CODE2SNAPSHOT: Using Code Snapshots for Learning Representations of Source Code

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Abstract—There are several approaches for encoding source code in the input vectors of neural models. These approaches attempt to include various syntactic and semantic features of input programs in their encoding. In this paper, we investigate CODE2SNAPSHOT, a novel representation of the source code that is based on the snapshots of input programs. We evaluate several variations of this representation and compare its performance with state-of-the-art representations that utilize the rich syntactic and semantic features of input programs.

Our preliminary study on the utility of CODE2SNAPSHOT in the code summarization and code classification tasks suggests that simple snapshots of input programs have comparable performance to state-of-the-art representations. Interestingly, obscuring input programs have insignificant impacts on the CODE2SNAPSHOT performance, suggesting that, for some tasks, neural models may provide high performance by relying merely on the structure of input programs.

Index Terms—models of source code, program representation, code as image

I. INTRODUCTION

Deep neural models are widely used to develop code intelligence systems [1, 2]. These models are powerful learning tools that provide a large hypothesis class and a large capacity for learning almost any arbitrary function. However, the representation of input programs as vectors can have a significant impact on the performance of the models.

Several representations for source code have been proposed in literature [3, 4]. These approaches try to encode the various syntactic and semantic features of input programs in the code embeddings. For example, CODE2VEC [5] or CODE2SEQ [6] encode paths in the abstract syntax trees of programs, GGNN [7] encodes the data and control dependencies of programs, FUNC2VEC [8] encodes paths in the extended call-graphs of programs, and so on.

The underpinning insight is that by encoding more information about the program in the feature vectors, the code intelligence model would be able to extract more patterns and insights, and are likely to perform better. Unfortunately, due to the opacity of the neural models, it is unclear what features these models capture from the input data. Recent studies suggest that models heavily rely on variable names [9, 10, 11] and a few tokens [12, 13, 14, 15, 16] for their prediction, and they can memorize data points for achieving high performance [17, 18].

In this paper, we explore a new source code representation, CODE2SNAPSHOT, in which, instead of using the traditional syntactic or semantic program features, we use program snapshots to represent any arbitrary code snippets. Additionally, we study the redacted snapshots of input programs that merely represent the structure of input programs. The main idea is that in real settings, seasoned programmers may get a hunch by merely looking at the structure of input programs.

We report the result of our preliminary study on the utility of CODE2SNAPSHOT for code summarization [19] and code classification [20] tasks. We compare its performance with the complex state-of-the-art representations, CODE2VEC and CODE2SEQ, that use richer syntactic and semantic features based on tokens and paths. Experiments on the most frequent method names and algorithm classes suggest that the simple snapshots of input programs can provide performance comparable to the complex neural code embeddings. However, the gap between the performance of CODE2SNAPSHOT and CODE2SEQ grows as we increase the size of dataset.

Contributions. We make the following contributions.

• We propose several source code embeddings based on the snapshots and structure of the input programs.

• We provide a preliminary result on the evaluation of our proposed embeddings for code summarization and code classification tasks.

Artifacts. The code and data of this study are publicly available at https://github.com/mdrafiqlurabin/Code2Snapshot.

II. RELATED WORK

Several source code embeddings have been proposed to encode source code as input vectors to neural networks [3]. For brevity and page limitation, here, we only mention the most relevant to our work.

Allamanis et al. [21] introduce a framework that uses sequences of tokens to represent the source code. Alon et al. [5] propose CODE2VEC which is a fixed-length representation of source code based on the bags of paths in the abstract syntax tree. Allamanis et al. [7] propose GGNN that includes a richer feature space including control and data dependencies from the source code. Hellendoorn et al. [22] proposed an RNN-based model using sequence-to-sequence type annotations for type inference.
Some works have been done in the area of using images of input programs for overcoming feature extraction challenges. Dey et al. [23] propose an approach for converting programs to images, where they use the intermediate representation of programs to generate a visual representation of input programs. Keller et al. [24] apply different visual representations of code and transfer learning for code semantics learning. Bilgin [25] also uses a colored image of syntax trees for representing input programs.

Unlike previous works, this work mainly focuses on the model’s reliance on the structure of input programs for intelligent code analysis.

III. METHODOLOGY

Figure 1 depicts a high-level view of our proposed approach. Given the dataset of input programs, we reformat the original program and take snapshots from the reformatted program, and then train with Convolutional Neural Networks (CNNs) for predicting target labels. Our approach contains the following key steps.

A. Reformattting Code

The original input program is often poorly aligned and has severe indentation problems such as extra spacing and newlines. It also includes random user comments and documentations. As a result, the original input program is not suitable for generating images, as we cannot get actual structural information from randomly aligned and commented code. To address these problems, we reformat the original program using JavaParser tool [26] that provides functions to analyze Java code. We remove documentations and comments from input programs, and adjust indentation of code by removing extra white spaces and line breaks.

B. Taking Snapshots

The Python Imaging Library (PIL) [27] provides image processing capabilities to add text on image. After reformatting the original program, we use the PIL library to take snapshots from the reformatted program. However, many programs contain more than a hundred lines of code and very long statements. Thus, the generated image from a larger program becomes extremely blurry when resized. For that reason, we shorten the size of a program by limiting statements up to 30 lines and a maximum of 120 characters per line. We simply filter out additional lines and characters from programs. We follow the below steps to take snapshots.

- Given a sample program, we first reformat the code and shorten the size of a larger program by filtering out extra lines and characters.
- Next, we create an image object with grayscale mode and white background and set the size of the image as a fixed window of 30 lines and 120 characters.
- We then adjust the spacing and font settings until finding a reasonable fit for the rendered text. In this work, we use ‘Times New Roman’ as default font with 50 points as requested size and 50 pixels as line spacing.
- After that, we read the actual text from the reformatted program and write the text on the image in black color.
- Finally, we convert the image object to PNG format and save it to a directory.

Now, instead of any complex learning of source code embeddings, we can feed these images to CNN models and train for a downstream task.

C. Training Models

We train multiple CNN models on the snapshots of input programs for predicting target labels such as method name or algorithm class. Before training, we apply image transformation and resize each image into “512 x 512” dimension in order to ensure that each image has the same size. We also apply normalization on images to ensure that each pixel has a similar data distribution. We train CNN models with the images of training set and validation set, and compute the performance on the images of test set. During training CNN models, in the code summarization task, we use the image of a method body as input and the name of that method as output. Similarly, in the code classification task, we use the image of code snippets as input and the corresponding algorithm class as output.

IV. EXPERIMENTAL SETTINGS

A. Task

We use two popular tasks to evaluate the CODE2SNAPSHOT representation: (a) code summarization [19], such as method name prediction (METHODPREDICTION), and (b) code classification [20], such as algorithm classification (CODECLASSIFICATION). The METHODPREDICTION is a supervised learning task wherein the inputs are the body of methods and the outputs are the corresponding method names. For example, given the following code snippet: “void f(int a, int b) { int temp = a; a = b; b = temp; }”, a trained model aims to predict the method’s name as “swap”. Similarly, in the CODECLASSIFICATION task, a model learns to classify the code snippets into different algorithm classes, e.g., “bubble sort”.

B. Dataset

For METHODPREDICTION task, we use JAVA TOP10 and JAVA TOP50, subsets of popular JAVA-LARGE and JAVA-SMALL datasets [6], respectively. The JAVA TOP10 dataset contains the top 10 most frequent methods from the JAVA-LARGE dataset. The training, validation, and test set contains a total of 10000 (1000 instances per label), 4847, and 7100 examples, respectively. The JAVA TOP50 dataset contains the top 50 most frequent methods from the JAVA-SMALL dataset. The training, validation, and test set contains a total of 27119, 1803, and 4265 examples, respectively.

For CODECLASSIFICATION task, we use JAVA-SORT dataset [20] that contains 1000 sorting algorithms crafted from GitHub and labeled into 10 algorithm classes. These are: bubble, bucket, heap, insertion, merge, quick, radix, selection, shell, and topological. The training, validation, and test set split is kept stratified at 70:10:20.
C. Input Types

Image. Using PIL [27], we generate three variations of the CODE2SNAPSHOT representation: a) ORIGINAL, b) REFORMATTED, and c) REDACTED. Figure 2 depicts examples of these representations.

- ORIGINAL: We use the original input programs as is to construct the visual representation of input programs. Figure 2a shows an example of this representation where comments, extra lines and spaces remain unchanged.
- REFORMATTED: We reformat the input programs to adjust indentation, remove comments. Moreover, for long programs, we include the first 30 lines of code. Figure 2b shows an example of the reformatted input program derived from the original input program of Figure 2a.
- REDACTED: We replace any alphanumeric characters in the reformatted input programs with “x”. Punctuations and mathematical operators remain intact. For example, “int i = 2;” becomes “xxx x = x;”. Figure 2c is the example of REDACTED on the reformatted program of Figure 2b.

Token. Using JavaParser [26], we traverse the abstract syntax tree of program and collect all tokens from the method body. We then represent a program as a sequence of tokens. For example, [int, i, =, 2, ;] is the list of tokens for an expression “int i = 2;”.

Path. Using JavaExtractor [5, 6], we extract and preprocess a bag of path contexts from Java files.

For example, a path context for the expression “int i = 2;” is “i, <NameExpr ↑ AssignExpr ↓ IntegerLiteralExpr>, 2”.

D. Models

Image-based Models. We use two classic convolutional networks: ALEXNET (an 8-layers deep convolutional neural networks [28] that consists of five convolutional layers, then two fully-connected hidden layers, and one fully-connected output layer) and RESNET (an 18-layer residual networks [29] that consists of one convolutional input layer, then four modules made up of two residual blocks with two convolution layers in each block, and a final fully connected layer).

Token-based Models. We create a simple recurrent neural network as baseline for learning method names from the sequence of tokens [21, 22] in method body. The network includes an embedding layer followed by a 2-layers bidirectional LSTMs and a final fully connected linear layer with softmax activation function. In the embedding layer, we use EmbeddingBag which computes the embedding of a method by taking the average of all token embeddings.

Path-based Models. We use two popular path-based models in this study: CODE2VEC [5] and CODE2SEQ [6]. The models use a bag of paths between two terminal nodes in the abstract syntax tree (AST) for representing an arbitrary source code as an embedding vectors. While CODE2VEC considered an entire path as single entry and learns monolithic path embeddings,
TABLE I: Results for different models and code embeddings.

(a) Task: METHOD NAME PREDICTION

| Dataset   | Model  | Input Types | Precision | Recall | F1-Score | Accuracy |
|-----------|--------|-------------|-----------|--------|----------|----------|
| JAVATop10 | ALEXNET| ORIGINAL    | 55.25     | 52.49  | 53.43    | 52.49    |
|           |        | REFORMATTED | 82.84     | 81.18  | 81.26    | 81.18    |
|           |        | REDACTED   | 80.26     | 78.58  | 78.68    | 78.58    |
|           | RESNET | ORIGINAL    | 65.03     | 61.76  | 61.83    | 61.76    |
|           |        | REFORMATTED | 84.40     | 83.82  | 83.78    | 83.82    |
|           |        | REDACTED   | 83.75     | 83.60  | 83.60    | 83.60    |
| BiLSTM    | TOKEN  | 69.72      | 67.87     | 67.52  | 67.87    | 67.87    |
| Code2Vec  | PATH   | 85.80      | 84.96     | 84.85  | 84.96    | 84.96    |
| Code2Seq  |        | 86.88      | 86.65     | 86.50  | 86.65    | 86.65    |

(b) Task: CODE CLASSIFICATION

| Dataset   | Model  | Input Types | Precision | Recall | F1-Score | Accuracy |
|-----------|--------|-------------|-----------|--------|----------|----------|
| JAVA-SORT | RESNET | ORIGINAL    | 40.96     | 33.33  | 29.00    | 33.33    |
|           |        | REFORMATTED | 44.87     | 46.30  | 44.84    | 46.30    |
|           |        | REDACTED   | 76.78     | 75.46  | 75.38    | 75.46    |
| Code2Vec  | PATH   | 87.84      | 87.85     | 87.81  | 87.85    | 87.85    |
| Code2Seq  |        | 77.91      | 77.10     | 76.59  | 77.10    | 77.10    |

CODE2Seq sub-tokenized each path and uses LSTMs to encode paths node-by-node.

Training Models. For each combination of dataset, model, and representation, we train a model up to 100 epochs. For training image-based models and token-based models, we use stochastic gradient descent optimizer and cross-entropy loss function. We train both ALEXNET and RESNET with the original configurations but modified the input and output layers for adjusting the size of input images and the number of target classes, respectively. For path-based models, we train both CODE2VEC and CODE2SEQ with the configurations used in the original work with the batch size of 128. Following the evaluation metrics commonly used in the literature [5, 6], we use the accuracy, precision, recall, and F1-score as metrics.

V. RESULTS

Table I shows the performance of different models and embeddings across various tasks and datasets of source code. The underlined values denote the best result in CODE2SNAPSHOT variations and the values in **bold** denote the best code embeddings overall.

A. Performance of the CODE2SNAPSHOT Variations

In this section, we compare the effectiveness of different variations of CODE2SNAPSHOT representation on the METHODPREDICTION and CODECLASSIFICATION tasks.

According to the results in Table I, REFORMATTED has consistently performed much better than ORIGINAL, more than 20 percentage points. Training CNN models with the images of original program perform poorly, perhaps because the original input programs often suffer from inconsistent indentation, random comments, large program body, etc. After reformatting the input programs and training with the images of reformatted programs, each CNN model significantly increases its performance in predicting method names or classifying code snippets into algorithms.

On average, in METHODPREDICTION task, the performance of the RESNET and ALEXNET models is between 20 and 30 percentage points higher on REFORMATTED images compared to ORIGINAL images. Comparing among CNN models, we can see that RESNET model achieves higher accuracy than ALEXNET models in both JAVATop10 and JAVATop50 datasets. The RESNET model on REFORMATTED images achieve more than 80% accuracy in JAVA10 dataset, and more than 60% accuracy in JAVA50 dataset.

Next, in CODECLASSIFICATION task, we train the best RESNET model with JAVA-SORT dataset and observe that the RESNET model achieves more than 45% accuracy on REFORMATTED images which is around 13% higher than ORIGINAL images.

The overall result seems consistent across the tasks and datasets used in this experiment. It may suggest that the visual code embeddings have the potential to be used for the tasks like METHODPREDICTION and CODECLASSIFICATION.

Observation 1: We get significant performance improvements with the image of refactored programs over original programs across all datasets and CNN models.

B. Comparison with State-of-the-art Code Embeddings

Here, we compare CODE2SNAPSHOT with the baseline token-based embeddings and the state-of-the-art path-based embeddings.

For METHODPREDICTION task, Table I shows that the ALEXNET model of REFORMATTED or REDACTED images consistently outperforms the BiLSTM model of tokens by more than 10 and 5 percentage points in JAVA10 and JAVA50 datasets, respectively. On the same setting, the RESNET model outperforms the BiLSTM model by around 15 percentage points in both datasets.

Comparing CODE2SNAPSHOT with path-based embeddings, we can see that, in JAVA10 dataset, the RESNET model of REFORMATTED images performs very close to the CODE2VEC model, and the CODE2SEQ model’s accuracy is only 3 percentage points higher. In the JAVA50 dataset, the gap between CODE2SNAPSHOT models and path-based models grows, as the accuracy of CODE2VEC and CODE2SEQ models are 5-8 percentage points higher than the best accuracy of RESNET models. On the other hand, in JAVA-SORT dataset, the RESNET model of REDACTED images performs very close to the CODE2SEQ model but has more than 10% gap with the CODE2VEC model.
C. Impact of Obscuring Images

To get an intuition of what actually the CODE2SNAPSHOT models learn, we use REDACTED representation where we replace any alphanumeric character with “x” (Figure 2c). In our experiments, REDACTED performs almost the same as REFORMATTED in METHOD PREDICTION task and around 30 percentage points higher in CODE CLASSIFICATION task. The results of REDACTED may suggest that models highly learn from the structure of programs. For example, for METHOD PREDICTION and CODE CLASSIFICATION tasks, models can predict the method names or classify the code snippets merely by identifying the structure of input programs, respectively.

Observation 2: REFORMATTED significantly outperforms token-based embeddings in both JAVATOP10 and JAVATOP50 datasets. Path-based embeddings perform slightly better than REFORMATTED and REDACTED.

Observation 3: REDACTED performed very close to (or even better than) REFORMATTED, suggesting that perhaps neural models merely capture the structure of input programs for some tasks.

VI. DISCUSSION AND FUTURE WORK

Neural models are opaque. It is hard to pinpoint what patterns do they learn from the input data and what is the best representation of the inputs to optimize their performance. We believe that our results show promising directions to better understanding the neural code intelligence models in general, and the representation of the source code in particular. The results of REDACTED may suggest that the neural models merely rely on the structure of the code. The encoding uses only black and white images for representing the source code. In the future, we plan to investigate if we enrich the feature vectors by colors, i.e., choosing different colors for different program constructs, or choosing the same colors for the same variable names, we can gain meaningful improvements. The main insight is that it might help the neural models to extract more complex patterns, in addition to the structure of the code.

Moreover, a potential explanation for the comparable performance of CODE2SNAPSHOT in METHOD PREDICTION and CODE CLASSIFICATION tasks might be that, in the real setting, the visual structure of code can guide developers to guess the labels. For example, a one line method is probably a getter-method. Therefore, it is unclear if CODE2SNAPSHOT can provide similarly promising results for tasks that require reasoning about the input programs, e.g., variable misuse or defect detection. We plan to explore the effectiveness of CODE2SNAPSHOT in such tasks. Despite our best effort, it is possible that experiments with different models, sizes of images, and font settings may produce different results. Our further plan also includes a detailed study with a variety of code intelligence tasks, embeddings, and datasets.

Lastly, the computer vision research community has made great advances in the interpretability of neural models [30, 31]. Representing source code as an image and using convolutional neural architectures would enable using the most recent techniques devised by that community and translating the results to the field of code intelligence.

VII. CONCLUSION

In this paper, we investigated CODE2SNAPSHOT that encoded the source code as a simple black and white image and provided a preliminary evaluation of its effectiveness in METHOD PREDICTION and CODE CLASSIFICATION tasks. We observed that this simple visual encoding is surprisingly effective in our study, even when replacing all alphanumeric characters of programs with a random letter ‘x’. The results warrant further investigation on the applicability of CODE2SNAPSHOT for other tasks and datasets. These initial results can enable further research to answer fundamental questions about the neural code intelligence models, i.e., what do they actually learn? and how they can be improved? We also plan to explore in such directions.

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