Assessing the Effectiveness of Syntactic Structure to Learn Code Edit Representations

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Abstract—In recent times, it has been shown that one can use code as data to aid various applications such as automatic commit message generation, automatic generation of pull request descriptions and automatic program repair. Take for instance the problem of commit message generation. Treating source code as a sequence of tokens, state of the art techniques generate commit messages using neural machine translation models. However, they tend to ignore the syntactic structure of programming languages.

Previous work, i.e., code2seq [5] has used structural information from Abstract Syntax Tree (AST) to represent source code and they use it to automatically generate method names. In this paper, we elaborate upon this state of the art approach and modify it to represent source code edits. We determine the effect of using such syntactic structure for the problem of classifying code edits. Inspired by the code2seq approach, we evaluate how using structural information from AST, i.e., paths between AST leaf nodes can help with the task of code edit classification on two datasets of fine-grained syntactic edits.

Index Terms—Neural network, Classification, Abstract Syntax Tree

I. INTRODUCTION

The recent explosion of open-source and the ready availability of online version-control systems such as GitHub [13] have led to an enormous amount of code in the public domain. This in turn has given rise to the phrase, code as data, which alludes to using code as input to machine learning models and creating tools that extract useful information from code. Deep learning methods, which have been very successful in solving problems related to natural language processing, translation, image classification and speech recognition, have recently been applied to code as well.

Take for instance the problem of creating code embeddings. Recent work has explored how code embeddings, akin to word embeddings in the field of natural language processing (NLP) [7], [29], [33], can be used to summarize code [4], [16], generate documentation [23], [30] and detect code clones [35], [36]. Even though in theory, software can be very complex, it appears that even a small statistical model can capture regularity in natural software to a great extent (naturalness hypothesis) [1]. These findings have encouraged the use of embedding-based techniques on code.

However, while the results of these recent efforts have been encouraging, we recognize that there are significant differences between natural language and code. Along with syntactic structure, code statements have long range correlations, much larger vocabulary than natural language and reduced robustness to minor changes [1]. Previous work attempts to capture such long range correlations by using syntactic structure: data and control-flow graphs of code [2], [31], [32], abstract syntax trees [3], [38] etc. It has largely focused on applying such techniques on whole code snippets (code snapshots) like individual methods or classes [5], [6].

In this paper, we ask the question, “Are techniques that capture syntactic structure useful in understanding code edits, rather than code snippets?” Some fundamental differences between code edits and code snippets should be brought to light. Code edits do not have a fixed context; they can span multiple files and different methods. On the other hand code snippets have a well-defined context, especially as explored in previous work, where they span only a single method of class [5], [6].

Our work is inspired by code2seq, which leverages the syntactic structure of programming languages to summarize a given code snippet. It is language agnostic. It represents a given code snippet as a set of path-contexts over its abstract syntax tree (AST), where each path is compressed to a fixed length vector using bi-directional LSTMs. It then uses the attention mechanism to get a weighted average of the path vectors to represent the code snippet in a vector space, and uses it to produce the code summary or caption.

In this paper, we use an approach similar to code2seq to learn distributed representations of code edits and use it for fine-grained code edit classification. We concentrate on two specific tasks: bug-fix classification (Section IV-A1) and code transformation classification (Section IV-A2). code2seq is reported to be the state of the art on the task of method
name generation [5], and the authors of code2seq claim that it is generalizable. This motivates us to test code2seq on code edit classification. We compare our approach to represent code edits with two other models: a) considering code as a collection of tokens in a Bag-of-words model and b) considering code as a sequence of tokens using an LSTM model.

Our results suggest that using syntactic structure such as path contexts does not help improve the efficacy of code edit classification. Based on our experience, we observe that:

- a) Previous work using syntactic structure [5], [6] concentrated on method name prediction, and therefore benefited heavily from the identifier names which are captured as part of the terminal nodes in AST. Code edit classification, on the other hand, does not benefit from specific identifier names.

- b) Training models for classifying code edits with syntactic constructs may require significantly more data than is currently available: code2seq used more than 15 million data-points for training while we have access to edit datasets of size in the order of tens of thousands. We believe that it is fundamentally difficult to collect millions of labelled code edits for reasons we describe in section VI.

We therefore conclude that using syntactic structure, while effective on code snippets, has a long way to go before it can be applied to learning code edit representations.

The main contributions of this paper can be summarized as follows:

- We propose a new code edit classification approach that uses syntactic structure of code along with the attention mechanism to learn distributed representation of code edits. We use this to classify bug-fixes and code transformations.

- We create a new code edit dataset generated by a set of C# code transformers named Roslynator analyzers [19] from the top 250 C# GitHub repositories based on their popularity and release the data at https://figshare.com/s/e2e4c6762c696825c6d1.

- We conduct experimental evaluations using two tasks: bug-fix classification on a data-set of Java bug-fixes (ManySStuBs4J dataset [21]), and code transformation classification using data obtained from the top 250 C# GitHub repositories based on their popularity. Our results provide promising empirical evidence that the baseline approach using LSTMs outperforms the approach that uses syntactic structure of code.

II. Motivation

Code edits fall into various categories such as bug-fixes, feature additions, and code refactorings. With bug-fixes, there is fine-grained classification such as those based on the bug-template, as defined in Section IV-A1. Learning representations of such code edits is useful for many tasks such as bug-fix classification (classifying which bug-fix template is applied on the code), commit message generation and recommendation systems for automatic program repair. However, class labelled data for code edits is relatively scarce, especially for big edits spanning over multiple lines. Recently, researchers have created datasets like ManySStuBs4J for bug-fixes in Java [21]. This has enabled us to concentrate on fine-grained bug-fix classification in this paper. Here is an example of one such fine-grained bug-fix. Consider a scenario, where we have two classes, class1 and class2, that inherit from the same parent class. Both these classes override a method from the parent class, and have their own implementation of this method. A developer has mistakenly called this method from class1 when it should be called from class2. The developer does not notice this error at compile time, but she later realizes her mistake and fixes this bug. Previous work has shown that such bug-fixes, which modify a small set of lines of code, are seen quite frequently during development phase [21].

Automatically classified bug-fixes can help the process of software development in many ways. For instance, we can use this information to decide the right set of reviewers to review a specific kind of bug-fix. It can be used for test selection; only tests relevant to the specific bug-fix need to be run. Also, it can be used for vulnerability management tasks, which is one of the most urgent security challenges faced by software community. As defined in [27], vulnerability management tasks ensure that the open-source components included in various products of a company are free from (known) vulnerabilities. Currently, the National Vulnerability Database is used to keep track of disclosed vulnerabilities, but
it has consistency and coverage issues. Moreover, this manual approach cannot scale with the increase in open-source code.

Automatic program repair [8], [10] is another use-case of learning code edit representations, where they are used to automatically generate code-patches or bug-fixes to solve issues similar to those which have occurred in the past [37].

We conduct experiments to evaluate our proposed model on simple classification tasks which have a deterministic solution. The aim of our work is not to solve the problem of bug-fix issues similar to those which have occurred in the past [37]. To evaluate if code embeddings learnt using syntactic structure of code help improve over baseline models that consider code as natural language, ignoring it’s syntactic structure.

III. MODEL ARCHITECTURE

We have built three models to evaluate whether syntactic structure captured using AST helps learn better representations of code edits. All of these models are classifiers, and they differ in the way we represent the input set of old and new code snippet. In this section, we describe the details of these three models and their construction.

1) edit2vec: This model uses the syntactic structure of code by representing it as a set of paths between different terminal nodes of AST, similar to the way syntax is captured in code2seq model. The code2seq model [3] was designed to generate method names from the method body. It followed the encoder-decoder architecture for Neural Machine Translation (NMT). While we draw inspiration from this work, our model differs significantly from code2seq in two ways:

• *Characterizing the code edit.* The input to the model has to capture the difference between the code before the edit and after the edit. The code2seq model did not need to do this since the input was just a code snippet containing the method body.

• *Classification, not generation.* Our task is one of classification, not generation. Hence we replace the decoder layer of code2seq with a classifier. In our implementation, we have used a softmax layer for multi-class classification.

Figure 1 shows the overall design of the edit2vec model. It should be noted that this model is language agnostic, and can be used with code changes of any length in a single file. We first explain how we represent a code edit as an input to our model.

a) *Path-Context Extractor:* We characterize a code edit as the pair \( \{c_{\text{old}}, c_{\text{new}}\} \) where \( c_{\text{old}} \) is the source code before the edit and \( c_{\text{new}} \) is the source code after the edit. Corresponding to \( \{c_{\text{old}}, c_{\text{new}}\} \), we build the Abstract Syntax Tree (AST) denoted by \( \{t_{\text{old}} \text{ and } t_{\text{new}}\} \) respectively. Similar to code2seq, we use the *path-context* as a means to capture the syntactic structure of code. For a given AST, the path-context is the shortest path from one terminal node (leaf) to another. We represent a path-context as sequences of terminal and non-terminal nodes; it starts with one terminal node, which is also called the *left-context*, then a set of non-terminal nodes, which we call as the *path*, follow. The last node, or the *right-context*, is the other terminal node of the path.

The source code can represent the method, the class or the file which was edited. An AST for such a source code can be large and hence it may contain a large number of path-contexts. Randomly selecting a certain number of path-contexts (as done in code2seq) might not capture the edit completely. Since we are dealing with smaller code edits, typically 1-2 lines of code, we restrict our source code to the lines of code that are changed. In addition to that, we filter out data-points which have more than 40 path-contexts in \( t_{\text{old}} \) or \( t_{\text{new}} \). We have decided to select 40 path-contexts as majority of the examples in our dataset have less than 40 path-contexts. In case the AST is very small and has fewer than 40 path-contexts, we pad the path-contexts with dummy values, to make the input size uniform.\(^1\) Note that, this model can be used with code changes of any length in a single file. However, we cannot use this model for changes spanning over multiple files.

In this way, for each pair of ASTs \( t_{\text{old}}, t_{\text{new}} \), we get \( P_{\text{old}}, P_{\text{new}} \), where \( P_{\text{old}} = \{p_{1}^{\text{old}}, \ldots, p_{40}^{\text{old}}\} \) is the set of 40 path-contexts from the AST \( t_{\text{old}} \) and \( P_{\text{new}} = \{p_{1}^{\text{new}}, \ldots, p_{40}^{\text{new}}\} \) is the set of 40 path-contexts from the AST \( t_{\text{new}} \). For example, there is a code edit where the arguments of a method are swapped. Table I shows how to get \( \{P_{\text{old}}, P_{\text{new}}\} \) from \( \{c_{\text{old}}, c_{\text{new}}\} \) for this example.

b) *Path-Context Encoder (PCE):* These path-contexts are input to the *Path-Context Encoder (PCE).* This uses a similar technique as code2seq to encode a path-context into a 128-dimensional vector called CPCV (Compact Path-Context Vector). Figure 2 shows the model architecture of the Path-Context Encoder. Consider a path-context \( p \) of Table I, \( \text{processURL}, \text{NE0}, \text{MCE}, \text{NE3}, \text{baseURL} \). The PCE encodes the path-context in the following way:

For terminal nodes (\( \text{processURL} \) and \( \text{baseURL} \)) in the path-context, i.e., the left and right contexts, the encoder first divides them into *sub-tokens;* the token ‘\( \text{processURL} \)’ splits into ‘\( \text{process} \)’ and ‘\( \text{url} \).’ The PCE uses a 32-dimensional embedding vector to represent each sub-token, and then averages the embedding vectors of the sub-tokens to obtain the final vector for this terminal node. This generates two vectors \( \text{v}_{\text{processURL}} \) and \( \text{v}_{\text{baseURL}} \).

For non-terminal nodes (NE0, MCE, NE3), the PCE first embeds them to three 128-dimensional embedding vectors, and feeds them to a bi-directional LSTM layer [15] of 160 hidden units. The output of this LSTM layer, which we call \( \text{v}_{\text{path}} \), thus encodes the path into a 160-dimensional vector.

The *PCE* concatenates the three vectors \( \text{v}_{\text{processURL}}, \text{v}_{\text{path}} \) and \( \text{v}_{\text{baseURL}} \) and feeds this to a fully-connected \( \text{tanh} \) layer, which consists 128 hidden units. We refer to the output of this layer as the *Compact Path-Context Vector (CPCV).* The CPCV is a vector representation of the input path-context \( p \).

c) *Code Encoder (CE):* Since there are not more than 40 path-contexts each for the old and new code \( \{c_{\text{old}}, c_{\text{new}}\} \).

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\(^1\)https://www.tensorflow.org/guide/keras/masking_and_padding
the PCE outputs 40 CPCVs each for $c_{old}$ and $c_{new}$. Each set of 40 CPCVs is input to Code Encoder (CE), which uses the attention mechanism described in the code2seq model to encode each set of CPCVs into 160-dimensional vector. We represent these vectors as $\{r_{old}, r_{new}\}$ corresponding to $\{c_{old}, c_{new}\}$ . Figure 3 shows the detailed model architecture for Code Encoder. The input is passed to ReLu layer followed by softmax layer which outputs the attention weights ($a_1, a_2, ... a_{40}$) for each CPCV. A weighted summation of CPCVs ($CPCV_1 \times a_1 + CPCV_2 \times a_2 + ... + CPCV_{40} \times a_{40}$) is passed through a fully connected $\tanh$ layer to output 160-D vector. Code Encoder is similar to what is used in code2seq model. Hence, in the interest of space, we do not describe it in detail.

d) Classifier: The vectors $r_{old}$ and $r_{new}$, obtained from the Code Encoder, are concatenated and passed through a classifier. The classifier is a neural network with a $\tanh$ layer of 80 hidden units, followed by a softmax layer, which outputs the class of the code edit.

e) Model Hyperparameters: The entire edit2vec model is trained end-to-end for 100 epochs, minimizing categorical cross-entropy loss using the 'Adam' [22] optimizer. In order to reduce over-fitting we use dropout layers in the bi-directional LSTM layer, one after the $\tanh$ layer of the Path-Context Encoder (dropout rate = 0.2), one after the $\tanh$ layer of the Code-Encoder (dropout rate = 0.4), and one after the $\tanh$ layer of the Classifier (dropout rate = 0.6). The dropout rates, the number of hidden units in each layer, the vector dimensions for path (128-D) and context (32-D) token embeddings, etc. are considered as model hyperparameters. The values of these hyperparameters are chosen after training and evaluating 400 edit2vec models with various combinations of hyperparameter values from a grid of values and then selecting the one that gives the best accuracy on the validation set in cross-validation [14].

2) LSTM: To compare with edit2vec, we build an LSTM-based model (LSTM) [13] that considers code as a sequence of tokens and ignores the syntactic structure. Given $\{c_{old}, c_{new}\}$, we tokenize each to a set of tokens. Each code token is then mapped to a 64-dimensional embedding vector. For both $\{c_{old}, c_{new}\}$, the sequence of tokens is input to a standard LSTM layer with 196 hidden units followed by a dropout layer (dropout rate = 0.8). Figure 4 describes the architecture of the LSTM model. The model outputs two 196-dimensional vectors $r_{old}^{LSTM}$ and $r_{new}^{LSTM}$ corresponding to $\{c_{old}, c_{new}\}$ respectively. The vectors $\{r_{old}^{LSTM}, r_{new}^{LSTM}\}$ are concatenated and then passed to a classifier. The classifier used here is same as defined in Section III-c.

3) Bag-of-words: This is the baseline model based on classical machine learning techniques. This model ignores both the syntactic structure as well as the sequence of the code tokens. It considers the code as a bag of words, regardless of their sequence in the code snippet.

Given $c_{old}$ and $c_{new}$, we tokenize each to a set of tokens.

| Old code | New code |
|----------|----------|
| $c_{old} = \text{processURL}(\text{message}, \text{depth}, \text{baseURL}, \text{url})$ | $c_{new} = \text{processURL}(\text{message}, \text{depth}, \text{url}, \text{baseURL})$ |
| |  |
We fit two different Bag-of-words based vectorizers, the count-based vectorizer\(^5\) and the tf-idf vectorizer\(^6\) on the merged set of tokens. Using the learnt vectorizer, we then separately vectorize \(c_{\text{old}}\) and \(c_{\text{new}}\), concatenate the two vectors and pass it to a classifier, to classify the edit. We test two different classifiers - the linear-kernel and the RBF-kernel support vector machine (SVM) classifiers.\(^4\) The count-based vectorizer gives more weightage to the word having high frequency where as in the tf-idf vectorizer, the weightage increases with the frequency of the token but is offset by the lexical frequency. We analyze the following two instances of code edit classification:

**Example 1:** \(\text{os.file(path)} \rightarrow \text{os.folder(path)}\)

In both the cases, the set of diff tokens are \{\text{file}, \text{folder}\}, but Example 1 belongs to class ‘different method same args’ whereas Example 2 belongs to ‘change caller in function call’. Using both \(c_{\text{old}}\) and \(c_{\text{new}}\) help generalize Bag-of-words and distinguish such code edits.

**IV. Experimental Setup**

In this section, we describe the two code edit classification tasks along with the two datasets we have used to evaluate the three models mentioned in Section III.

**A. Code Edit Classification Task**

Given the source code before edit (\(c_{\text{old}}\)) and source code after edit (\(c_{\text{new}}\)), the code edit classification task is to predict the class of the edit that was applied on \(c_{\text{old}}\) to generate \(c_{\text{new}}\). We analyze the following two instances of code edit classification:

1) **Bug-fix Classification**: The ManySSStuBs\(^*\) data-set\(^2\) consists of 63,923 labelled single-line bug-fix changes mined from 1000 popular open-source Java projects. The bug-fixes are classified into one of 16 bug templates (the simple stupid bug templates - SSStB). Given \(c_{\text{old}}\) and \(c_{\text{new}}\), this task is to predict the bug-template that was applied on \(c_{\text{old}}\) to generate \(c_{\text{new}}\).

a) **Filtering And Pre-processing**: We first tokenize the source code snippets into tokens such as identifiers, keywords, constants, symbols and other elements. We use Python’s javalang\(^7\) module for tokenizing and parsing the code. We remove all data-points where either the \(c_{\text{old}}\) or \(c_{\text{new}}\) were not tokenizable by the javalang module. This filters out 3,739 data-points.

Next, from the remaining 60,184 data-points belonging to 16 different templates, we remove data-points belonging to the three templates - ‘missing throws exception’, ‘delete throws exception’, ‘change modifier’ as \(c_{\text{old}}\) and \(c_{\text{new}}\) are missing for data-points of these templates in the dataset. We further remove data-points from template ‘change unary operator’ because the Path-Context Extractor provided by the authors of code2seq\(^5\) was not able to capture \(c_{\text{old}}\) and \(c_{\text{new}}\) properly. Finally, we remove data-points of ‘change caller in function call’ template because they were already a part of the other templates.

Though our design and implementation can randomly select 40 path contexts from code, for the sake of this experiment, we filter out the data-points where the number of path-contexts were greater than 40. The idea is to keep the input to the edit2vec model completely descriptive of the syntactic change, and therefore, give it every chance to outperform LSTM and Bag-of-words.

The filtering and pre-processing leaves us with 28,960 data-points belonging to 11 classes. Table III provides an overview of these classes.\(^5\) This number may seem like a relatively

\(^{\text{https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html}\)}

\(^{\text{https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html}}\)

\(^{\text{https://github.com/mast-group/mineSStuBs}}\)

\(^{\text{https://pypi.org/project/javalang/}}\)

\(^{\text{https://github.com/mast-group/mineSStuBs contains the list of all the 16 bug-templates, along with a brief description and the number of data-points for each bug-template.}}\)
small set of data-points for deep-learning-based techniques. However, as we explain in Section VI, code edit classification inherently suffers from a shortage of well-labeled data, a fact that previous work has also confirmed [21].

We divide the 28,960 data-points into 26,322 training samples and 2,638 testing samples. We perform stratified sampling so that the proportion of each bug template or class in the training and test set are equal.

2) Code Transformation Classification: We created a dataset of edits generated by a set of C# code transformers named Roslynator analyzers [19], which analyze source code, list out parts which are not in compliance with a rule, and transform them if there is a code fix. For instance, analyzer RCS1049 transforms input source code if (var1 == false) to if (!var1). Given c old and c new, this task is to predict the Roslynator analyzer that was applied on c old to generate c new.

Our dataset contains 12,784 code edits generated by applying 10 analyzers. Table III provides an overview of this dataset over top 250 C# projects from GitHub based on their popularity. The edits are annotated with the Roslynator analyzer that has generated them. We divide the 12,784 obtained data-points into 11,617 training samples and 1,167 test samples. Here too, we perform stratified sampling so that the proportion of samples belonging to any Roslynator analyzer is the same in training and test set.

| Bug-template                        | Description                                                                 | No of samples |
|-------------------------------------|-----------------------------------------------------------------------------|---------------|
| change caller in function call      | Checks whether a function call expression the caller object for it was replaced with another one. | 1488          |
| change numeral                      | Checks whether a numeric literal was replaced with another one                | 4779          |
| change operand                      | Checks whether one of the operands in a binary operation was wrong.          | 741           |
| change operator                     | Checks whether a binary operator was accidentally replaced with another one of the same type | 1711          |
| different method same args          | Checks whether the wrong function was called.                               | 9383          |
| less specific if                    | Checks whether an extra condition which either this or the original one needs to hold (|| operand) was added in an if statement’s condition. | 2095          |
| more specific if                    | Checks whether an extra condition (&& operand) was added in an if statement’s condition | 1836          |
| overload method deleted args        | Checks whether an overloaded version of the function with less arguments was called | 1040          |
| overload method more args           | Checks whether an overloaded version of the function with more arguments was called | 3820          |
| swap arguments                      | Checks whether a function was called with two of its arguments swapped      | 536           |
| swap boolean literal                | Checks whether a Boolean literal was replaced                               | 1531          |

TABLE II: Descriptions of various SStUB templates, and the number of samples associated with the template.

To evaluate the performance of the models, we train the model with the optimal set of hyperparameters obtained from hyperparameter tuning and use the average classification accuracy values of 3 runs of 10-fold cross-validation. Table LV contains evaluation results for both bug-fix classification and the code transformation classification tasks.

The format of the table is as follows: the first column shows the classification model. The second and third column lists the average accuracy values for bug-fix classification with and without canonicalization (described later in this section) the last two columns lists the same for code transformation classification respectively.

For both tasks, LSTM outperforms the other models in terms of classification accuracy (without canonicalization). Clearly, the LSTM model which considers code as a sequence of tokens improves the classification accuracy significantly over using Bag-of-words. This is because many code edits are position-sensitive and the sequence of tokens plays a significant role in classification. For instance, one example of ‘swap arguments’ class has the source code before edit (c old) = waitForJobExecutor(3000, 500) and source code after edit (c new) = waitForJobExecutor(500, 3000). The only change in the code before and after the edit is the order of arguments in the method call. Such an order or sequence of tokens is well handled by LSTM model but Bag-of-words fails to capture this kind of change as the set of tokens for source code both before and after the edit remains the same.

The edit2vec model, which captures the syntactic structure of code using path-contexts, does improve the classification accuracy (without canonicalization) over the Bag-of-words model but it does not outperform the LSTM model. At first, we found these results counter-intuitive as we expected to see an improvement in accuracy with the
use of syntactic structure. As the difference between the accuracy values of both the models is not much, we perform statistical significance tests to confirm if the difference in the performance is statistically significant. For both LSTM and edit2vec, we first perform normality test over 30 accuracy values, from 3 runs of 10-fold cross validation, using the D’Agostino-Pearson test [11], testing the null hypothesis that the accuracy values are normally distributed. We obtain a p-value of 0.51 and 0.41 for LSTM and edit2vec respectively, proving that they are indeed normally distributed. Since both the distributions are normal, we perform Student’s t-test [20] on the 30 accuracy values, for the LSTM and edit2vec models, the null hypothesis being that the distributions are identical. The p-value is $2.4 \times 10^{-11}$ which clearly shows that the distributions are not identical, and the difference in the performance of the two models is statistically significant.

To further understand why LSTM does better than edit2vec, we examine, through visualizations, how well-separated and “clean” the outputs from the two models are. As the data-points belong to 11 different classes, we expect the code edit representations to form 11 clusters in the intermediate latent space. So, we visualize the outputs from the layer before the softmax classification layer for both edit2vec and LSTM. We reduce these output vectors to 2-dimensional vectors using t-SNE [23], and plot them, as shown in Figure [6]. From the plots, we see that some classes of edits like ‘swap arguments’ (shown in light blue) and ‘overload method deleted args’ (shown in pink) are clearly separated from each other but there is significant overlap of the clusters for ‘change caller in function call’ (red) and ‘different method same args’ (black). We manually looked at some of the examples from these two classes and found that they are very similar to each other, which makes their separation more difficult from other classes. For instance, in ‘change caller in function call’ class, var1.var2(param1, param2) is changed to var3.var2(param1, param2) where as in ‘different method same args’, var1.var2(param1, param2) is changed to var1.var3(param1, param2).

Although both edit2vec and LSTM were not able to differentiate properly between many clusters, we also observed that edit2vec was not able to distinguish properly between some fairly different edits (for instance, classes ‘different method same args’ (black) and ‘overload method more args’ (grey)), which were well separated by LSTM.

To understand why edit2vec does not perform as well as LSTM for fairly different edits, we manually analyzed some of the data-points from the test set which were correctly classified by LSTM but incorrectly by edit2vec. One such case is shown in Figure [5]. The type of change (different method same args) is the same in both the cases. Even the path$_{old}$ and path$_{new}$ are the same, the only difference is the left and right context tokens. The LSTM model classified both correctly. edit2vec classifies the first example correctly but fails to the classify the second example correctly. We found many similar examples in our manual analysis.

Based on such manual analyses of test data that LSTM correctly classifies but edit2vec does not, we hypothesize that the edit2vec model relies heavily on the context tokens, and not as much on the path. Previous work [6] too has made a similar observation where the authors did an ablation study to understand the contribution of each component of the path-context for the task of method name prediction and showed that the context tokens contributed significantly higher than the path of non-terminal nodes. The dependence of the model on the context tokens is good and, in fact, advantageous for method name prediction, which was the task targeted by both code2seg and code2vec, because context tokens and method names have semantic relationships in a method. In contrast, semantics of context tokens serve no purpose in code edit classification, as the class of the code edit does not depend on individual tokens, but on the order of the tokens.

Consequently, to understand whether the token names were confounding our classification tasks, we repeat our experiments by dropping meaningful tokens in the path context and replacing them with canonical values. The canonicalization process is briefly explained as follows:

- Rename all identifiers with standard variable names like var1 and var2. For example, getConfig.getID() is changed to var1.var2().
- Replace all integer, float and string constants with

| Analyzer tag | Description                                      | No of samples |
|--------------|--------------------------------------------------|---------------|
| RCS1001      | Add braces (when expression spans over multiple lines) | 443           |
| RCS1032      | Remove redundant parentheses                      | 516           |
| RCS1049      | Simplify boolean comparison                       | 574           |
| RCS1085      | Use auto-implemented property                     | 2163          |
| RCS1123      | Add parentheses according to operator precedence  | 1428          |
| RCS1124      | Inline local variable                             | 1067          |
| RCS1146      | Use conditional access                            | 3368          |
| RCS1163      | Rename unused parameter to ‘_‘                    | 2053          |
| RCS1168      | Change parameter name to base name when they are not the same | 816           |
| RCS1220      | Use pattern matching instead of combination of ‘is‘ operator and cast operator | 356           |

TABLE III: Descriptions of various analyzer tags, and the number of samples associated with the tags.
Fig. 5: Examples that are both correctly classified by LSTM, but only Example 5a is correctly classified by edit2vec.

We reevaluate the models with canonicalized context tokens for both the bug-fix classification and code transformation classification task. In the case of bug-fix classification, we see that the performance of edit2vec has improved significantly. But at the same time, the LSTM model has also improved. We confirmed that even with such canonical inputs, LSTM performs statistically better than the edit2vec model. Performing the Student t-test, with the null hypothesis: accuracy values from LSTM and edit2vec have equal distributions, resulted in a p-value of $1.53 \times 10^{-26}$. It again shows that the difference between the performance of the two models is statistically significant. With such canonicalization, the performance of the Bag-of-words model (linear classifier) reduces, which shows that Bag-of-words relies heavily on identifier names and not on the syntax of the code. For code transformation classification, though there is slight improvement in the performance of both LSTM and edit2vec after canonicalization, the improvement is not significant. This may be because of the larger code snippets in the code transformation dataset, when compared to the bug-fix dataset; the number of canonicalized variables in a code snippet are higher in the former case, defeating the purpose of canonicalization to some extent. In this case too, LSTM performs better than edit2vec.

We manually analyzed the mis-classified canonicalized data. For the canonicalized dataset, there were 30 examples where the LSTM model classified correctly but the edit2vec failed to classify them correctly. But there were 10 other examples which edit2vec classified correctly but LSTM model failed. By analyzing these examples, we learned that edit2vec captures some high-level syntactic representation of code which LSTM is not able to capture. Also, in Figure 6a for LSTM model, we see that the class 'different method same args' (black) is clustered into three sub-clusters, which is not the case for edit2vec (Figure 6b). On manual analysis of some examples from each sub-cluster, we observed that they are grouped based on the number of arguments in a method. Methods having no arguments form one sub-cluster, methods with one argument form another sub-cluster and methods having more than one arguments form the third sub-cluster, even though they all belong to the same class. This sub-division within the cluster is not present for edit2vec model. This also supports that edit2vec is able to capture some high-level syntactic representation of code which LSTM fails to capture, but this representation is not sufficient to classify edit, specifically simpler and single-line edits. Single-line edits (specially SStubs) seem to occur frequently compared to other types of code edits, and are easy to label, specifically in open-source code.

VI. THREATS TO VALIDITY

While our findings do indicate that syntactic structure does not help code edit classification tasks, we recognize some threats to validity in this section.
A. Threats to Internal Validity

In this section, we address threats to internal validity.

a) Lack of data.: It is well-understood that present-day neural networks require large amounts of data to classify with high accuracy. The LSTM model has 269,147 parameters, whereas the edit2vec model has 490,892 parameters. edit2vec is more data-hungry, compared to LSTM. It is indeed possible that with significantly more data, edit2vec’s performance will improve significantly over what we report.

However, collecting clean data for code edit classification is fundamentally difficult because it requires significant amounts of manual effort to confirm that labels for training data are indeed correct. It has been found [12] that commit messages and descriptions written by developers are very often not descriptive enough, and in many cases, they are completely meaningless. Also, developers tend to push multiple changes together in a commit, which makes it even more difficult to label smaller fixes within a commit. So fundamentally, we cannot use data from millions of commits of open source GitHub repositories. For our analysis, we use the ManyStuBs4J dataset [21], which contains a particular set of classes of bug-fixes. These were collected from commits which have more descriptive commit messages, and their commit messages contain specific keywords like ‘error’, ‘bug’, ‘fix’ etc. that help to decide if a commit is a bug-fix or not. However, this work shows that the average frequency of bug-fixes is about 1 per 1600-2500 lines of code, whereas the average length of a code snippet (method), as used by code2seq, is about 7 lines of code. Hence, narrowing in on bug-fixes reduces the data available by at least two orders of magnitude.

b) Encoding specifics.: We use the path-context as a fundamental unit of capturing syntactic structure. It is possible that a different representation of syntactic structure could improve the performance of edit2vec. However, our choice was driven by previous work which has successfully used the path-context construct [5], [6]. It is also possible that a radically different model architecture will show different results. However, our choice of the model is done rigorously, by rigorously tuning the hyperparameters and choosing the best of 400 different models, and so we are confident that the design of the model will not significantly change our conclusions.

B. Threats to External Validity

In this section, we address threats to external validity. While we have concentrated on two tasks across two languages, there may be other code edit classification tasks that could benefit from the use of syntactic structure. Also, our study is on relatively small code edits. It is possible that syntactic structure will help in classifying larger code edits. However, there is a tussle between larger code edits and accurately labelled data. Larger code edits make it even more difficult to collect accurately labelled data, since a summarization of the code edit would have to be more descriptive. Previous work [21] have found that single-line edits occur relatively often (1 per 1600-2500 lines of code), making them potentially a promising dataset which can be used for various applications related to code edits.

VII. RELATED WORK

This paper takes inspiration from three categories of related work: using NLP techniques on code, using syntactic structure to learn code embeddings and different ways of learning distributed representation of code edits. In this section, we describe the related work in these areas.

A. Using NLP Techniques On Code

Inspired from the naturalness hypotheses and availability of enormous amount of code in the public domain, the use of natural language based embedding techniques on code has increased significantly where code is considered as a sequence of tokens. CODE-NN by Iyer et al. [16] presents an end-to-end neural attention model using LSTMs to generate summaries of C# and SQL code. Their model outperforms the baseline models that use a tf-idf based approach. Li et al. [9] compare various techniques including CODE-NN for neural code search and show that attention based weighting scheme on code embeddings outperforms more sophisticated techniques like CODE-NN. All of these approaches to learn embeddings of code tokens ignore the syntax of the code. They deal with well defined blocks of code (like functions or classes).

B. Code Embeddings Using Syntactic Structure

As mentioned in Section I, code has syntactic structure and long range correlations which make them different from natural language. Prior work has explored capturing such long range correlations by using data and control-flow graphs of code, abstract syntax trees [2], [3], [31], [32], [38], etc.

Two of the most recent works in this space are code2vec [6] and code2seq [5]. Both these techniques are used to represent entire code-snippets (methods) and are tested for method name prediction. In both these techniques, the code snippet is represented as a set of path-contexts extracted from its AST. An attentional mechanism is used over a set of randomly sampled path-contexts, while predicting or generating the method name. There are differences in the way embeddings are learnt for path-contexts. Path-context is considered as a single token in code2vec. Whereas, it is considered as a sequence of tokens in code2seq. code2seq has achieved the state of the art performance in code summarization (specifically method name prediction) and this inspired us to use this source code embedding technique to learn embeddings for code edits.

Gated graph neural networks (GGNNs) [24] are another way to learn features for graph-structured inputs. Using these networks, ASTs are extended to graphs, by adding a variety of code dependencies as edges, to model code semantics [3]. The tree based capsule network [17] is another such technique which captures both syntactic structure and dependency information in code, without the need of explicitly adding dependencies in the trees or splitting a big tree into smaller ones. All of these techniques are used to represent entire code snippets, and not code edits.
C. Learning Distributed Representation of Code Edits

Most of the work related to code edits are targeted for specific applications like commit message generation, automatic program repair etc. The first works on commit message generation, by Loyola et al. [26] and Jiang et al. [18], use attentional encoder-decoder architecture to generate commit messages from git diffs. Loyola et al. [26] use vanilla architecture where Jiang et al. [18] used a modified architecture with RNNs in the encoder. Liu et al. [25] evaluate the performance of NMT-based techniques for commit message generation. They show that the performance of NMT-based techniques declines significantly when automatically generated trivial commit messages were removed from the data. Liu et al. [25] propose a simpler technique based on Nearest Neighbour algorithm (NNGen). In this case, the diff vectors are presented as a bag-of-words and cosine similarity between the diff vector of the input and the training data is used to find the nearest commit for the given input.

Closely related work to ours in this space is commit2vec [27] where Lozoya et al. have compared AST based code representation learnt by code2vec [6] with other models based on LSTMs and bag-of-words, for binary classification of security related commits. They use transfer learning by using pre-trained embeddings from code2vec and another pretext task of predicting the priority of Jira tickets, both of which have large training data available. They observe that AST-based representation gives superior performance over other representations and pre-training the embeddings from a highly relevant pretext task further improves the results. They have tested it on a small dataset of 1950 commits. Also, they have used code2vec-based embeddings and the task is binary classification. In our case, we use code2seq-based approach for multi-class classification problem on a much larger dataset from two different languages.

Another related work in this space is DeepBugs [34], a name based bug-detection technique. They model it as a binary classification problem and use semantic representations or embeddings of identifier names for classification. They also ignore the syntactic structure of the code while learning the embeddings.

Allamanis et al. [37] introduced the problem of learning distributed representation of edits. They propose a neural network based technique to combine the structure and semantics of code edits. They evaluate their model on the task of generating new code given old code and edit representation as input. Based on the results, they conclude that graph based edit encoder (which uses tree representation of code) often fails to capture simpler edits and it does not outperform the sequence based edit-encoder. Our observations from the results of code edit classification have similar conclusions; AST based representation of code does not help improve over the baseline approach of considering code as a sequence of tokens, i.e., LSTM

VIII. Conclusion

In this work, we introduced a code edit classification approach (edit2vec) that uses syntactic structure along with attention mechanism to learn distributed representation of code edits. We conducted experimental evaluations of this model on two tasks: bug-fix classification and code transformation classification and compared the performance of the model with baseline approaches that used LSTM and Bag-of-words.
For both the tasks, we observe that the AST-based approach does not outperform the LSTM model. We observe that even though edit2vec captures some high-level syntactic representation of code, which LSTM is not able to capture, this complex representation is not required in case of simpler and smaller edits. We believe that it is difficult to get large labelled datasets for code edits. While we have evaluated AST-based models on relatively small datasets of few thousand examples, further development is needed both in the area of getting labelled datasets and exploring these models for different tasks. We hope that our work inspires others to work in this interesting space.

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