can vary from developer to developer and does not

![Image of code structure transformation](image-url)

Figure 3: Transforming an obfuscate source code block into its proper structure, which will help in capturing the structural dependencies.
present any useful information, whereas their data types can help in capturing the context information. So we encode such information to capture the contextual information of source code. For this purpose, we use java parser[1] to parse the source code files to extract their abstract syntax tree (AST). An AST is a tree representation of the abstract syntactic structure of the source code. These ASTs help us encode the type information of source code tokens. The exact values of literals (Int, float, long, double, byte, String Literals, etc) have no impact in code suggestion while keeping them makes the data noisy. We encode all literal values to their base data types according to the Java language grammar[2]. For example given `System.out.println("Hello World")`, the string value "Hello World" is of type `String` according to java language grammar. We encode it with its literal type `String` combined with a special token `Val`. Similarly, the value of identifier `a` in `a = 1.1` is not important, so we encode `1.1` with its literal type `Float` along with a special token `Val`.

![Figure 4: An example of encoding a parsed Java AST with our Code Regularizer.](image)

A challenging issue in source code modeling is to encode the variable and class object identifiers. Java is a strong static type language, which means types of such declarations need to be defined before use. In [Fig. 4] one can see an encoding example for variable and class object identifiers. We encode all primitive type variable identifiers into their resolved data types. In [Fig. 4] one

[2]https://docs.oracle.com/javase/specs/jls/se7/html/jls-18.html
Table 1: Common source code encoding examples encoded by our Code Regularizer

| Code Token     | Token Type       | Special Token |
|----------------|------------------|---------------|
| i              | Int Var          | IntVar        |
| "HelloWorld"   | String Literal   | StringVal     |
| null           | Literal          | null          |
| outFile        | File             | FileVar       |
| ex             | Exception        | ExceptionVar  |
| lstID          | List<Int>        | IntListVar    |
| char           | CharVal          | CharVar       |
| true           | Boolean          | true          |
| inputFile.open() | File            | FileVar.open() |

can see we encode all instances of primitive type variable identifier i with its resolved data type Int combined with a special token Var. To encode class object identifiers we use a symbolic resolver\(^2\) to resolve class objects type. It takes a java project and analyzes all files in it, and then it resolves an instance of the class object. In above example the class object identifier admins is replaced with its class type Admin combined with a special token Var.

Furthermore, we encode the complex data types such as ArrayList<String>. We encode it with its subtype String followed by its base type ArrayList combined with special identifier Var. We leave special code tokens (true, false, null) unencoded. Unlike literals, variables, and class objects, such tokens reflect constant behavior, which does not need encoding. We also leave class methods and function names to their original code tokens. This novel encoding approach helps us build an open vocabulary without compromising any code token. Table 1 shows some popular code tokens and their resolved types encoded by our novel approach.

Programming languages strictly follow the rules defined by their grammar. Each line in a programming language starts with a language reserved identifier, variable or class object declaration, assignment statements, etc. whereas an assignment statement can only have a variable name, object instance or array index on the left-hand side. Similarly, source code languages follow block rules such as try-catch/final, do-while where one must follow the other. By capturing such information, it can help improve the accuracy of source code models.

4.3. Tokenization and Vocabulary Building

In this work, we consider a large size of vocabulary for modeling source code without compromising any source code token. Unlike previous works \(^4\), \(^5\), we do not remove any source code tokens which helps CodeGRU to capture
Table 2: Vocabulary statistics between projects.

|             | Min | Max    | Mean   | Median |
|-------------|-----|--------|--------|--------|
| $V_{Norm}$  | 5159| 37979  | 15128.6| 15128.6|
| $V_{CodeGRU}$ | 4378| 27362  | 11220.2| 9621.0 |

source code regularities much more effectively. To build the vocabulary first, we tokenize the source code files at token level as shown in Fig. 5. Each unique source code token corresponds to an entry in the vocabulary. Then, we vectorize the source code where each source code token has a position integer value. In Table 2 one can see the vocabulary statistics, where $V_{Norm}$ shows the vocabulary statics without Code Regularizer and $V_{CodeGRU}$ shows the vocabulary statistics with Code Regularizer.

Figure 5: Process of building vocabulary for language models.

4.4. Variable Size Context Learning

The proposed CodeGRU uses GRU [12] to perform variable size context learning. The CodeGRU takes a source code program as line wise sequence of code tokens $X$. Here the goal is to produce the next token $y$ by satisfying the context of $X$. We can express a code statement $S$ at line $L$. Then a source code program can be represented as $(l^i, \tau^i)$ where $l^i$ is the line number and $\tau^i$ is tokenization of $S$ at $l^i$. It breaks each $l^i$ into several $\tau^i$ by iteratively increasing the context on each iteration. The CodeGRU learns the source code context at $(l^i, \tau^i)$ and keeps increase the $\tau^{i+1}$ until it reaches the upper bound limit of $l^i$. When the CodeGRU reaches the upper bound limit of $l^i$, it increases $l^{i+1}$ and keeps learning the source code context. The proposed approach removes the limitation of the sliding window approach used by previous models [10, 25, 34] where the right context for the next code token may not be captured in that given window. This way CodeGRU iteratively learns over the source code with variable context size which shows improvement in modeling source code.

Further, here we expect the CodeGRU to assign the high probability to the next source code suggestion by having a low Cross-entropy. The Cross-entropy is a cost function to observe how best the model works. A low value of Cross-
entropy indicates a good model. It can be expressed as 

\[ H_{P(b|C)} \approx -\frac{1}{m} \sum_{i=1}^{m} \log_2 P(b(\tau^i|\tau^{i-1}) \] (8)

5. Empirical Evaluation

In this section, we provide an empirical evaluation of CodeGRU. We train and evaluate our models on Intel(R) Xeon(R) CPU E5-2620 v4 2.10GHz with 16 cores and 64GB of ram running CentOS 7 operating system, equipped with an NVIDIA Tesla K40m with 12GB of GPU memory along with 2880 CUDA cores. The average train and test time statistics are summarized in Table 3. Table 3 also shows the source code suggestion and the source code generation time. On average, it takes 1-7 days to fully train and evaluate a single project and it takes 10-30 minutes to test the trained project. It takes less than 30 milliseconds for source code suggestion and source code generation tasks.

To evaluate the performance of CodeGRU, we aim at answering the following questions:

- **RQ1:** Does the proposed approach outperform the state-of-the-art approaches?
- **RQ2:** How well CodeGRU performs in source code suggestion and source code generation tasks?
- **RQ3:** To what extent CodeGRU helps reduce the vocabulary size?
- **RQ4:** What applications CodeGRU can be applied in to facilitate software developers?

To answer the research question (RQ1), we compare the performance of the proposed approach with the state-of-the-art approaches [49, 25, 34] in order to find out the performance improvement of the proposed approach. To answer the research question (RQ2), we evaluated the CodeGRU with mean reciprocal rank (MRR) with state-of-art approaches [49, 25, 34] in order to evaluate how well CodeGRU performs in term of source code suggestion and generation tasks. To answer the research question (RQ3), We provide the statistical results for vocabulary with our proposed approach and without our proposed approach. To answer the (RQ4), we discussed and visualized two case studies in section 6.

5.1. Dataset

To build our code database, we collected open-source java projects from GitHub summarized\(^1\) in Table 3. We choose the projects used in previous references [49, 25, 34]. The Table 3 shows the version of the projects, files count

\(^1\)https://github.com/yaxirhuxxain/Source-Code-Suggestion
Table 3: Average time statistics of deep learning based models.

| Train (days) | Test (minutes) | Code Suggestion (milliseconds) | Code Generation (milliseconds) |
|--------------|----------------|-------------------------------|-------------------------------|
| 1-7          | 10-30          | <30                           | <30                           |

Table 4: List of java projects used for evaluation. Each project is open source and gathered at its latest version at the time of this study. The table shows the name of the project, version of the project, line of code (LOC) count, total code tokens count and unique code tokens in each project.

| Projects | Version | LOC  | Code Tokens |
|----------|---------|------|-------------|
|          |         |      | Total       | Unique     |
| ant      | 1.10.5  | 84076| 555216      | 12334      |
| cassandra| 3.11.3  | 90087| 796988      | 15669      |
| db40     | 7.2     | 146721| 1005485     | 17333      |
| jgit     | 5.1.3   | 101777| 786703      | 14020      |
| poi      | 4.0.0   | 258230| 1992844     | 37979      |
| maven    | 3.6.0   | 49152| 373115      | 7105       |
| batik    | 1.10.0  | 72683| 494842      | 12927      |
| jts      | 1.16.0  | 56544| 432047      | 9082       |
| itext    | 5.5.13  | 141435| 1128560     | 19678      |
| antlr    | 4.7.1   | 35828| 264077      | 5159       |

in each project, total number of code lines, total code tokens and unique code tokens found in each project without any transformation. We split each project into ten equal folds. From which one folds is used for testing and rest are used for training purpose. After each model training, we rebuild the model so that previous model’s training do not have any impact on the afresh model.

5.2. Baselines

We train several baseline models for the evaluation of this work. In this section, we briefly describe the baselines for comparison in detail.

We compare our work against the n-gram model used in Hindle et al. [25], RNN model used in White et al. [49] and DNN model used in Nguyen et al. [34]. Further, we train three different models RNN+, GRU and CodeGRU. RNN+ is a variation of vanilla RNN trained by using our proposed approach. GRU based model is trained similar to previous works [25, 49] by treating source code as simple text and with fixed size window approach. The CodeGRU model is trained by using our proposed approach with variable size context as described earlier in section 4. For training purposes, we use the valid java source code files. Each source code file is first tokenized and vectorized as discussed earlier in section 4.3. Then we encode each vector into a binary encoded matrix. This binary encoded matrix is also known as One-hot encoding where each column’s index is zero and the vocabulary indexed column has the value one. Then, we
Table 5: Deep learning models architecture summary.

| Type         | Size  | Activations       |
|--------------|-------|-------------------|
| Input Code embedding | 300   |                   |
| Estimator RNN,GRU | 300   | tanh              |
| Over Fitting Dropout | 0.25  |                   |
| Output Dense VNorm, VCodeGRU | softmax |
| Loss Categorical cross entropy |       |
| Optimizer Adam | 0.001 |                   |

map the vocabulary to a continuous feature vector of dense size 300 similar to Word2Vec. This approach helps us build a dense vector representation for each vocabulary index without compromising over the semantic meaning of the source code tokens.

We use similar settings for each model as in previous studies. We train a 7-gram model with Good Turing smoothing. The Table 5 shows the architecture of deep learning based models. We use 300 hidden units for each model training. We use Adam optimizer with the learning rate as 0.001. To control over fitting we use Dropout at the rate of 0.2. We ran each model for 100 epochs with the batch size of 512. When a model is fully trained, we outsource the trained model in hierarchical data format (HDF5) format along with model settings. We train four models simultaneously to get most out of the NVIDIA Tesla K40m CUDA cores.

5.3. Metrics

We choose the top-k accuracy and mean reciprocal rank (MRR) metrics as used in the previous works. We calculate top-k accuracy, where \(k=1,2,3,5,10\). We also evaluated the CodeGRU with mean reciprocal rank (MRR) metric. The MRR is a rank based evaluation metric in which suggestions that occur earlier in the list are weighted higher than those that occur later in the list. MRR is the average of the reciprocal ranks of suggested code token list for given code sequences \(C\). The MRR produces a value between 0-1, where the value 1 indicates perfect source code suggestion model. The MRR can be expressed as

\[
MRR = \frac{1}{|C|} \sum_{i=1}^{|C|} \frac{1}{y^i}
\]

(9)

where \(C\) is set of code sequences and \(y^i\) refers to the index of the first relevant prediction.

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1https://github.com/yaxirhuxxain/Source-Code-Suggestion
5.4. Results

The accuracy scores of all the models are shown in Table 6. One can see the simple RNN+ model outperforms other baseline [49, 25, 34] models. Previous works do not consider source codes contextual, syntactical and structural dependencies but still our proposed approach out-performs them. Table 6 shows the accuracy scores as done in previous works. We observe that both RNN+ and CodeGRU models perform better when the project size is large. The itext project is the largest one in our data set. One can see in Table 6 it gains the highest accuracy score of 66.52 @ k=1 and it gains 87.25 @ k=10, whereas previous models gains much lower score 56.54 @ k=1 and 82.57 @ k=10. Further, Table 6 shows that accuracy of CodeGRU model improves tremendously when variable size context is used as compared to the fixed size context based GRU model.

Table 7 shows the model evaluation results for code suggestion task. The MRR score lies between 0-1, and a higher value indicates a better source code suggestion. One can see even our simple RNN+ model outperforms baseline models. The max MRR score of our model is 0.744, and the min score is 0.625. Further, we observe that the MRR score of RNN+ and CodeGRU increase with the data size. One can see in Table 7 that the itext project which is the largest one in our code database, it gained the MRR score of 0.744 which means that our proposed approach can give very accurate suggestion in its top five suggestion list.

5.5. Impact of Code Sampler and Code Regularize on Vocabulary

Natural language based models train the model on a finite vocabulary and remove the tokens from the test dataset which are not present in training. This approach is not practical in terms of source code where software developers continuously use new variables, class objects, and function names. Previous works [25, 49] use a similar approach, where they remove all code tokens not appearing in training data set to build an open vocabulary at the time of testing. Apart from previous approaches, this work does not remove any code token even if it does not appear at training time. Our work can not only predict the next code token according to the correct syntax of grammar but also can capture the correct context for next source code suggestion. The CodeGRU is capable of suggesting the next code token even in the presence of an unseen token. Our novel Code Sampler and Code Regularize techniques can help build an open vocabulary without compromising any source code token. Table 8 shows the vocabulary statistic with and without our proposed approach. Our approach helps us reduce the vocabulary size up to 10%-50%.

5.6. Impact of Variable Size Context based Learning

To evaluate the impact of our variable size context learning on the model performance, we train RNN+ model as described earlier in section 5.2. We set the upper bound limit of the context to n = 20 as in previous works [49, 25]. Table 7 shows that RNN+ gains the MRR score of 0.732 with variable length
Table 6: Accuracy comparison of CodeGRU with previous works. $k$ is the accuracy count.

| Projects | N-grams | Previous Works | Our Work | CodeGRU |
|----------|---------|----------------|----------|---------|
|          | $k$     | RNN            | DNN      | $RNN+$  | GRU     |
| ant      | 1       | 11.31          | 59.46    | 60.34   | 61.63   | 62.73   | 62.82   |
|          | 3       | 12.35          | 73.94    | 74.61   | 77.49   | 74.72   | 78.36   |
|          | 5       | 12.66          | 77.00    | 77.09   | 80.45   | 77.57   | 81.14   |
|          | 10      | 12.76          | 79.97    | 80.51   | 83.33   | 80.31   | 83.96   |
| cassandra| 1       | 09.39          | 51.64    | 54.74   | 57.94   | 52.72   | 54.25   |
|          | 3       | 10.64          | 67.61    | 68.17   | 69.29   | 68.15   | 70.11   |
|          | 5       | 10.81          | 71.61    | 73.23   | 74.86   | 73.19   | 74.07   |
|          | 10      | 10.98          | 75.59    | 77.07   | 83.05   | 75.82   | 77.67   |
| db4o     | 1       | 08.52          | 50.48    | 51.21   | 52.80   | 53.85   | 54.52   |
|          | 3       | 09.23          | 68.15    | 69.37   | 70.26   | 70.39   | 71.85   |
|          | 5       | 09.34          | 72.61    | 72.98   | 74.66   | 74.31   | 75.92   |
|          | 10      | 09.41          | 76.54    | 77.12   | 82.17   | 80.76   | 82.98   |
| jgit     | 1       | 11.41          | 58.51    | 53.80   | 61.33   | 60.01   | 62.29   |
|          | 3       | 12.96          | 72.24    | 70.01   | 76.12   | 74.29   | 76.91   |
|          | 5       | 13.15          | 74.65    | 75.64   | 79.10   | 77.48   | 79.91   |
|          | 10      | 13.30          | 78.98    | 79.75   | 82.17   | 80.76   | 82.98   |
| poi      | 1       | 00.12          | 56.34    | 59.31   | 64.10   | 63.85   | 66.57   |
|          | 3       | 17.93          | 72.96    | 73.76   | 78.84   | 77.48   | 80.59   |
|          | 5       | 18.09          | 76.95    | 77.47   | 82.02   | 80.88   | 83.69   |
|          | 10      | 18.24          | 80.77    | 81.79   | 85.41   | 84.25   | 86.98   |
| maven    | 1       | 12.28          | 55.17    | 57.16   | 60.65   | 60.93   | 60.17   |
|          | 3       | 13.16          | 64.00    | 62.86   | 74.99   | 73.93   | 74.54   |
|          | 5       | 14.03          | 76.19    | 77.65   | 78.13   | 77.15   | 77.78   |
|          | 10      | 14.47          | 79.39    | 80.54   | 81.59   | 80.37   | 81.52   |
| batik    | 1       | 13.29          | 47.57    | 58.89   | 61.24   | 51.47   | 62.61   |
|          | 3       | 13.97          | 75.24    | 76.15   | 76.09   | 68.36   | 76.92   |
|          | 5       | 14.04          | 78.24    | 79.21   | 80.13   | 73.12   | 81.03   |
|          | 10      | 14.47          | 80.30    | 81.71   | 84.01   | 76.61   | 84.86   |
| jts      | 1       | 12.66          | 54.23    | 57.28   | 58.49   | 55.37   | 59.68   |
|          | 3       | 14.07          | 70.83    | 72.45   | 74.16   | 71.65   | 74.76   |
|          | 5       | 14.17          | 74.52    | 75.21   | 77.81   | 75.04   | 78.45   |
|          | 10      | 14.34          | 78.06    | 80.75   | 81.58   | 78.38   | 82.34   |
| itext    | 1       | 12.85          | 55.33    | 56.54   | 66.31   | 59.48   | 66.52   |
|          | 3       | 15.22          | 72.49    | 68.01   | 80.90   | 73.64   | 80.74   |
|          | 5       | 15.58          | 75.96    | 78.16   | 83.84   | 76.97   | 84.04   |
|          | 10      | 15.80          | 79.42    | 82.57   | 87.06   | 80.25   | 87.25   |
| antlr    | 1       | 10.30          | 54.04    | 55.14   | 57.55   | 64.88   | 58.77   |
|          | 3       | 18.78          | 73.15    | 73.33   | 74.29   | 77.31   | 75.61   |
|          | 5       | 19.35          | 76.71    | 77.15   | 77.92   | 80.23   | 79.27   |
|          | 10      | 19.43          | 79.81    | 80.52   | 81.43   | 83.13   | 82.87   |

context in the itext project, while the score drops to 0.620 with RNN model when a fixed size context windows approach is used. We further evaluate both models for code generation task. One can see in Table 9 that, our $RNN+$ with variable size context learning technique can easily generate the next whole sequence with accurate context and syntax, while the fixed size context RNN model fails to generate very accurate sequences. It shows that variable size context learning over code sequence can help improve the prediction of next code token tremendously. We also observe that CodeGRU can accurately predict the next code token within its top five suggestions bracket almost all the time. Moreover, we observe with variable size context learning over the source code helps to predict the whole next sequence of code with accurate syntax and
Table 7: The MRR score comparison of CodeGRU with previous works.

| Projects | Previous Works | Our Work |
|----------|----------------|----------|
|          | N-grams | RNN | DNN | RNN+ | GRU | CodeGRU |
| ant      | 0.118   | 0.677 | 0.686 | 0.698 | 0.686 | 0.710 |
| cassandra| 0.100   | 0.587 | 0.596 | 0.607 | 0.603 | 0.625 |
| db4o     | 0.088   | 0.569 | 0.591 | 0.616 | 0.620 | 0.632 |
| jgit     | 0.122   | 0.649 | 0.669 | 0.686 | 0.669 | 0.694 |
| poi      | 0.169   | 0.598 | 0.613 | 0.692 | 0.702 | 0.736 |
| maven    | 0.129   | 0.669 | 0.670 | 0.676 | 0.675 | 0.678 |
| batik    | 0.136   | 0.647 | 0.667 | 0.693 | 0.614 | 0.703 |
| jts      | 0.133   | 0.627 | 0.633 | 0.664 | 0.637 | 0.675 |
| itext    | 0.141   | 0.620 | 0.676 | 0.732 | 0.661 | 0.744 |
| antlr    | 0.179   | 0.609 | 0.615 | 0.661 | 0.719 | 0.678 |

Table 8: Impact of Code Sampler and Code Regularize on vocabulary. The table shows the total count of code tokens, where \( V_{Norm} \) shows the vocabulary size without our approach and \( V_{CodeGRU} \) shows the vocabulary size with our proposed approach.

| Projects | Code Tokens | \( V_{Norm} \) | \( V_{CodeGRU} \) | % Decrease |
|----------|-------------|-----------------|-------------------|------------|
| ant      | 555216      | 12334           | 9578              | 22.34%     |
| cassandra| 796988      | 15669           | 14055             | 10.30%     |
| db4o     | 1005485     | 17333           | 14800             | 14.61%     |
| jgit     | 786703      | 14020           | 11222             | 19.96%     |
| poi      | 1992844     | 37979           | 27362             | 27.95%     |
| maven    | 373115      | 7105            | 5957              | 16.16%     |
| batik    | 494842      | 12927           | 9064              | 25.24%     |
| jts      | 432047      | 9082            | 6313              | 32.49%     |
| itext    | 1128560     | 19678           | 9055              | 53.98%     |
| antlr    | 264077      | 5159            | 4378              | 15.14%     |

Table 9: The impact of variable size context with fixed size context on CodeGRU for code generation task.

| Code Input | Variable size context | Fixed size context |
|------------|-----------------------|--------------------|
| )While     | )While ( intvar >= intval ) | )While () != null |
| if (       | if ( intvar < intval ) | if ( xsltablecellvar | intvar + |
| String Var | String Var = stringval | String Var areareference stringval |

context. We visualize CodeGRU in section 6 in detail for code suggestion and code generation tasks.
6. Use Cases of CodeGRU

In this section, we will discuss and visualize two use cases of CodeGRU, (1) code suggestion, which aims to suggest multiple predictions for the next code token and (2) code generation, which aims to generate the whole next source code sequence.

6.1. Code Suggestion

CodeGRU is capable of ranking the next code token suggestions by calculating the likelihood based on a given context. In [Fig. 6](a) one can see an example for code suggestion task where a software developer is writing a simple for loop at line six and the most probable suggestion should be `int` but in visual studio code it does not show such suggestion. In [Fig. 6](b) one can see that our CodeGRU suggests the correct next code token `int` at the top of its suggestion list. In [Table 10](a) one can clearly see CodeGRU successfully suggests the next code token in its top three suggestion list almost all the time. We can also observe that the CodeGRU suggest the next source code token by capturing the correct context and syntax according to the Java language grammar.

6.2. Code Generation

Unlike previous works [49, 25, 34], the CodeGRU can generate the whole next code sequence. We take the same example discussed earlier in [Fig. 6](a) where a developer is writing a source code for ( at line 6 in visual studio code. As [Fig. 6](c) shows CodeGRU successfully capture the correct context and suggests the whole sequence of code `for( int intvar = intval ; intvar < intvar ; intvar ++ )` with correct syntax. This approach can help reduce the efforts of a software developer tremendously. In [Table 11](a) we summarized some common code generation examples generated by our CodeGRU model.

7. Threats to Validity

*Internal:* All models are developed using keras version 2.2 with tensorflow version 1.1 backend. Although our experiments are detailed and results have
Table 10: Use case of CodeGRU for code suggestion task. The input is a variable length code and the output is the list of top-ranked suggestions recommended by CodeGRU.

| Code Input                                                                 | Top three code suggestion with CodeGRU.                                                                 |
|----------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|
| for ( \['int', 'codegenerateorextension', 'string'\]                                                                   | \['int', 'codegenerateorextension', 'string'\]                                                             |
| private static final \['string', 'class', 'int'\]                                                                     | \['string', 'class', 'int'\]                                                                                |
| if ( StringArrayListVar . \['add', 'addall', 'write'\]                                                                | \['add', 'addall', 'write'\]                                                                              |
| for ( String StringVar : \['contains', 'add', 'addall'\]                                                              | \['contains', 'add', 'addall'\]                                                                          |
| } catch ( \['exception', 'ioexception', 'recognitionexception'\]                                                         | \['exception', 'ioexception', 'recognitionexception'\]                                                     |
| listVar . \['add', 'seek', 'antlr'\]                                                                                  | \['add', 'seek', 'antlr'\]                                                                                |
| for ( int intVar = intval \[';','(','.'\]                                                                             | \[';','(','.'\]                                                                                        |
| } else \['\(','','if','return'\]                                                                                     | \['\(','','if','return'\]                                                                                |
| hashmapVar . \['add', 'close', 'write'\]                                                                              | \['add', 'close', 'write'\]                                                                               |
| } while \['(','','='\]                                                                                               | \['(','','='\]                                                                                         |

Table 11: Use case of CodeGRU for code generation task, where the input is a variable length code and output is the next code sequence generated by our CodeGRU along with correct context and syntax.

| Code Input                                                                 | Code generation with CodeGRU.                                                                  |
|----------------------------------------------------------------------------|---------------------------------------------------------------------------------------------|
| for( int for( int intVar = intval ; intVar < intval ; intVar ++ ) {       | for( int for( int intVar = intval ; intVar < intval ; intVar ++ ) {                         |
| public static public static class nongreedyconfigs extends baselexertdescriptor | public static class nongreedyconfigs extends baselexertdescriptor                           |
| } While                                                                   | } While ( intVar != token . eof ) ;                                                          |
| if ( stringarrayVar                                                        | if ( stringarrayVar . length == intval ) { system . gettext                                  |
| private static final                                                     | String StringVar = stringval ; assertequals ( stringVar , stringVar ) ;                     |
| while ( stringVar                                                         | private static final string || stringarrayVar = stringarrayVal ;                          |
| String temp () ( return StringArrayListVar .                               | String temp () ( return StringArrayListVar . add ( stringVar                                |
| } catch ( )                                                             | } catch ( ( exceptionexceptionVar )                                                       |
| ) else if                                                                | } else if ( intVar >= intVar                                                                  |

shown the effectiveness of our approach but still neural networks are in its infancy. Change in neural network settings or evaluating with a different project version it may possible to have different results.

External: Further, all the source code projects used in this study are collected from GitHub, a well-known source code repositories provider. It is not necessary that the projects used in this study represent other languages source code or Java language source code entirely. Use of different projects or languages may affect the working of our approach.
8. Conclusion and Future Work

This paper proposed CodeGRU, a novel approach for source code modeling by capturing source code's contextual, structural and syntactical dependencies. Different from previous works, we do not treat source code as simple text. This work introduces several new components such as Code Sampler and Code Regularizer. These components help to reduce the vocabulary size up to 10%-50% and helps overcome out of vocabulary issue. Further, CodeGRU can learn source code with variable size context. This work has shown that CodeGRU can not only predict the next code token according to the correct context and syntax of the grammar but also can predict variable names, class objects, class methods and much more. We have also visualized the use cases of CodeGRU for code suggestion and code generation tasks. With our novel approach, the CodeGRU suggested the next code token almost all the time in its top three suggestion list. Moreover, it is also capable of generating the whole next code sequence, which is difficult for previous works to do.

In the future, we would like to evaluate our approach for the dynamic typed languages such as Python. In dynamic type languages, a source code token can have different token types which makes it difficult to capture token types. We also aim at providing an end to end solution which can help software developers directly utilize these models. Another limitation of deep learning based approaches is computation power, where training a new model require additional resources. A common software developer cannot afford to have a server or GPU based computer to train and utilize these models. There is a need for centralization of these languages model which can directly benefit software developers with minimum effort.

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