DeepClone: Modeling Clones to Generate Code Predictions

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ABSTRACT

During software development, programmers often tend to reuse the code for common functionalities, available in other source code repositories. This activity helps them to reduce time and effort to develop code, instead of building it from scratch. Code clones are candidates for reuse in an exploratory or rapid development, as they represent often repeated functionality in software systems. To facilitate code clone reuse, we propose a novel approach, DeepClone, where we utilize a deep learning algorithm for modeling code clones and predicting the next possible set of tokens (up to the cloned method body) based on the user input so far. The generated predictions aim to potentially help developers to write code rapidly with minimum tuning of values later on. DeepClone applies natural language processing techniques to learn from a large code corpus (the BigCloneBench dataset), and generates code tokens (full clone methods where applicable) using the model learned. We have quantitatively evaluated our solution to assess (1) our model’s quality and its accuracy in token prediction, and (2) its performance and effectiveness in clone method prediction. With a high quality and accurate model as the foundation, we further discuss scenarios for exploiting our approach.

CCS CONCEPTS

• Computing methodologies → Neural networks; • Software and its engineering → Language features; • Reusability; • Automatic programming; • Software development methods;

KEYWORDS

natural language modeling, deep learning, code clone, code prediction

1 INTRODUCTION

Many software development and maintenance tasks rely on searching the source code effectively [69]. However, the structure of source code makes it difficult to be read in a linear fashion like normal text and hinders an effective code search. It is also tedious and impractical to read the entire source code of large software systems. Writing new source code is an expensive activity, consuming considerable time and effort. To overcome this limitation, developers frequently perform ad hoc code reuse [38], which requires selectively reading the source code to identify the relevant parts of the code for reuse [75]. Often, programming of well-defined problems amounts to a simple look-up [75], first in one’s own, and then in others’ code repositories, followed by judicious copying and pasting. The bigger the dataset of code available, the more likely it is that one will find what one is looking for [25]. For this purpose, developers require features such as code snippet search, code predictions, code auto-completion and code generation, which can help them to write code quickly and easily. These problems have been usually solved by language modeling.

Claude Shannon is considered to be a founder of language modeling [72, 73]. Shannon used this technique to predict the next element following some given text and bound the entropy of the English language. Since then, several language models have been developed to perform difference tasks. A language model (LM) estimates the likelihood of sequences of tokens based on a training dataset, by assigning probabilities to tokens (words, subwords, or punctuation marks) or character sequences (sentences or words occurring after a given sequence [39]). There are different techniques such as statistical ones and deep neural networks (DNN), which have been applied for LMs including n-gram, graphed-based, and context sensitive models [6, 8, 56]. Both techniques have led to great results on natural language processing (NLP) tasks mainly, because in practice natural language is often repetitive and predictable [31], thus can be modeled using both techniques. However, statistical modeling techniques does not perform well, when the size of vocabulary is very large. During the software development life-cycle, developers declare new identifier names at a far higher rate, which degrade the performance of statistical language models [41].

Deep neural network (DNN) techniques, on the other hand, are extremely powerful machine learning models that achieve excellent performance on various difficult problems such as speech recognition [21] and visual object recognition [44]. A recent study [41] shows that deep neural network (DNN) techniques indeed outperform statistical language modeling techniques. Their power arises from the fact that they can perform arbitrary parallel computation for a modest number of steps. A surprising example of the power of DNNs is their ability to sort N N-bit numbers using only 2 hidden layers of quadratic size [66]. Various DNN techniques have been applied on source code to perform language modeling [14], by learning the features from a large source code dataset. DNN techniques involve an algorithm that improves automatically through experience based on data. It is a way to discover a new algorithm from the experience, and involves the study of algorithms that can extract information automatically. These LMs have been referred as neural language model (NLM). NLMs have been used to perform various tasks such as speech recognition [20], machine translation [36], comment generation [34], fault detection [64], code completion [54][57], code clone detection [81, 90], code search [28] and code summarization [35].
One such application of a language model is code prediction, which has received a good deal of attention from the software engineering researchers [15, 16, 92]. It involves automated techniques for aiding software development and maintenance by proposing next likely tokens on the basis of user inputs. A prediction model is capable of automatically learning features for representing source code, and using them for next token prediction in a sequence. Neural Language Models (NLMs) represent code tokens in a continuous vector space, which has attractive properties. Pythia [82] is an AI assisted code completion approach, which generates ranked lists of method, and API recommendations at edit time. Similarly, Deep TabNine [2] has been recently launched, which is an auto-complete tool trained on approximately two million GitHub files that intends to enhance software developer workflows.

These models can be refined by tuning several parameters such as layering, epoch value, batch size and the size of token sequences. Hence, by keeping these benefits of deep learning, we have used them to build a prediction model. Neural language models can outperform carefully tuned n-gram models, when modeling natural language [37]. Researchers have applied various types of deep neural networks (DNN) for language modeling such as Recurrent Neural Network (RNN) [53, 94], its variants such as Long Short Term Memory (LSTM) [32, 42, 77], and Transformer based Generative Pre-Training 2 (GPT-2) [62], a successor of GPT [60], for performing code predictions.

These code predictions are at the level of a fixed threshold token length. We believe that method level clones of arbitrary length, extracted from a large code repository, can enhance regular code generation and prediction applications. Code clones are repeated patterns in the code, which are usually created with the copy-and-paste practice mentioned above. According to Roy and Cordy [68], around 5 to 50% of the code in software applications can be enclosed in clones, which can be of several granularity levels such as line, method, file, and directory. Most of the time clones are considered to be harmful for a software system, and mainly researchers work on techniques for avoiding and eliminating clones [10, 11, 88, 93]. However, Kapser and Godfrey [40] observe that code clones are not always bad, as they can also have positive effects on the software development in certain circumstances. One of the positive use cases is exploratory development, where the rapid development of a feature is required and the remedial unification of newly generated clone is not clearly justified. Also, a piece of cloned code is expected to be more stable and poses less risk than new development. Hence, it can be argued that developers need to reuse code for desired software features in a way that supports opportunistic programming for increased productivity.

We believe that clone methods can be considered as a useful component for a language model, as they can be used to capture the common code practices of developers, which then can be used for code predictions and completions to the new developer. In this work, we exploit the re-usability aspect of code clones for the purpose of source code modeling in predicting code tokens by applying a deep learning algorithm. We believe that our approach can help in improving the quality of code prediction up to full clone method bodies with arbitrary length. In this paper, we have made the following contributions:

1. We present the first attempt in literature for explicitly modeling of code clones using deep learning to be utilized for code/clone method prediction.
2. Our approach can generate predictions up to the full cloned method body (with arbitrary length) on the basis of user input.
3. We have quantitatively evaluated our approach using the BigCloneBench dataset, in terms of model quality and performance in various tasks including token prediction, and clone method prediction.

2 RELATED WORK
In this section, we present related work covering source code language modeling techniques, and the role of learning based techniques in the field of code clones.

2.1 Language Modeling
To the best of our knowledge no techniques have been presented to model code clones for predicting clone methods. However, many techniques have been introduced to perform language modeling for various other tasks such as token prediction and completion. White et al. [91] apply Recurrent Neural Network (RNN) to model Java source code and evaluate its performance on code prediction task. Bold [16] specifically models Java language method statements and compare the performance with English language datasets trained by Long Short Term Memory (LSTM). He argues that method statements highly resemble with English language sentences and can be comparable with each other. He compares the performance of models on predicting a next element and demonstrate that LSTM can achieve performance trained on the Java datasets higher than the English dataset. Hindle et al. [31] make a fair comparison between software and natural language by discovering that software is much more repetitive and well structured than natural language. So, it is much simpler to model Java code by using n-grams rather than the English language. They compare the performance of language models on next element prediction task and demonstrate that n-gram models trained on Java dataset performs much better as compared to n-gram models trained on English language dataset. Hellendoorn and Devanbu [30] notice that source code based neural language models (NLMs) under-perform due to the unlimited scope of the vocabulary size, as in software development life cycle identifiers keep on coming with higher rates, and limiting vocabulary is not a good solution with NLMs. So, they propose a nested scope, dynamically updatable, unlimited vocabulary count-based ngram model, which outperforms the LSTM model on the task of token prediction. In contrast, Rafael et al. [41] solve the issue of unlimited scope of vocabulary size by applying byte-pair encoding (BPE) technique in modeling the code. They compare the performance of n-gram and Gated Recurrent Unit (GRU) language models trained on source code datasets, and demonstrate that NLM can outperform on code completion and bug detection tasks if BPE technique is applied.

2.2 Code Clones
The only work we have come across that uses clone methods for recommending code completion is by Shamsa [3]. However, the
clone methods considered in this system are based on a different notion of similarity — similar API calls.

Learning based approaches have been extensively used for clone detection. White et al. [90] use recursive neural network (RNN) for clone detection. Wei et al. [89] use the LSTM model for the functional clone detection problem by learning supervised deep features. CCLEArner [48] extracts tokens from known method-level code clones and non-clones in a given codebase to train a classifier, which is then used to detect clones. Tufano et al. [85] use a deep learning based approach to automatically learn code similarities from different representations. Vara et al. [7] propose a method to increase the precision of code clone detection using machine learning techniques. They apply 19 clone class metrics to capture different characteristics of code clones and use them to train a decision tree model.

3 BIGCLONEBENCH FOR CODE CLONES

In the literature, there exist a few code clone benchmark data sets, such as OCD benchmark [63], Bellon’s benchmark [13], Murakami et al.’s benchmark [55] and BigCloneBench [78–80]. The largest one is BigCloneBench, which consists of over 8 million manually validated clone method pairs in IJaDataset 2.0 [1]— a large Java repository of 2.3 million source files (365 MLOC) from 25,000 open-source projects. BigCloneBench contains clones with both syntactic and semantic similarities.

BigCloneBench contains the references of starting and ending lines of method clones existing in the code repository. In forming this benchmark, methods that potentially implement a given common functionality were identified using pattern based heuristics. These methods were manually tagged as true or false positives of the target functionality by judges. All true positives of a functionality were grouped as a clone class, where a clone class of size \(n\) contains \(\binom{n}{2}\) clone pairs. The clone types and similarity of these clone pairs were later identified in a post-processing step. Currently, BigCloneBench contains clones corresponding to 43 distinct functionalities. Further details can be found in the relevant publications [78–80].

BigCloneBench has been primarily developed to measure and compare the recall of clone detection tools [70, 78–80]. However, it can also be used for other clone and software studies [80]. Li et al. [48] have developed a DNN-based clone detector, CCLEArner, using BigCloneBench.

3.1 Dataset Preparation

IJaDataset [1] is very large, and outside the scalability limits of most clone detection tools. However, the clone detection tools do not need to be executed for the entire IJaDataset, only for the files containing reference clones in BigCloneBench. SvaJlenko et al. [78–80] provide a reduced version of IJaDataset, which contains only the relevant source files and is distributed into a number of smaller subsets for clone detection. There is one subset per functionality in BigCloneBench. Each functionality in this subset includes all the files, which contain methods tagged as true or false positive of that functionality in the creation of BigCloneBench. Therefore each subset is a realistic subject system, containing both true and false positive clones. We have performed pre-processing steps to build our mutually exclusive training, testing, and validation datasets. The training set is used to train our DeepClone language model. After each training epoch, the trained model is evaluated on the validation set and its performance helps in assessing the convergence against hyper-parameters (e.g., learning rate in gradient searches). The validation set is not used to learn any of the model parameters. The testing set is used for empirical evaluation of our DeepClone model. Table 1 demonstrates the post-processing steps on an example of binary search clone method.

3.1.1 Filtering. We have applied the following query to extract true positive clone methods from BigCloneBench dataset and their references in IJaDataset.

```sql
select distinct a.functionality_id, b.type, b.name, b.startline, b.endline from clones a
join functions b on a.function_id_one=b.id
union
select distinct a.functionality_id, b.type, b.name, b.startline, b.endline from clones a
join functions b on a.function_id_two=b.id
```

In the above query, we have applied the union operation to discard duplicated results. The "functions" table contains information about true and false positive clone method, including filename, starting and ending line position of the clone method, the type id of the method. Whereas the "clones" table contains the list of true positive clone method pair information including syntactic similarity and validity measures. The result allows us to include all the files, which have true positive clone methods, and discard those files, which have only false positive clone methods from the reduced version of IJaDataset.

3.1.2 Distribution. In this step, we need to distribute the set of files into training, validation, and testing datasets. We have adopted a strategy of stratified sampling [83] in order to ensure that all types of clone methods appear in training, validation and testing datasets. We distribute the set of files existing in each functionality folder, into portions such as 80% training, 10% validation, and 10% testing. Then, we copy those files belonging to three separate folders such as training, validation, and testing. If any of the file already exist in one of those folders, we discard that specific file, therefore avoid exact duplication. This means that the file has already been moved to one of the specific folder type such as training, validation, and testing. Allamanis [5] also notices that the negative impact has been occurred on model performance, if same file has been used for training and testing. Tables 2 and 3 depict the detailed statistical overview of our datasets, which we have used for training, validation and testing. We have only mentioned the titles of the functionalities in Table 2, and excluded further details. Those are out of scope for this paper and can be found in the BigCloneBench dataset.

3.1.3 Marking. Researchers in the past have used special meta-tokens to solve various problems. Pichotta and Mooney [59] place \(\langle S\rangle\) and \(\langle/ S\rangle\) meta-tokens in modeling sentences for prediction. Chen et al. [18] insert \(\langle\text{START\_BUG}\rangle\) and \(\langle\text{END\_BUG}\rangle\) meta-tokens in the buggy lines of the source code, which helps in automatically
reparing programs. We have marked the regions of the true positive clone methods, by placing the meta-token ⟨soc⟩ at the start, and ⟨eoc⟩ at the end of a clone method in the IJaDataset files, by tracing the clone method references from the BigCloneBench dataset.

3.1.4 Normalization and Tokenization. We have adapted Javalang\(^1\) Python library, which contains a lexer and parser for Java 8 programming language. This library helps us to normalize our code by removing whitespaces, extra lines, comments, as well as to tokenize the code.

3.1.5 Replacement. For each set of files, we have replaced integer, float, binary, and hexadecimal constant values with the ⟨num, val⟩ meta-token. Similarly, we have replaced string and character values with ⟨str, val⟩. This reduces our vocabulary size, which leads to faster training of the model. This technique has been used by several researchers in the same manner for data preparation [22, 41, 91].

3.1.6 Merging. We have merged all the tokenized data existing in the training, validation and testing folders, and placed them into separate text files, i.e. train.txt, valid.txt, and test.txt. These tokens are separated by the space character. Table 3 gives a statistical overview of our experimental dataset.

4 DEEPCLONE MODEL

In this section, we discuss our approach in modeling code clones using GPT-2 and the experimental setup used to conduct our study.

4.1 Generative Pretrained Transformer 2 (GPT-2)

OpenAI developed a large-scale unsupervised language model called GPT-2 (Generative Pretrained Transformer 2) [60–62] to generate several sound sentences of realistic text by extending any given seed. GPT-2 is a large transformer-based language model with 1.5 billion parameters, trained on a dataset of 8 million web pages. GPT-2 is trained with a simple objective: predict the next word, given all of the previous words within some text. It is a direct scale-up of GPT, with more than 10X the parameters and trained on more than 10X the amount of data. This model has been trained on a large corpora of web pages and social media. We focus on fine-tuning a GPT-2 transformer [60–62] pre-trained model for generating code clones, even though it has been trained on English language. But, we apply fine-tuning of a pre-trained model on IJaDataset (Java language dataset), as it exists a large amount of overlapping vocabulary with English language. Secondly, GPT-2 is claimed to be so powerful that the threat of its harmful use is high. Moreover, GPT-2 transformer has demonstrated impressive effectiveness of pre-trained language models on various tasks, particularly sound text generation. This architecture was first developed to solve problems in natural language processing. GPT-2 has in built Byte Pair Encoding tokenizer (BPE).

During software development, the number of unique identifiers increases with the size of the codebase [6]. This problem makes it infeasible to train LMs on large corpora. BPE is an algorithm originally designed for data compression, in which bytes that are not used in the data replace the most frequently occurring byte pairs or sequences [26]. BPE provides several benefits [41]. First, no token is considered out-of-vocabulary. Unknown tokens at test time are represented by subsequences. Second, it dynamically adapts the frequency of the sequences by merging common subsequences and keeping less frequent tokens as is. Common tokens will be represented by a single token, while infrequent ones will be split in prefixes, suffixes and roots. This confirms that each sequence is common enough to have valuable embeddings. Finally, it allows for a very precise control of the vocabulary size, by tweaking the number of merges performed. A larger vocabulary will contain more complete tokens and less sequences, whereas smaller ones will contain longer sequences. It has been reported in the literature that neural language modeling (NLM) along-with BPE outperforms several traditional approaches, e.g. using n-grams [30].

GPT-2 model further simultaneously performs well on a variety of language tasks including question answering, reading comprehension, summarization, and translation [62]. We further notice that in general, better pre-trained models lead to better performance on fine-tuned or transfer tasks [58]. Fine-tuning is one approach to transfer learning, which is to adjust feature weights according to the new dataset on some already trained model. Previously, GPT-2 Transformer has been successfully fine-tuned on different types of datasets. Kim et al. [43] have used GPT-2 transformer for code prediction by revealing the syntactic structure of code to the network. Ziegler et al. [95] have applied a reinforcement learning method on the 774M GPT-2 model to support human-preferred text more often. Lee et. al [46] fine tune 345M, a GPT-2 based pre-trained model of medium version, to patent claim generation by providing various experiment results for qualitative analysis and future research. Deep TabNine [2], a software programming productivity tool to predict the next chunk of code, has been successfully fine-tuned by using GPT-2, on approximately two million GitHub files capturing numerous programming languages. DeepClone is initially inspired by Deep TabNine, and we have fine-tuned only those files of IJaDataset, which contains true positive clone methods from BigCloneBench dataset.

4.2 Model Configurations

We selected a small version (117) of GPT-2 based pre-trained model as our base model, as it can not take too much time and resources to fine-tune. Other versions are quite bigger in size. Similarly, a small version is enough to prove our approach. The 117 pre-trained model contains 50257 vocabulary size, 117M parameters, 12-layers, 768-hidden, and 12-heads. We have fine-tuned our DeepClone model on the partition of a GPU-1080Ti cluster (276 CPU cores, 329728 CUDA cores, 5.9 TB memory)\(^2\), for approximately 9 hours by using HuggingFace Transformer Library. In our experiment, we have performed training and evaluation with batch size per GPU of 1 for 5 epochs. We have used a learning rate of 5e-5 and the gradient accumulation steps (number of update steps to accumulate before performing a backward/update pass) as 5. Default values have been used for other hyper-parameters, as mentioned in the language modeling code\(^3\).

\(^1\)https://github.com/c2nes/javalang

\(^2\)https://userinfo.surfsara.nl/

\(^3\)https://github.com/huggingface/transformers/blob/master/examples/language-modeling
Table 1: An example of the preprocessing steps applied on a clone method body

| Original |
|----------|
| //Heuristics: //((c-b,a-z,A-1)\(\times\)s\(\times\)((c-b,a-z,A-1)\(\times\)s\(\times\)(c-b,a-z,A-1))
| // imid = inim + (imax - inim)/2;
| public static int binarySearch(int arr[], int key, int inim, int imax) {
| //Implementation: Recursive, primitive type
| if(imax < inim)
| return -1;
| int imid = (imid+imax)/2;
| if(arr[imid] > key)
| return binarySearch(arr,key,imid+1,imax);
| else
| return binarySearch(arr,key,imid+1,imax);
| }

| Marking |
|---------|
| //Heuristics: //((c-b,a-z,A-1)\(\times\)s\(\times\)((c-b,a-z,A-1)\(\times\)s\(\times\)(c-b,a-z,A-1))
| // imid = inim + (imax - imin)/2;
| <&gt; public static int binarySearch(int arr[], int key, int inim, int imax) {
| //Implementation: Recursive, primitive type
| if(imax < inim)
| return -1;
| int imid = (immin+imax)/2;
| if(arr[imid] > key)
| return binarySearch(arr,key,imid,imax-1);
| else if(arr[imid] &lt; key)
| return binarySearch(arr,key,imid+1,imax);
| else
| return imid;
| }

| Normalization and Tokenization |
|------------------------------|
| &lt;@&gt; public static int binarySearch(int arr [], int key , int inim , int imax )
| ( if ( imax &lt; inim ) return &lt; num_val &gt ;
| if ( arr [ imid ] &gt; key )
| return binarySearch ( arr , key , inim , imid - &lt; num_val &gt ;
| else if ( arr [ imid ] &lt; key )
| return binarySearch ( arr , key , imid + &lt; num_val &gt ; , imax )
| }

| Replacement |
|-------------|
| &lt;@&gt; public static int binarySearch(int arr [], int key , int inim , int imax )
| ( if ( imax &lt; inim ) return &lt; num_val &gt ;
| if ( arr [ imid ] &gt; key )
| return binarySearch ( arr , key , inim , imid - &lt; num_val &gt ;
| else if ( arr [ imid ] &lt; key )
| return binarySearch ( arr , key , imid + &lt; num_val &gt ; , imax )
| }

5 EMPIRICAL EVALUATION

In order to determine the performance of our approach, we have performed both intrinsic and extrinsic evaluations.

5.1 Intrinsic Evaluation

Intrinsic evaluation refers to the evaluation of a model by measuring its quality. For this purpose we have used perplexity (as done in [16, 22, 91, 94]), which is an inverse of cross-entropy (as used in [30, 41]). Perplexity is a measurement of how well a given language model predicts sample data. It estimates the average number of code tokens to select from at each point in a sequence [6, 52]. It is a natural evaluation metric for language models, which represent a probability distribution over a subsequence or an entire dataset.

\[
P(L) = \exp\left(-\frac{1}{M} \sum_{i} \log P(t_{i}|t_{0} : t_{i-1})\right)
\]

The formula for perplexity is presented in Equation 1. \(P(t_{i}|t_{0} : t_{i-1})\) is the conditional probability assigned by the model to the token \(t\) at index \(i\). By applying \(\log\) of conditional probability, cross-entropy loss is calculated. \(M\) refers to the length of tokens. Hence,
Table 2: Detailed statistics of the training, validation, and testing datasets along with experimental results

| Functionality Id | Name                                      | Files | Clone Methods | Syntactic Similarity |
|------------------|--------------------------------------------|-------|---------------|----------------------|
|                  |                                            | Training | Validation | Testing | Training | Validation | Testing | PPL | µ  | σ² |
| 2                | Download From Web                          | 655    | 82           | 82      | 715      | 97         | 94      | 2.209 | 0.466 | 0.024 |
| 3                | Secure Hash                                | 983    | 123          | 124     | 1072     | 132        | 132     | 2.176 | 0.444 | 0.031 |
| 4                | Copy File                                  | 2088   | 260          | 261     | 2454     | 306        | 295     | 2.267 | 0.372 | 0.031 |
| 5                | Decompress zip archive                      | 4      | 1            | 0       | 8        | 1          | 0       | -    | 0.392 | 0.043 |
| 6                | Connect to FTP Server                      | 137    | 18           | 18      | 173      | 24         | 25      | 2.652 | 0.383 | 0.029 |
| 7                | Bubble Sort Array                          | 106    | 13           | 14      | 133      | 19         | 15      | 2.096 | 0.498 | 0.046 |
| 8                | Setup SVN                                  | 19     | 2            | 3       | 19       | 2          | 3       | 4.562 | 0.458 | 0.045 |
| 9                | Setup SCV Event Handler                    | 6      | 1            | 2       | 7        | 2          | 2       | 3.085 | 0.310 | 0.040 |
| 10               | Execute update and rollback.               | 349    | 44           | 44      | 567      | 56         | 71      | 2.278 | 0.415 | 0.030 |
| 11               | Initialize Java Eclipse Project.           | 16     | 2            | 3       | 17       | 2          | 4       | 2.672 | 0.400 | 0.042 |
| 12               | Get Prime Factors                          | 16     | 2            | 2       | 17       | 2          | 2       | 3.923 | 0.586 | 0.044 |
| 13               | Shuffle Array in Place                     | 48     | 6            | 7       | 65       | 7          | 7       | 4.144 | 0.496 | 0.07  |
| 14               | Binary Search                              | 251    | 31           | 32      | 315      | 34         | 34      | 2.814 | 0.347 | 0.017 |
| 15               | Load Custom Font                           | 19     | 2            | 3       | 21       | 2          | 3       | 2.982 | 0.414 | 0.029 |
| 17               | Create Encryption Key Files               | 14     | 2            | 2       | 17       | 2          | 2       | 2.931 | 0.378 | 0.04  |
| 18               | Play Sound                                 | 25     | 3            | 4       | 31       | 5          | 5       | 3.746 | 0.485 | 0.024 |
| 19               | Take Screenshot to File                    | 69     | 9            | 8       | 82       | 12         | 9       | 3.049 | 0.421 | 0.030 |
| 20               | Fibonacci                                  | 168    | 21           | 22      | 169      | 21         | 22      | 2.168 | 0.372 | 0.022 |
| 21               | XMPP Send Message                          | 18     | 2            | 3       | 20       | 2          | 3       | 3.147 | 0.484 | 0.024 |
| 22               | Encrypt to File                            | 49     | 7            | 8       | 59       | 8          | 8       | 2.406 | 0.420 | 0.028 |
| 23               | Resize Array                               | 224    | 27           | 29      | 317      | 44         | 36      | 2.484 | 0.487 | 0.031 |
| 24               | Open URL in System Browser                | 219    | 28           | 29      | 295      | 37         | 36      | 2.516 | 0.400 | 0.039 |
| 25               | Open File in Desktop Application          | 54     | 9            | 7       | 82       | 12         | 8       | 2.517 | 0.376 | 0.037 |
| 26               | OCCL                                       | 16     | 2            | 3       | 18       | 2          | 3       | 6.686 | 0.597 | 0.030 |
| 27               | Call Method Using Reflection              | 294    | 37           | 37      | 329      | 39         | 41      | 2.183 | 0.402 | 0.041 |
| 28               | Parse XML to DOM                          | 122    | 15           | 16      | 157      | 21         | 19      | 2     | 0.435 | 0.031 |
| 29               | Convert Date String Format                | 35     | 4            | 5       | 43       | 10         | 6       | 3.28  | 0.295 | 0.052 |
| 30               | Zip Files                                  | 783    | 97           | 99      | 1119     | 136        | 135     | 2.272 | 0.411 | 0.027 |
| 31               | File Dialog                               | 194    | 26           | 24      | 364      | 30         | 43      | 2.361 | 0.376 | 0.043 |
| 32               | Send E-Mail                               | 178    | 23           | 23      | 190      | 25         | 25      | 1.781 | 0.430 | 0.036 |
| 33               | CRC32 File Checksum                       | 142    | 21           | 19      | 217      | 29         | 28      | 2.761 | 0.341 | 0.031 |
| 34               | Execute External Process                  | 306    | 38           | 39      | 375      | 40         | 47      | 2.086 | 0.373 | 0.037 |
| 35               | Instantiate Using Reflection              | 582    | 73           | 73      | 656      | 83         | 99      | 3.115 | 0.350 | 0.026 |
| 36               | Connect to Database                       | 126    | 16           | 17      | 167      | 20         | 19      | 2.137 | 0.368 | 0.036 |
| 37               | Load File into Byte Array                 | 104    | 13           | 14      | 124      | 16         | 16      | 2.274 | 0.421 | 0.035 |
| 38               | Get MAC Address String                    | 15     | 2            | 3       | 18       | 2          | 3       | 2.745 | 0.470 | 0.017 |
| 39               | Delete Folder and Contents                | 175    | 23           | 24      | 218      | 27         | 30      | 3.022 | 0.497 | 0.032 |
| 40               | Parse CSV File                            | 125    | 14           | 18      | 161      | 16         | 25      | 2.004 | 0.433 | 0.038 |
| 41               | Transpose a Matrix                        | 333    | 42           | 41      | 395      | 45         | 50      | 2.527 | 0.388 | 0.051 |
| 42               | Extract Matches Using Regex              | 337    | 43           | 44      | 405      | 47         | 48      | 2.921 | 0.420 | 0.028 |
| 43               | Copy Directory                            | 65     | 8            | 10      | 118      | 15         | 15      | 2.289 | 0.480 | 0.024 |
| 44               | Test Palindrome                           | 15     | 1            | 3       | 133      | 16         | 19      | 1.668 | 0.903 | 0.04  |
| 45               | Write PDF File                            | 122    | 15           | 15      | 129      | 15         | 15      | 2.304 | 0.431 | 0.034 |
perplexity is an exponentiation of the average cross entropy loss from each token [0, M].

**Training Evaluation.** At each checkpoint (500 logging step) of the training steps, we have evaluated the DeepClone model performance by calculating the perplexity on the validation set. Figure 1a describes the variations in perplexity on the validation set after each checkpoint, which takes place at each 500 log step. We observe that we achieve the lowest perplexity P1 (2.145) at step 24500. Figure 1c displays the convergence of the learning rate after each checkpoint. Learning rate helps in determining how quickly or slowly a neural network model learns a problem, by adjusting the weights of a network with respect to the value of loss function. Whereas, loss function is to calculate a model error, which identifies how well a model predicts the expected outcome for any data point in the training set. GPT-2 uses cross-entropy loss function, which is to measure the performance of a language model, whose output is a probability value between 0 and 1. Figure 1b displays a convergence of training losses after each checkpoint of 500 steps, which indicates how well a model behaves after each checkpoint of optimization. The loss value is finally minimized to 0.75 at step 24500, which is a sign of a well optimized deep learning model. Figure 2 describes the training process of DeepClone Model, which mentions the steps described in Section 3, used to perform the fine-tuning of our model. We have published our training results online⁴.

⁴https://tensorboard.dev/experiment/lk1XqD8RMgtMjmVvQ95g

### Table 3: Final Distribution of BigCloneBench Dataset

|            | Files | Clone Methods | Tokens     |
|------------|-------|---------------|------------|
| Training   | 9,606 | 11,991        | 16,933,894 |
| Validation | 1,208 | 1,499         | 2,130,360  |
| Testing    | 1,234 | 1,502         | 2,235,982  |
| Total      | 12,048| 14,992        | 21,300,236 |

**Model Evaluation.** We computed an overall perplexity of 2.146 on the testing dataset for our DeepClone model, as denoted by P2 in Table 4. We have achieved a much better perplexity compared to the previous source code LMs [16, 22, 91]. These models, though, use different corpora and deep learning architecture than ours and hence are not directly comparable. We believe our better performance can be attributed to the fact that we model a more repetitious body of code (i.e. clones) to begin with, as well as that we use a pre-trained model based on the powerful GPT-2 transformer.

Besides the overall perplexity on the testing dataset as previously elaborated in the paper, we again calculate the perplexity using the testing dataset, but without the clone method markers (i.e. (soc) and (eoc)). Our motivation for this additional measurement is as follows. Hindle et al. [31] observe that due to the repetitive nature of the code, there exist predictable statistical properties, which n-gram language models can capture and leverage for software engineering tasks. The sign of a good model is that it can capture the patterns in the dataset very well, which is particularly important for the task of clone method prediction. In Table 4, we can see an increase when comparing the original perplexity score of 2.146 (P2) and the perplexity on the testing dataset without clone markers of 2.182 (P3). This means that our DeepClone model performs better, when the code has clone methods marked with (soc) and (eoc) tokens.

The DeepClone model has been successfully fine-tuned on the BigCloneBench dataset by using a powerful GPT-2 based pre-trained model.

**Evaluation per Clone Method.** In order to determine which clone method snippets are more predictable compared to the others, we calculated an average perplexity score (PPL) for each type of clone method snippet (see Table 2). We first extracted the code snippet for each type of clone method for our testing dataset, and calculated the perplexity score. The scores, as depicted in Table 2, indicate how likely these can be predicted by our DeepClone model.

We also analyze several factors which can effect the perplexity of clone methods. BigCloneBench contains scores of syntactic similarity between each clone method pairs on the basis of tokens, which have been calculated by using a line-based metric after normalization such as removing comments etc. We have calculated mean (µ) and variance (σ²) to determine the overall syntactic similarity of all the clone methods per each type of functionality, as mentioned in Table 2.

We observe that the perplexity scores vary according to the syntactic similarity between clone methods, as well as the number of clone method snippets in the training set. From the results, we can see that the "Test palindrome" type of clone method (number 44), which is used to test if a string is a palindrome, has the lowest perplexity score. This represents that our DeepClone model can predict that clone method snippet very well. We can attribute this to the fact that those types of clone method snippets have quite high mean syntactic similarity (0.903), along with very low variance (0.040). Similarly, 133 total clone method snippets have been used in the training, which is not a reasonably high number.

Figure 2: DeepClone training process
Similarly, we have also observed quite high perplexity scores for some particular clone methods such as “GCD” (number 26), to find greatest common denominator, meaning that not all well predicted. This can be due to having less clone method snippets (total 18) trained in the DeepClone Model. We have noted that “Decompress zip archive” clone method (number 5) has not been evaluated, due to having too few code clone files used in the training and validation dataset.

We cannot claim that syntactical similarity and number of clone methods in the training set alone determine the perplexity performance. There are other many factors which need to observed. In BigCloneBench, there are many false positive clone methods, which may be syntactically similar to true positive clone methods. True positive clone methods may also have syntactically similarity with other parts of the code. Similarly, clone type can be another factor as well. Those and other more well-known factors such as hyper-parameters are left to be explored in the future.

For the majority of the clone methods, DeepClone achieves a successful prediction.

Non-Clone Method vs Clone Method. Allamanis [5] notices that a language model achieves low perplexity scores for code duplication, and high perplexity score for less duplicated code. In order to observe that difference, we calculated the perplexity scores for all the clone method snippets and non-clone method snippets in the testing dataset. We extracted clone method snippets by tracing the tokens, which come inclusively between ⟨soc⟩ and ⟨eoc⟩ token. All other snippets were considered to be a part of non-clone method snippets. We then calculated the perplexity for each snippet. Finally, we took an average of the perplexities for both type of code snippets. P4 represents the average perplexity score for the clone method snippets, and P5 represents the average perplexity of the non-clone method snippets. The result (Table 4) depicts that DeepClone successfully predicts clone method snippets much better than non-clone method snippets in general.

DeepClone predicts clone code method snippets more accurately than non-clone ones.

### 5.2 Extrinsic Evaluation

Extrinsic evaluation refers to the evaluation of a model’s performance on specific tasks. We evaluated DeepClone on the tasks of token prediction, and clone method prediction.

**Token Prediction.** We collect the top 10 predictions from our DeepClone model, and compute the top-k accuracy (the fraction of times the correct prediction appears in the top k predictions) for k ∈ [1, 10].

| Perplexity | Accuracy | Top 1 | Top 3 | Top 5 | Top 10 |
|------------|----------|-------|-------|-------|--------|
| P1 2.145   | P2 2.146 | P3 2.182 | P4 2.410 | P5 2.767 | MRR 84.329% |
|            |          |       |       |       | 77.808% |
|            |          |       |       |       | 90.040% |
|            |          |       |       |       | 92.766% |
|            |          |       |       |       | 94.999% |

Table 4: DeepClone evaluation results on the testing dataset

Clearly, the results suggest that the proposed DeepClone model is able to more accurately model pre-processed Java source code containing clone methods. The table also indicates that there is almost 77.808% chance to get a correct token in the first option, and 94.999% chance to have a correct output in the top-10 predicted outcomes. To further quantify the accuracy of DeepClone Model for token prediction task, we report an MRR score of 83%, which indicates an excellent performance in evaluating a ranked list of predictions.

Clone Method Prediction. We further measure the effectiveness of our DeepClone model in predicting code tokens for clone method task. This demonstrates our model’s effectiveness in providing ease to the developer’s work by generating the clone method snippet. In order to predict a chunk of subsequence from a clone method based on the user input, there exist several text generation methods such as beam search [86], sampling with temperature [4, 24], top-k sampling [23] and nucleus sampling [33]. All these methods have a specific decoding strategy to shape the probability distribution of language model such as assign higher probability to higher quality text. Among these text generation methodologies, we choose nucleus sampling as it outperforms other methodologies [33]. Nucleus sampling is claimed to be the best strategy for generating large form of high quality text, comparable to human written text. By having GPT-2 well fine-tuned, DeepClone model, along with nucleus sampling, we can expect informative set of code tokens for clone method predictions. For this purpose, we extracted subsequences of 20 tokens from the testing dataset, and moved the window one step ahead to obtain further subsequences. Among those, we randomly selected 1,144 subsequences containing 22,880 tokens, in which ⟨soc⟩ token is a part of each subsequence, which
indicates a start of clone method. We passed these subsequences one by one to our DeepClone model, and we kept on predicting new tokens with nucleus sampling (threshold value 0.9) until the meta-token (eoc) (i.e. end of clone) appears. With this experiment, we successfully generated 151,348 tokens associated with clone method snippets. In combination with some additional effort to generate meaningful clone method snippets in a single pass. We conclude that our DeepClone model not only helps developers to code rapidly, but also provides a meaningful set of code tokens for a clone method.

6 DISCUSSION

The approach we have proposed leads to promising results. The metrics in the training phase (learning rate approaching 0, minimized loss) and in the validation phase (perplexity of 2.145) all indicate a fine-tuned model. The series of perplexity scores, we calculated allows us to conclude that our DeepClone model can predict regularities successfully in terms of clone markers, including the code in general and the individual clone snippets in particular. The extrinsic evaluation reveals that we achieve a quite high accuracy, notably 95% in the top 10 suggestions, as well as larger number of tokens than a threshold-based strategy even with an extremely generous configurations of t = 50 or even 100. Furthermore, threshold-based strategies cannot give a user an informative set of code tokens in a single pass. These informative code tokens can be of variable length, as the length of clone method tokens varies. By marking the clone method regions in the code dataset, it helps DeepClone to generate meaningful clone method snippets in a single pass. We conclude that our DeepClone model not only helps developers to code rapidly, but also provides a meaningful set of code tokens for a clone method.

DeepClone provides ease to the developer by generating not only a larger set of tokens, but also informative ones.

6.1 Potential Use Cases for DeepClone

The DeepClone model can be utilized to assist developers in various use cases. Some of these have already been mentioned above: predicting the next token (as typically done by many LMs), and whole clone method body. The latter, while seemingly straightforward, can be enhanced with a more elaborate ranking and retrieval mechanism rather than simply generating the most likely sequence of tokens one after another. For that purpose, the additional information in the BigCloneBench dataset, including the exact clone method clusters (hence various methods representing the same functionality), clone types and so on can be exploited. Another use case might involve clone refactoring (and avoidance), by recommending clone method call instead of predicting a complete clone method snippet. In combination with some additional effort of transforming the clone methods into reusable assets (e.g. in the form of libraries), the prediction could be tweaked to avoid cloning in the first place and generate method calls instead. Finally, the model can be used to perform code search for the common functionality.

6.2 Limitations and Threats to Validity

Our work has certain limitations. The proposed approach is the first step, which raises the granularity level to method for code prediction. However, we cannot expect exactly the same clone method predicted or completed, as trained by our DeepClone model. In prediction tasks, generating well-formed outputs is challenging, which is well known in natural language generation [47, 74]. However, the desired output might be a variation of another, previously observed sample [27, 29, 45, 49, 76]. This is because of the nature of language modeling. Language model is a probabilistic model, which can generate multiple possibilities of code snippet, based on the user input. The space of possible clone methods that could be generated grows exponentially with the length of the clone methods. By having V tokens in the vocabulary, there can be $V^N$ possible clone methods of length N that could be sampled. An extension would involve displaying the most similar cloned methods (as is) from the dataset to the user. BigCloneBench contains clone method references of only those snippets, which belong to the selected list of 43 common functionalities. It does not contain references of all the clones in the dataset. Although the dataset is enough to prove our methodology, there is a possibility to model all the clones in the dataset, which may result in interesting findings. Similarly, we observe that syntactic similarity on the overall clone methods and the number of clone methods used in training can effect perplexity. However, there can be several other factors such as clone type, syntactic similarity over false positive clones, and GPT-2 hyper-parameters. In our study, we relied on the HuggingFace transformer implementation of GPT-2 to train and evaluate DeepClone model. While GPT-2 is a reliable implementation that has been utilized in a number of NLP experiments [9, 67, 71], it is still an emerging project. However, our results and trends are aligned with those that have been obtained in the field of NLP. Hence, we are positive that the results are reliable.

Allamanis [5] discusses the negative effects of code duplication in the evaluation of language models and proposes two strategies in order to avoid biased evaluation results. The first one is to remove the duplicated code before actually developing a model, and the second one is to down-weight duplicated samples in the loss function and performance metrics. This might have implications for our study, although our motivation for this work is modeling cloned code in the first place. Therefore we claim our true data distribution by definition includes duplication. Furthermore, in his study he only considers exact and near-miss file duplicates. Clones can be of several types and granularity levels such as simple, structural and method [12], which might need to be considered as well. On the other side, he remarks on the common cloning practice and potentially positive use of clones, which we agree with and have tried to exploit in this paper.

As can be expected from a DNN-based study, we could not evaluate all the possible combinations (hundreds) of hyper-parameter
due to the resources needed. There is a risk in the choice of hyper-
parameters for deep learning methods. The change in training,
validation or testing set or the variation in hyper-parameters may
impact the performance of the anticipated method. For this reason,
we also did not evaluate other NLM architectures such as GRU [19],
LSTMs [32], additional neural cache variants [51, 87] or QRNns [17].
The dataset used in this study is collected from BigCloneBench,
a well-known cloned code dataset. It does not necessarily mean that
the codebase used in this study represents Java language source
code entirely (threat to external validity). As for the clone method
prediction, we only use nucleus sampling [33]. There are various
other text generation methods such as beam search [86], sampling
with temperature [4, 24], and top-k sampling [23], which can be
explored for predicting clone method snippet.

7 CONCLUSION AND FUTURE WORK
In this work, we proposed DeepClone, a deep learning-based cloned
code language model. We performed intrinsic and extrinsic evalua-
tions to determine the performance of DeepClone model in predict-
ning clone methods. The extensive evaluation of this work suggests
that the proposed approach significantly improves the model's
performance by exploiting the concept of deep learning and code
clones. Following from this work, we would like to exploit our model
in the potential use cases, which are discussed above (see Section 6.1). From a fundamental point of view, though, our ap-
proach can be improved in several different ways as future work.
Our model can be improved by hyper-parameter optimizations
[50], as well as better training (e.g. on a larger dataset or larger
pre-trained GPT-2 models). Furthermore, we plan to investigate
how we can tackle different types and granularity levels of code
clones such as simple clones, structural clones, and file clones [12].

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