Evaluation Methodologies for Code Learning Tasks

Pengyu Nie, Jiyang Zhang, Junyi Jessy Li, Raymond J. Mooney, and Milos Gligoric
The University of Texas at Austin
{pynie@, jiyang.zhang@, jessy@austin., mooney@cs., gligoric@}utexas.edu

Abstract—There has been a growing interest in developing machine learning (ML) models for code learning tasks, e.g., comment generation and method naming. Despite substantial increase in the effectiveness of ML models, the evaluation methodologies, i.e., the way people split datasets into training, validation, and testing sets, were not well designed. Specifically, no prior work on the aforementioned topics considered the timestamps of code and comments during evaluation (e.g., examples in the testing set might be from 2010 and examples from the training set might be from 2020). This may lead to evaluations that are inconsistent with the intended use cases of the ML models. In this paper, we formalize a novel time-segmented evaluation methodology, as well as the two methodologies commonly used in the literature: mixed-project and cross-project. We argue that time-segmented methodology is the most realistic. We also describe various use cases of ML models and provide a guideline for using methodologies to evaluate each use case. To assess the impact of methodologies, we collect a dataset of code-comment pairs with timestamps to train and evaluate several recent code learning ML models for the comment generation and method naming tasks. Our results show that different methodologies can lead to conflicting and inconsistent results. We invite the community to adopt the time-segmented evaluation methodology.

I. INTRODUCTION

Over the last several years, there has been a growing interest in applying machine learning (ML) models to tasks that process source code and the natural language elements, such as comment generation [1]–[12], code generation [13], [14], method naming [11], [15]–[18], and code completion [19]. This growing body of work has introduced sophisticated models based on advanced ML, such as deep neural networks [1], [2], [8], [15]–[17], graph neural networks [3], [11], [20]–[22], and transformers [9], [23]. Substantial progress has been reported over years, usually measured in terms of automatic metrics, including BLEU [24], precision, recall, and F1 scores.

Despite a solid progress in applying ML to these tasks, the evaluation methodology, i.e., the way we obtain training, validation, and testing sets, in this domain is solely based on standard ML practices, without taking into account common practices in software engineering and software evolution. This gap could lead to inflated values for automatic metrics reported in papers, e.g., BLEU could be much higher than it would be in practice, and misunderstanding if a model might actually be useful once adopted.

The key missing piece in prior work is the description of the targeted use cases for their ML models. For example, in prior work, it was not clear if the models should be used in a batch-mode use case (i.e., applying the model to a repository at a specific point in time $\tau$) or a continuous-mode use case (i.e., using the model while code is being developed). One use case might be considered more realistic than another, and the results might differ across use cases for the same groups of models. Thus, it is insufficient to only report the task being targeted in a paper, and it is necessary to explain intended use cases for the ML models. Once the task and use cases are clearly defined, an appropriate evaluation methodology (or potentially several methodologies) should be used. This would also help future research to set up a fair comparison of ML models.

Prior work on code learning has targeted almost only the batch-mode use case. However, batch-mode does not match the most realistic use case. In contrast, the continuous-mode use case may reflect more realistic usages: in continuous-mode, a developer trains a model at some point in time and then uses the model at some later point in time. Figure 1 illustrates this use case. Few papers on code learning tasks evaluated models in the continuous-mode use case or took into account the notion of time when creating training, validation, and testing sets; we are only aware of three work on defect prediction [25], program repair [26], and bug localization [27]. In batch-mode, the examples that end up in a training set might be code snippets that were included in a repository in 2020 and the examples that end up in a testing set might be code snippets from 2010. Considering that programming languages evolve (e.g., new language features are being introduced) and coding styles are constantly revised, results obtained in batch-mode could be very different from those obtained in continuous-mode.

In this paper, we study recent literature on ML models for comment generation and method naming tasks. By reasoning about their evaluation methodologies (which we call mixed-project and cross-project), we define two use cases that could be evaluated by these methodologies. No prior work, in the aforementioned areas, takes into account time when code was committed into repositories.

Next, we define a more realistic use case when a developer...
uses a fixed model continuously over some period of time. We describe an appropriate evaluation methodology for this use case: time-segmented. We do not claim that this is the only realistic use case, but definitely the one that we wrongly assumed has been widespread in the literature.

Finally, we evaluate several existing ML models (targeting comment generation and method naming tasks) using three evaluation methodologies (mixed-project, cross-project, time-segmented). Our goals were to (1) understand the impact of methodologies on automatic metrics, which are commonly used to judge the performance of models, and (2) check if different methodologies result in conflicting conclusions.

We highlight two key findings. First, depending on the used methodology, we might end up with conflicting conclusions, i.e., using one methodology model A is better than model B and using another methodology model B is better than model A. Second, our results show that the absolute values for automated metrics vary widely across the three methodologies, which indicates that models might be useful only for some use cases. Thus, it is imperative that future work describe what use case is being targeted and use the appropriate evaluation methodology. In an ideal scenario, each model would be evaluated for all known use cases, but that is not feasible due to high computational costs associated with training large-scale ML models.

In summary, this paper argues that we need to more diligently choose evaluation methodology and report results of ML models for code learning tasks. Regardless of whether or not the conclusions of prior work hold across methodologies, we should always choose the methodology appropriate for the targeted task and use case. We hope that the community will join us in the effort to define the most realistic use cases and further the evaluate methodology for each use case.

II. PRELIMINARIES

We briefly define symbols and functions that we use to define methodologies and explain our experiment setup. We write $\tau$ to denote a specific point in time; $\tau^{-1}$ is earlier than $\tau$ (i.e., $\tau^{-1} < \tau$), and $\tau^{-2}$ is earlier than $\tau^{-1}$. Furthermore, we write $\mathcal{E}$ to denote a set of examples. The content of a single example is task dependent. Consider the comment generation task (generating a natural language summary comment given a code snippet, e.g., a method), an example is a method-comment pair. We write $\mathcal{P}$ to denote a set of projects from which examples are derived.

We define a function $\text{extract}(\tau, p)$ that extracts all examples from the project $p$ at $\tau$.

Then, we define a function $\text{shuffle}(\text{List})$ that takes a list (of examples or projects) as the input and returns a list with the same items in a random order.

Finally, we define a function $\text{split}(\text{List}, r_x, r_y, r_z)$ that takes a list of examples, the ratios for training ($r_x$), validation ($r_y$), and testing ($r_z$) as inputs, and requires that $r_x + r_y + r_z = 1$. It splits the input list into three lists such that the number of examples in the first/second/third list is $r_x r_y r_z$ of the total number of examples from all projects in the input list.

III. METHODOLOGIES

Table I lists recent work on comment generation and method naming. Each row shows information for one paper; two citations in a single row indicate that the conference paper was extended into a journal paper. The first group of papers targets comment generation and the second group targets method naming. The last three columns show which methodology/methodologies were used in the evaluation in each paper.

In this section, we first summarize two commonly used methodologies: mixed-project (Section III-A) and cross-project (Section III-B). Then, we introduce a novel time-segmented methodology (Section III-C).

A. Mixed-Project

The mixed-project methodology, which is the most commonly used in prior work based on Table I, extracts examples at a single point in time ($\tau$) from various projects ($\mathcal{P}$), then randomly shuffles the examples and splits them into training, validation, and testing sets. More formally, the sets are obtained by the following formulas:

$$\mathcal{E} = \bigcup_{p \in \mathcal{P}} \text{extract}(\tau, p)$$

$$\mathcal{E}_{\text{train}}, \mathcal{E}_{\text{val}}, \mathcal{E}_{\text{test}} = \text{split}(\text{shuffle}(\mathcal{E}), r_x, r_y, r_z)$$

Figure 2 illustrates the mixed-project methodology, where each box represents a project and each circle represents an example. This methodology is time-unaware, i.e., it does not consider if examples in the testing sets are committed into a project before or after examples in the training or validation sets.
TABLE I: Methodologies Used in Prior Work; We Use the Highlighted Lines in Our Experiments.

| Task                  | Authors       | Reference Year | Language       | Metrics                          | Methodology          |
|-----------------------|---------------|----------------|----------------|----------------------------------|----------------------|
| Comment Generation    | Iyer et al.   | 2016           | C#, SQL        | BLEU, METEOR, ROUGE-L-F1, CIDER   | ✓ x x               |
|                       | Wan et al.    | 2018           | Python         | BLEU, METEOR, ROUGE-L-F1, CIDER   | ✓ x x               |
|                       | LeClair et al.| 2019           | Java           | BLEU, ROUGE-L-F1, ROUGE-2-F1, F1 | ✓ x x               |
|                       | Hu et al.     | 2019           | Java           | BLEU, METEOR, Precision, Recall, F1 | ✓ x x               |
|                       | LeClair et al.| 2020           | Java           | BLEU, ROUGE-L-F1                  | ✓ x x               |
|                       | Cai et al.    | 2020           | SQL, Python    | BLEU, ROUGE-L-F1, ROUGE-2-F1     | ✓ x x               |
|                       | Ahmad et al.  | 2020           | Java, Python   | BLEU, METEOR, ROUGE-L-F1          | ✓ x x               |
|                       | Cai et al.    | 2020           | Python         | BLEU, METEOR, ROUGE-L-F1          | ✓ x x               |
|                       | Ahmad et al.  | 2021           | Java, Python, Ruby, JavaScript, Go, PHP | BLEU | ✓ x x               |

| Method Naming         | Allamanis et al. | 2016 | Java | Precision, Recall, F1, Exact Match Accuracy | ✓ x x               |
|                       | Fernandes et al.| 2019 | Java, C# | ROUGE-L-F1, ROUGE-2-F1, F1 | ✓ x x               |
|                       | Xiong et al.    | 2019 | Java | Precision, Recall, F1 | ✓ x x               |
|                       | Alon et al.     | 2019 | Java | Precision, Recall, F1 | ✓ x x               |
|                       | Yonai et al.    | 2019 | Java | Top-10 Accuracy | ✓ x x               |
|                       | Nguyen et al.   | 2020 | Java | Precision, Recall, F1 | ✓ x x               |

| Sum                   | n/a            | n/a            | n/a            | n/a                             | 15 4 0               |

B. Cross-Project

The cross-project methodology, also commonly used in prior work, extracts examples at a single point in time (τ) from various projects (P) as well. Unlike the mixed-project methodology, the cross-project methodology splits the set of projects into three disjoint sets for training, validation, and testing. Thus, the examples from one project are contained in only one of the training, validation, and testing sets. Figure 3 illustrates this methodology. More formally, the sets are obtained by the following formulas:

\[
P_{\text{train}}, P_{\text{val}}, P_{\text{test}} = \text{splitprj}(\text{shuffle}(P), r_x, r_y, r_z)
\]

\[
E_{\text{train}} = \bigcup_{p \in P_{\text{train}}} \text{extract}(\tau, p)
\]

\[
E_{\text{val}} = \bigcup_{p \in P_{\text{val}}} \text{extract}(\tau, p)
\]

\[
E_{\text{test}} = \bigcup_{p \in P_{\text{test}}} \text{extract}(\tau, p)
\]

The cross-project methodology is explicitly evaluating the ability to generalize a model to new projects. However, cross-project is also time-unaware, i.e., it does not consider if the examples from a project that is in the testing set come before or after the examples from the projects in the training set.

C. Time-Segmented

We propose a novel methodology: time-segmented. Unlike the methodologies explained earlier, the time-segmented methodology is time-aware, i.e., the examples in the training set were available in the projects before the examples in the validation set, which were in turn available before the examples in the testing set. Figure 1 illustrates this methodology.

\[
E_{\text{train}}^\tau = \bigcup_{p \in P} \text{extract}(\tau^{-2}, p)
\]

\[
E_{\text{val}}^\tau = \bigcup_{p \in P} \text{extract}(\tau^{-1}, p) \setminus E_{\text{train}}^\tau
\]

\[
E_{\text{test}}^\tau = \bigcup_{p \in P} \text{extract}(\tau, p) \setminus E_{\text{train}}^\tau \setminus E_{\text{val}}^\tau
\]

IV. USE CASES

As we saw in the previous section, methodologies are used to set up experiments and obtain an appropriate dataset split for the evaluation. However, methodologies do not describe the envisioned use of an ML model. Prior work picked one methodology or another merely for the purpose of setting up experiments, but we argue that ML models should be described with respect to use cases, i.e., how will the developers use the models eventually. Once a use case is chosen, an appropriate methodology can be selected to evaluate the model. Figure 4 illustrates our suggestion.

In this section, we define three use cases. The first two use cases are “extracted” from prior work. Namely, we reason
about the mixed-project and the cross-project methodologies used in prior work and try to link each to a (somewhat) realistic use case. The third use case that we describe is inspired by our own development and can be evaluated using the time-segmented methodology. Note that we do not try to provide an exhaustive list of use cases, but rather to start off this important distinction between a use case and an evaluation methodology. We will introduce the use cases via examples. (Although we describe examples by using the comment generation task, our story holds for any other code learning task.)

A. In-Project Batch Use Case

Consider Alice, a developer at a large software company. Alice has been developing several software features in her project over an extended period of time (since \( \tau^{-1} \)), but she only wrote comments for a part of her code. At one point (\( \tau \)), she decided it was time to add documentations for the methods without comments. She wants to use an ML model that can automatically generate comments. Alice decides to train a model using already existing examples (i.e., method-comment pairs for the methods with comments) in her code and the examples (available at time \( \tau \)) from several other projects on GitHub. We call this \textit{in-project batch use case}, because Alice trains a new model every time she wants to use the model, and she applies it to a large amount of methods that may be added before or after the methods in the training set. This use case can be evaluated using the mixed-project methodology (Section III-A).

Prior work that used the mixed-project methodology (Table I) fits under this use case. Because prior work did not set any limit on timestamps for examples in training and testing sets, the time period between examples in the two sets can be arbitrarily large (in either direction).

B. Cross-Project Batch Use Case

In this case, we assume that Alice works on a project (since \( \tau^{-1} \)) without writing any documentation for her code. At some point (\( \tau \)), Alice decides to document all her methods. Again, she wants to use an ML model to help her get the task done. Since Alice does not have any comments in her code, she decides to only train on other projects available on GitHub (at time \( \tau \)). She uses all examples (i.e., method-comment pairs) in the training set. Once the model is trained, she uses it to generate comments for all the methods in her project. We call this \textit{cross-project batch use case}, because Alice trains a new model at a specific time point and applies it to all the methods on a new project. (Note that once she integrates the comments that she likes, she can use them in the future for training a new ML model, which matches in-project batch use case, or potentially she could decide to ignore the methods without comments. She wants to use an ML model that can automatically generate comments. Alice decides to train a model using already existing examples (i.e., method-comment pairs for the methods with comments) in her code and the examples (available at time \( \tau \)) from several other projects on GitHub. We call this \textit{in-project batch use case}, because Alice trains a new model every time she wants to use the model, and she applies it to a large amount of methods that may be added before or after the methods in the training set. This use case can be evaluated using the mixed-project methodology (Section III-A).

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C. Continuous Use Case

In this case, Alice writes comments for each method around the same time as the method itself. For example, Alice might integrate a model for comment generation into her IDE that would suggest comments once Alice indicates that a method is complete. (Updating and maintaining comments as code evolves [30]–[32] is an important topic, but orthogonal to our work.) Before using the model starting from \( \tau^{-1} \), Alice would have to train the model on the data available in her project and other projects at \( \tau^{-1} \). She can keep using the same model for as long as she wishes, e.g., until \( \tau \) when she decides to train a new model. We call this \textit{continuous-mode}, because the only data that can be used to train the model is the data from the past. This use case can be evaluated using the time-segmented methodology (Section III-C).

The model should be retrained once in a while, e.g., when a new programming language version is introduced that adds new syntax into the language and developers start adopting the syntax. Finding an appropriate frequency at which to retrain the model is a topic worth exploring in the future.

V. Experiment Setup

In this section, we describe our experiment setup for comparing the methodologies. The goal of the experiment is to train models following each methodology and evaluate the models on \textit{common sets of testing examples}. We evaluate and compare the models by reporting the automatic metrics that are commonly used in prior work. Our setup is generic and could be used for any code learning task; we focus on comment generation and method naming in this work, and we will introduce the details of task-specific steps in Section VII.

We extend the notation from Section II to accurately describe our experiment setup. Starting from a dataset \( \mathcal{E} = \bigcup_{p \in \mathcal{P}} \text{extract}(\tau, p) \), we split \( \mathcal{E} \) into training, validation, and testing sets following each of the three methodologies. Moreover, we coordinate the ways of split for the three methodologies such to compare each pair of methodologies using as much common testing examples as possible. Figure 5 illustrates our steps to achieve these goals, and Table 5 lists the formulas of the sets after splitting. We describe the steps in details below with the help of Figure 5 and Table 5.

1) We first obtain the examples in each project using the \texttt{extract} function on three selected time points \( \tau^{-2} \), \( \tau^{-1} \), \( \tau \). The step 1 in Figure 5 illustrates this, where the entire box represents the examples from a project, and the horizontal lines represent the examples being segmented into three parts by \( \tau^{-2} \) and \( \tau^{-1} \). We denote the obtained examples sets as: \( \mathcal{E}^{\tau,p} = \text{extract}(\tau, p); \mathcal{E}^{\tau^{-1},p} = \text{extract}(\tau^{-1}, p); \mathcal{E}^{\tau^{-2},p} = \text{extract}(\tau^{-2}, p) \). Then, we time-segment the examples in each project to obtain: the examples \textit{after} \( \tau^{-2} \) and \textit{before} \( \tau^{-1} \), denoted as \( \mathcal{E}^{\tau^{-1} \setminus T^{\tau^{-1},p}}, = \mathcal{E}^{\tau^{-1},p} \setminus \mathcal{E}^{\tau^{-2},p} \); and the examples \textit{after} \( \tau^{-1} \) and \textit{before} \( \tau \), denoted as \( \mathcal{E}^{\tau^{-1} \setminus \tau^{-1},p} = \mathcal{E}^{\tau,p} \setminus \mathcal{E}^{\tau^{-1},p} \).
2) Split the examples in each project into training, validation, testing segments given the ratios $r_x, r_y, r_z$, using the following formulas:

\[
\begin{align*}
&\mathcal{X}^{\tau-1,p}_{\text{train}} \cap \mathcal{X}^{\tau-2,p}_{\text{val}} \cap \mathcal{X}^{\tau-2,p}_{\text{test}} \\
&= \text{split}(\mathcal{X}^{\tau-2,p}_{\text{train}}, r_x, r_y, r_z) \\
&\mathcal{X}^{\tau-1\tau-2,p}_{\text{train}} \cap \mathcal{X}^{\tau-1\tau-2,p}_{\text{val}} \cap \mathcal{X}^{\tau-1\tau-2,p}_{\text{test}} \\
&= \text{split}(\mathcal{X}^{\tau-1\tau-2,p}_{\text{train}}, r_x, r_y, r_z) \\
&\mathcal{X}^{\tau-1,p}_{\text{train}} \cap \mathcal{X}^{\tau-1,p}_{\text{val}} \cap \mathcal{X}^{\tau-1,p}_{\text{test}} \\
&= \text{split}(\mathcal{X}^{\tau-1,p}_{\text{train}}, r_x, r_y, r_z)
\end{align*}
\]

In our experiment, we choose $r_x = 70\%, r_y = 10\%, r_z = 20\%$ following common machine learning practice [33]. The step 2 in Figure 5 illustrates this, where the vertical lines represent splitting the time-segmented examples sets into training, validation, and testing segments.

3) Split the projects to training, validation, and testing sets ($r_x = 70\%, r_y = 10\%, r_z = 20\%)$:

\[\mathcal{P}_{\text{train}}, \mathcal{P}_{\text{val}}, \mathcal{P}_{\text{test}} = \text{split}(\text{shuffle}(\mathcal{P}), r_x, r_y, r_z)\]

The step 3 in Figure 5 illustrates this, where each box represents one project, and the annotations below the boxes show the range of $\mathcal{P}_{\text{train}}, \mathcal{P}_{\text{val}}$, and $\mathcal{P}_{\text{test}}$.

4) Group appropriate segments to obtain the training, validation, and testing sets of the mixed-project (MP), cross-project (CP), and time-segmented (T) methodologies according to their requirements. The step 4 in Figure 5 illustrates this, and the left part of Table II lists the formulas for this step. We will refer to the testing sets obtained in this step as traditional testing sets (TestT for short).

5) For each pair of methodologies, we take the intersection of their traditional testing sets to get the common testing set (TestC for short) of this pair. The step 5 in Figure 5 illustrates this, and the right part of Table II lists the formulas for this step. The common testing set can be used to compare the models trained using different methodologies. For example, a model trained on the training set of the mixed-project methodology and a model trained on the training set of the time-segmented methodology can be compared on the common testing set of the pair of the mixed-project and time-segmented methodologies. In
We train each model under each methodology three times and provide in the original papers.

for all models, we use the exact same hyper-parameters

VI. TASKS

This section describes code learning tasks in our study: comment generation and method naming. For each task, we (1) give a brief background, (2) select several recent well-studied machine learning models (see Table I), and (3) describe the automatic metrics for the task. We gave our best to select well-studied and representative models whose code are available. We took the existing code with minimal modifications to fix some data processing issues and export the results in the format that is compatible with our scripts.

A. Comment Generation

Developers frequently write comments in natural language together with their code to deliver messages to their users (e.g., via API comments) and to communicate among themselves (e.g., via todo comments) [34]–[36]. Unfortunately, writing and maintaining comments is tedious and error-prone, leading to incorrect or outdated comments, which leads to inconsistencies and bugs [37]–[40]. The task of comment generation tries to automatically generate comments from code. Prior work [8], [9] mostly focused on generating an API comment (e.g., JavaDoc summaries) given a method body.

Models. We selected three models from recent prior work (highlighted rows in the comment generation part of Table I):

- DeepComHybrid, a model from Hu et al. [2], [8].
- Transformer, a model from Ahmad et al. [9].
- Seq2Seq, a classic model which is the base architecture of many models, including DeepComHybrid and Transformer; implementation taken from Ahmad et al. [9].

Automated metrics. We use four automated similarity metrics that are frequently used in prior work: BLEU, METEOR, ROUGE-L-F1, and exact match accuracy. All models consider a method or a comment as a sequence of subtokens (splitting tokens of the form CamelCase and snake_case), thus we measure the metrics on subtoken level. Specifically, we measure the metrics on each pair of prediction subtokens and gold subtokens, and then compute the average over all examples in the testing set. BLEU [24] measures the number of n-grams in the prediction that also appear in the gold (specifically, we measure average sentence-level BLEU-4 as many prior work on comment generation [1], [8], [9] did). METEOR [41] measures the similarity by identifying possible alignments between the prediction and the gold using various linguistics heuristics, and has been shown to have high correlation with human judgments in natural language processing tasks like machine translation. ROUGE-L-F1 [42] measures the similarity based on the longest common subsequence (LCS) statistics (we report its F1 measurement as prior work [9] did). Exact match accuracy is 100% if the prediction is exactly the same with the gold, 0% otherwise. For example, given the gold “retrieves all refs of the github command ”, the prediction “retrieves all refs of the github repository ” gets BLEU 36.6, METEOR 70.3, ROUGE-L-F1 75.0%, and exact match accuracy 0.0%.

TABLE II: The Formulas to Get the Training (Train), Validation (Val), and Traditional Testing (TestT) Sets for each Methodology, and the Common Testing (TestC) Set for Each Pair of Methodologies.

| Methodology | Set | Formula |
|-------------|-----|---------|
| MP          | Train | $\bigcup_{p \in P} (E_{train}^{p-2} \cup E_{train}^{p-1} \cup E_{train}^{p})$ |
|             | Val   | $\bigcup_{p \in P} (E_{val}^{p-2} \cup E_{val}^{p-1} \cup E_{val}^{p})$ |
|             | TestT | $\bigcup_{p \in P} (E_{test}^{p-2} \cup E_{test}^{p-1} \cup E_{test}^{p})$ |
| CP          | Train | $\bigcup_{p \in P} (E_{train}^{p-2} \cup E_{train}^{p-1} \cup E_{train}^{p})$ |
|             | Val   | $\bigcup_{p \in P} (E_{val}^{p-2} \cup E_{val}^{p-1} \cup E_{val}^{p})$ |
|             | TestT | $\bigcup_{p \in P} (E_{test}^{p-2} \cup E_{test}^{p-1} \cup E_{test}^{p})$ |
| T           | Train | $\bigcup_{p \in P} E_{train}^{p}$ |
|             | Val   | $\bigcup_{p \in P} E_{val}^{p}$ |
|             | TestT | $\bigcup_{p \in P} E_{test}^{p}$ |

theory, we could compare all three methodologies on a set of common examples: $\bigcup_{p \in P} E_{test}^{p-1}$, but in practice, this set is too small (far less than 4% of the set of all examples when we use 20% of data for testing in the mixed-project and cross-project methodologies) and does not contain enough examples.

6) Finally, we perform two postprocessing steps on the obtained dataset. To avoid being impacted by the differences in the number of training examples for different methodologies, we downsample the training sets of the three methodologies to the same size (i.e., the size of the smallest training set) randomly. As a common practice in ML, we remove noisy examples (e.g., meaningless and duplicate examples) from the validation, traditional testing, and common testing sets, formalized as a task-specific clean(List) function which takes a list of examples as inputs and returns a list of examples after cleaning.

We train each model under each methodology three times and each run is initialized using different random seed. In addition, for all models, we use the exact same hyper-parameters provided in the original papers.
B. Method Naming

Descriptive names for code elements (variables, methods, classes, etc.) are a vital part of readable and maintainable code [43], [44]. Naming methods is particularly hard and important, because the names need to be both concise—usually containing only a few tokens—and comprehensible—such that they describe the key functionality of the code [45].

Models. We selected two models from recent prior work (highlighted rows in the method naming part of Table I):

- Code2Vec, a state-of-the-art model from [17].
- Code2Seq, a state-of-the-art model from [16].

Automated metrics. We use five automated similarity metrics that are frequently reported in prior work: precision, recall, F1, exact match accuracy, and subtoken-level accuracy. Code2Seq generates method names as sequences of subtokens, but Code2Vec suggests method names by pointing to names in the training examples; we measure all metrics on subtoken level by splitting Code2Vec’s suggested names into subtokens. We measure the metrics on each pair of prediction subtokens and gold subtokens, and compute the average over all examples in the testing set. Precision, recall, and F1 compare the unique subtokens in the prediction against the unique subtokens in the gold (these metrics are commonly used in many prior work on method naming [15]–[17]). Subtoken-level accuracy measures the number of subtokens in the predictions that is correctly predicted at the correct location, and is normalized by the number of subtokens in the prediction or the gold, whichever is longer. For example, given the gold “getDropDownAnchor”, the prediction “getDropDown” gets precision 100.0%, recall 75.0%, F1 42.9%, subtoken-level accuracy 75.0%, and exact match accuracy 0.0%.

VII. DATASETS

This section describes the datasets we collected to facilitate our experiments following the steps described in Section V. We could not easily reuse existing datasets from prior work for our experiments because the timestamps of examples are not available in those datasets. We started by collecting examples of methods with comments from open-source GitHub projects, and then performed task-specific postprocessing to get the dataset for each task.

Projects selection. We initially chose 1,793 popular Java projects on GitHub: 1,000 Java projects with the highest number of stars (indicating how many GitHub users bookmarked a project) and another 793 Java projects whose owner is one of the famous open-source organizations on GitHub [46]. We chose to use only Java projects because most prior work focused on this language (see Table I). Then, we only kept the projects meeting the following criteria: (1) the number of stars should be larger than 20; (2) the lines of code of the project (as reported by GitHub API [47]) should be at least 1,000,000 but no more than 2,000,000, to keep the number of examples balanced across projects; (3) the project should have at least one commit after Jan 1st 2018. 160 projects matched our criteria.

Collecting the raw dataset. For each project and for each year in 2019, 2020, and 2021, we identified the last commit in the project before Jan 1st of that year, checked-out to that commit, used JavaParser [48] to parse all Java files, and collected examples in the form of (method, comment, name, project, year) tuples, where comment is the first sentence in the JavaDoc of the method. We discarded the examples where: (1) the method or the comment contains non-English characters (157 and 5,139 cases respectively); (2) the code is longer than 10,000 characters (60 cases); (3) the method body is empty, i.e., abstract method (77,769 cases); (4) the comment is empty after removing tags such as @inheritdoc (21,779 cases). If two examples are identical except for the “year” label, we would keep the one with the earliest year (e.g., two examples from 2018 and 2019 years have identical method, comment, name, and project, so we only keep the 2018 one). We ended up with 77,475 examples in the raw dataset.

The extract (c.f. Section II) can be implemented as: extract(p, τ) = {(m, c, n, p, t)|t ≤ τ}. Then, we follow the steps described in Section V to split the raw dataset into training, validation, traditional testing sets for each methodology and common testing set for each pair of methodologies.

Comment generation. The clean function (c.f. Section V, step 6) for comment generation does two things: (1) removes duplicate examples with the same method-comment pairs; and (2) removes the examples whose comments only contain punctuation marks like “.”. Table III shows the statistics of the comment generation dataset, after applying clean function based on the raw dataset. The columns, from left to right, are: the training, validation, traditional testing sets of the mixed-project, cross-project, time-segmented methodologies; and then the traditional testing sets of MP ∩ CP, MP ∩ T, CP ∩ T. The rows, from top to bottom, are: the number of data; the average number of subtokens in methods; the percentage of examples whose number of subtokens in the method is less than 100, 150, 200; the average number of subtokens in comments; the percentage of examples whose number of subtokens in the comment is less than 20, 30, 50.

Method naming. To obtain the method naming dataset, for each example in the raw dataset, we replaced the appearances of its name from its code to “METHODNAMEMASK” such that the models cannot cheat by looking for the name in the signature line or in the method body of recursive methods. The clean function (c.f. Section V, step 6) for method naming then removes duplicate examples with the same method-name pairs. Table IV shows the statistics of the method naming dataset. The columns, from left to right, are: the training, validation, traditional testing sets of the mixed-project, cross-project, time-segmented methodologies; and then the traditional testing sets of MP ∩ CP, MP ∩ T, CP ∩ T. The rows, from top to bottom, are: the number of data; the average number of subtokens in methods; the percentage of examples whose number of subtokens in the method is less than 100, 150, 200; the average number of subtokens in names; the percentage of examples whose number of subtokens in the name is less than 2, 3, 6.
TABLE III: Comment Generation Dataset Metrics.

| Statistic | MP | CP | T |
|-----------|----|----|---|
| #Example  | 50,879 | 7,523 | 50,879 |
| avg | 89.84 | 89.70 | 89.83 |
| ≤100     | 74.97 | 74.82 | 76.55 |
| ≤150     | 84.47 | 83.96 | 85.50 |
| ≤200     | 89.86 | 89.42 | 90.74 |

TABLE IV: Method Naming Dataset Metrics.

| Statistic | MP | CP | T |
|-----------|----|----|---|
| #Example  | 50,879 | 7,523 | 50,879 |
| avg | 88.15 | 89.70 | 89.83 |
| ≤100     | 75.45 | 74.64 | 76.81 |
| ≤150     | 84.75 | 83.89 | 85.83 |
| ≤200     | 90.03 | 89.47 | 90.80 |

VIII. RESULTS AND FINDINGS

We first show the results for comment generation and method naming tasks, and then list the key observations and findings from our experiment. Recall that we trained each model three times, and the reported automatic metrics are the average of the three runs. We conducted statistical significance testing using bootstrap tests [49] under confidence level 95%.

A. Results

Table V shows the automatic metrics for the comment generation models trained on the three methodologies on the common testing sets. The table has four parts that contain (from top to bottom) the BLEU, METEOR, ROUGE-L-F1, and exact match accuracy metrics. Each row contains the results of one model (name at column 1); each column contains the results trained on the training set of one methodology (name at row 1) and evaluated on the common testing set involving that methodology (name at row 2). The best results for each (training, common testing) sets combination are in bold text. The results marked with the same prefix Greek letter are not statistically significantly different.

B. Findings

Depending on the methodology, one model can perform better or worse than another. On method naming task, we found that Code2Seq outperforms Code2Vec only in cross-project methodology but not the other methodologies. This observation is consistent on all metrics. See Table VI and let us take F1 metric as an example: comparing the mixed-project and cross-project methodologies on their common testing set (F1 part, columns 2–3), Code2Vec gets higher F1 when trained on the mixed-project training set (14.4 vs. 6.5), but Code2Seq gets higher F1 when trained on the cross-project training set (27.0 vs. 20.3). We hypothesize the reason of Code2Vec being better on the other two methodologies is that Code2Vec has a simpler architecture that works better when suggesting names that are similar to the ones in the training set (which is the case for the mixed-project and time-segmented methodologies).
This finding suggests that a model may work better for one use case but not another—in this case, Code2Seq performs better in the cross-project batch use case, but Code2Vec performs better in the in-project batch use case and the continuous-mode use case. Thus, users of ML models can favor one model in one use case, but a different model in another use case.

**Depending on the methodology, the differences between models’ results may or may not be observable.** For example, for comment generation, on the common testing set of cross-project and time-segmented methodologies when using the METEOR metric (Table V, METEOR part, columns 6–7), Transformer significantly outperforms Seq2Seq when trained on the time-segmented training set, but does not when trained on the cross-project training set. Similar observations can be made on the results of the BLEU and exact match accuracy metrics for comment generation, and the results of the exact match accuracy metric for method naming. If two models’ results are not statistically significantly different, then it is likely that the model with higher score just looks better by chance, thus the difference is not observable in practice. We could not find reference points for these findings in prior work (unfortunately, Ahmad et al. [9] did not evaluate Seq2Seq against Transformer even though it was provided in their replication package).

**Results under the mixed-project methodology are inflated.** We found that the results under the mixed-project methodology are always higher than the other two methodologies. For example, in Table V: comparing the mixed-project and cross-project methodologies (BLEU part, columns 2–3), all models get better BLEU if trained on mixed-project; and comparing the mixed-project and time-segmented methodologies (BLEU part, columns 4–5), all models also get better BLEU if trained on mixed-project. Considering that the mixed-project methodology represents a less realistic use case than the other two methodologies, the mixed-project methodology always overestimates the models’ usefulness. As such, we suggest that the mixed-project methodology should never be used unless the model is targeted specially for the in-project batch use case (Section IV).

**Results under the cross-project methodology may be under-estimation of the more realistic continuous-mode use case.** We found that the results under the cross-project methodology are always lower than the results under the time-segmented methodology. This can be observed in all parts in both tables by comparing columns 6–7. We have argued that the continuous-mode use case is more realistic than others (Section IV). This suggests that the usefulness of the models in prior work using the cross-project methodology may have been under-estimated.

**Findings in prior work may not hold when using a different methodology or a different dataset.** We found that the findings reported by prior work may not hold in our experiment: for example, the finding “Code2Seq outperforms Code2Vec” from Alon et al. [16] does not hold when using mixed-project and time-segmented methodologies; for another example, the finding “DeepComHybrid outperforms Seq2Seq”
Projects selection. We selected medium-sized popular projects from GitHub as representatives of the open-source projects. Future work could perform our experiments in an industrial setting or a different set of projects.

Programming languages selection. We selected Java which largely was dominant in prior work (see Table I). Although future work could evaluate our steps on various programming languages, based on the results from prior work, we expect our findings to hold.

Models selection. We selected a few well-studied ML models from recent literature. Adding more models is computationally costly (for training the models on all methodologies), but may lead to other interesting observations. Our replication package can be used as the starting point for future comparisons.

Reproducibility of prior work. We used the replication packages provided in the original papers of the models whenever possible. We made (small) updates to all models’ code to: (1) upgrade outdated data processing code (because of our dataset contains examples with new programming language features that were not considered in the past); (2) export evaluation results in the format that is compatible with our scripts. We integrated these updates in our replication package.

Uncertainties of ML models. The ML models exhibit non-determinism during the training process by design, which can mostly be controlled by setting a random seed at the beginning of training [50]. We train each model three times, each time with a different random seed, to alleviate these uncertainties.

X. RELATED WORK

A. Evaluation Methodologies

To our best knowledge, only three prior work on code learning took into account the notion of time during evaluation: one work by Tan et al. on defect prediction [25], one work by Lutellier et al. on program repair [26], and one work by Pradel et al. on bug localization [27]. They designed time sensitive evaluation procedures which are similar to our time-segmented methodology. However, their evaluation procedures were designed specifically for one task, while ours can be generalized to any code learning task in theory.

Tu et al. [51] revealed the data leakage problem when using issue tracking data in the literature caused by the unawareness of the evolution of issue attributes. In our study, we revealed that a similar problem (unawareness of the timestamps of examples in the dataset) exists broadly in the evaluation of code learning tasks, and we propose a time-segmented methodology that can be used in future research.

We focus on studying the evaluation methodologies for code learning tasks in this work. A recent study suggests that similar methodologies problem may exist in natural language processing as well [52]. They pointed out that the ML models evaluated in standard cross-validation methodology (similar to our mixed-project or cross-project methodologies) may incur significant bias on realistic examples, as the models cannot adapt to the new norms, language, and ways of communicating produced by social movements.

B. Comment Generation and Method Naming

Comment generation is the task of generating a natural language summary from a given code snippet. Method naming is the task of generating a concise natural language name from a given method. Both tasks are also referred to as code summarization or code comprehension. Table I already listed the prior work on these two tasks. Here, we briefly discuss their recent progress.

Around 2016, the first work for comment generation [1] and method naming [15] were developed based on encoder-decoder neural networks and attention mechanism. Other prior work extended this basic framework in many directions: by incorporating tree-like code context such as AST [2], [4], [5], [8], [12]; by incorporating graph-like code context such as call graphs and data flow graphs [3], [11], [21], [22]; by incorporating path-like code context such as paths in AST [16], [17]; by incorporating environment context, e.g., class name when generating method names [18]; by incorporating type information [10]; or by using more advanced neural architecture such as transformer [9].

Recently, pre-trained models for code learning were built [28], [29], [53] on large datasets using general tasks (e.g., masked language modeling), and these models can be fine-tuned on a couple of code learning tasks, including comment generation and method naming. Evaluating the pre-trained models involves an additional pre-training set other than the regular training, validation, and testing sets. In theory, our methodologies can be extended to fit pre-trained models; for example, in the time-segmented methodology, the pre-training set should contain examples that are available in the projects before the examples in all other sets. No prior work on pre-trained models has considered the timestamps of examples during pre-training or evaluation.

XI. CONCLUSION

We introduced and formalized a novel time-segmented methodology for evaluating ML models for code learning tasks. This methodology stands in sharp contrast to those used in the literature—mixed-project and cross-project—that do not take into account timestamps of code and comments during evaluation of models. Next, we used the three methodologies to compare several ML models. Our results led to conflicting findings: the best model heavily depend on the used methodology. Furthermore, we showed that the results obtained via mixed-project are over-estimation and those obtained via cross-project are under-estimation of actual performance. We hope that future work on code learning tasks will clearly define the use case their ML model targets and choose appropriate methodology, which in most cases should be time-segmented.
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REFERENCES

[1] S. Iyer, I. Konstas, A. Cheung, and L. Zettlemoyer, “Summarizing source code using a neural attention model,” in Annual Meeting of the Association for Computational Linguistics, 2016, pp. 2073–2083.
[2] X. Hu, G. Li, X. Xia, D. Lo, and Z. Jin, “Deep code comment generation,” in International Conference on Program Comprehension, 2018, pp. 200–210.
[3] A. LeClair, S. Haque, L. Wu, and C. McMillan, “Improved code summarization via a graph neural network,” in International Conference on Program Comprehension, 2020, p. 184–195.
[4] A. LeClair, S. Jiang, and C. McMillan, “A neural model for generating natural language summaries of program subroutines,” in International Conference on Software Engineering, 2019, pp. 795–806.
[5] Y. Wan, Z. Zhao, M. Yang, G. Xu, H. Ying, J. Wu, and P. S. Yu, “Improving automatic source code summarization via deep reinforcement learning,” in Automated Software Engineering, 2018, pp. 397–407.
[6] Y. Liang and K. Q. Zhu, “Automatic generation of text descriptive comments for code blocks,” in AAAI Conference on Artificial Intelligence, 2018, pp. 5229–5236.
[7] X. Hu, G. Li, X. Xia, D. Lo, and Z. Jin, “Summarizing source code with transferred API knowledge,” in International Joint Conference on Artificial Intelligence, 2018, pp. 2259–2275.
[8] X. Hu, G. Li, X. Xia, D. Lo, and Z. Jin, “Deep code comment generation with hybrid lexical and syntactical information,” Empirical Software Engineering, vol. 25, no. 3, pp. 2179–2217, 2020.
[9] W. U. Ahmad, S. Chakraborty, B. Ray, and K.-W. Chang, “A transformer-based approach for source code summarization,” in Annual Meeting of the Association for Computational Linguistics, 2020, pp. 4998–5007.
[10] R. Cai, Z. Liang, B. Xu, Z. Li, Y. Hao, and Y. Chen, “TAG : Type auxiliary guiding for code comment generation,” in Annual Meeting of the Association for Computational Linguistics, 2020, pp. 291–301.
[11] P. Fernandes, M. Allamanis, and M. Brockschmidt, “Structured neural summarization,” in International Conference on Learning Representations, 2019.
[12] S. Xu, S. Zhang, W. Wang, X. Cao, C. Guo, and J. Xu, “Method name suggestion with hierarchical attention networks,” in Workshop on Partial Evaluation and Program Manipulation, 2019, pp. 10–21.
[13] P. Yin and G. Neubig, “A syntactic neural model for general-purpose code generation,” in Annual Meeting of the Association for Computational Linguistics, 2017, pp. 440–450.
[14] W. Ling, P. Blunsom, E. Grefenstette, K. M. Hermann, T. Koczysk, F. Wang, and A. W. Senior, “Latent predictor networks for code generation,” in Annual Meeting of the Association for Computational Linguistics, 2016.
[15] M. Allamanis, H. Peng, and C. Sutton, “A convolutional attention network for extreme summarization of source code,” in International Conference on Machine Learning, 2016, pp. 2091–2100.
[16] U. Alon, S. Brody, O. Levy, and E. Yahav, “code2seq: Generating sequences from structured representations of code,” in International Conference on Learning Representations, 2019.
[17] U. Alon, M. Zilberstein, O. Levy, and E. Yahav, “code2vec: Learning distributed representations of code,” Proceedings of the ACM on Programming Languages, vol. 3, no. POPL, pp. 1–29, 2019.
[18] S. Nguyen, H. Phan, T. Le, and T. Nguyen, “Suggesting natural method names to check name consistencies,” in International Conference on Software Engineering, 2020, p. 1372–1384.
[19] M. Allamanis, M. Brockschmidt, and M. Khademi, “Learning to represent programs with graphs,” in International Conference on Learning Representations, 2018.
[20] F. Scarselli, M. Gori, A. C. Tsoi, M. Hagenbuchner, and G. Monfardini, “The graph neural network model,” IEEE Transactions on Neural Networks, vol. 20, no. 1, pp. 61–80, 2008.
[21] K. Xu, L. Wu, Z. Wang, Y. Feng, and Y. Sheinin, “SQL-to-text generation with graph-to-sequence model,” in Empirical Methods in Natural Language Processing, 2018, pp. 931–936.
[22] H. Yonai, Y. Hayase, and H. Kitagawa, “Mercem: Method name recommendation based on call graph embedding,” in Asia-Pacific Software Engineering Conference, 2019, pp. 134–141.
[23] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, “Attention is all you need,” in Advances in neural information processing systems, 2017, pp. 5998–6008.
[24] K. Papineni, S. Roukos, T. Ward, and W.-J. Zhu, “BLEU: a method for automatic evaluation of machine translation,” in Annual Meeting of the Association for Computational Linguistics, 2002, pp. 311–318.
[25] M. Tan, L. Tan, S. Dara, and C. Mayeur, “Online defect prediction for imbalanced data,” in International Conference on Software Engineering, vol. 2, 2015, pp. 99–108.
[26] T. Latelier, H. V. Pham, L. Pang, Y. Li, M. Wei, and L. Tan, “CoCoNuT: combining context-aware neural translation models using ensemble for program repair,” in International Symposium on Software Testing and Analysis, 2020, pp. 101–114.
[27] M. Pradel, V. Murali, R. Qian, M. Machalica, E. Meijer, and S. Chandra, “Scalife: bug localization on millions of files,” in International Symposium on Software Testing and Analysis (ISSTA), 2020.
[28] Z. Feng, D. Guo, D. Tang, N. Duan, X. Feng, M. Gong, L. Shou, B. Qian, T. Li, J. Jiang, and M. pre-trained model for programming and natural languages,” in Findings of the Association for Computational Linguistics: EMNLP, 2020, pp. 1536–1547.
[29] W. U. Ahmad, S. Chakraborty, B. Ray, and K.-W. Chang, “Unified pre-training for program understanding and generation,” in Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 2021.
[30] S. Panthaplackel, P. Nie, M. Gligoric, I. J. Li, and R. J. Mooney, “Learning to update natural language comments based on code changes,” in Annual Meeting of the Association for Computational Linguistics, 2020, pp. 1853–1868.
[31] Z. Liu, X. Xia, M. Yan, and S. Li, “Automating just-in-time comment updating,” in Automated Software Engineering, 2020, pp. 585–597.
[32] B. Lin, S. Wang, K. Liu, X. Mao, and T. F. Biyssyandet, “Automated comment update: How far are we?” in International Conference on Program Comprehension, 2021, p. to appear.
[33] S. University. (2020) Splitting into train, dev and test sets. http://cs230.stanford.edu/blog/split/.
[34] Y. Padoleau, L. Tan, and Y. Zhou, “Listening to programmers—taxonomies and characteristics of comments in operating system code,” in International Conference on Software Engineering, 2009, pp. 331–341.
[35] P. Nie, J. J. Li, S. Khurshid, R. J. Mooney, and M. Gligoric, “Natural language processing and program analysis for supporting to-do comments as software evolves,” in Workshop on Natural Language Processing for Software Engineering, 2018, pp. 775–778.
[36] L. Pascarella, M. Bruntink, and A. Bachelli, “Classifying code comments in java software systems,” in Empir Softw Eng, 2019.
[37] L. Tan, D. Yuan, G. Krishna, and Y. Zhou, “/*comment: Bugs or bad comments?!,” in Symposium on Operating Systems Principles, 2007, pp. 145–158.
[38] S. H. Tan, D. Marinov, L. Tan, and G. T. Leavens, “@comment: Testing javadoc comments to detect comment-code inconsistencies,” in International Symposium on Software Testing and Analysis, 2012, pp. 260–269.
[39] I. K. Ratol and M. P. Robillard, “Detecting fragile comments,” in Automated Software Engineering, 2017, pp. 112–122.
[40] S. Panthaplackel, J. J. Li, M. Gligoric, and R. J. Mooney, “Deep just-in-time inconsistency detection between comments and source code,” in AAAI Conference on Artificial Intelligence, 2021, p. To appear.
[41] S. Banerjee and A. Lavie, “METEOR: An automatic metric for MT evaluation with improved correlation with human judgments,” in Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization, 2005, pp. 65–72.
[42] C. Lin and F. J. Och, “Automatic evaluation of machine translation quality using longest common subsequence and skip-bigram statistics,” in Annual Meeting of the Association for Computational Linguistics, 2004, pp. 605–612.
[43] E. W. Hirst and B. M. Ostvold, “Debugging method names,” in European Conference on Object-Oriented Programming, 2009, pp. 294–317.
[44] M. Allamanis, E. T. Barr, C. Bird, and C. Sutton, “Suggesting accurate method and class names,” in Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering, 2015, pp. 38–49.

[45] D. Lawrie, C. Morrell, H. Feild, and D. Binkley, “What’s in a name? a study of identifiers,” in International Conference on Program Comprehension, 2006, pp. 3–12.

[46] GitHub, Inc. (2020) Collection: Open source organizations. https://github.com/collections/open-source-organizations [Accessed on Dec 15, 2020].

[47] ——. (2021) GitHub REST API. https://docs.github.com/en/rest.

[48] J. Team. (2020) JavaParser : Analyse, transform and generate your Java codebase. https://javaparser.org/.

[49] T. Berg-Kirkpatrick, D. Burkett, and D. Klein, “An empirical investigation of statistical significance in NLP,” in Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, 2012, pp. 995–1005.

[50] H. V. Pham, S. Qian, J. Wang, T. Lutellier, J. Rosenthal, L. Tan, Y. Yu, and N. Nagappan, “Problems and opportunities in training deep learning software systems: An analysis of variance,” in Automated Software Engineering, 2020, pp. 771–783.

[51] F. Tu, J. Zhu, Q. Zheng, and M. Zhou, “Be careful of when: an empirical study on time-related misuse of issue tracking data,” in Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering, 2018, pp. 307–318.

[52] E. M. Bender, T. Gebru, A. McMillan-Major, and S. Shmitchell, “On the dangers of stochastic parrots: Can language models be too big?”, in Conference on Fairness, Accountability, and Transparency, 2021, pp. 610–623.

[53] D. Guo, S. Ren, S. Lu, Z. Feng, D. Tang, S. Liu, L. Zhou, N. Duan, A. Svyatkovskiy, S. Fu, M. Tufano, S. K. Deng, C. Clement, D. Drain, N. Sundaresan, J. Yin, D. Jiang, and M. Zhou, “GraphCodeBERT: Pre-training code representations with data flow,” in International Conference on Learning Representations, 2021.