Towards Using Data-Centric Approach for Better Code Representation Learning

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Abstract
Despite the recent trend of creating source code models and applying them to software engineering tasks, the quality of such models is insufficient for real-world application. In this work, we focus on improving existing code learning models from the data-centric perspective instead of designing new source code models. We shed some light on this direction by using a so-called data-influence method to identify noisy samples of pre-trained code learning models. The data-influence method is to assess the similarity of a target sample to the correct samples to determine whether or not such the target sample is noisy. The results of our evaluation show that data-influence methods can identify noisy samples for the code classification and defection prediction tasks. We envision that the data-centric approach will be a key driver for developing source code models that are useful in practice.

1. Introduction
Research in the area of Deep learning for code (Liu et al., 2021; Li et al., 2016; Allamanis et al., 2016; Watson et al., 2020; Allamanis et al., 2018; Mou et al., 2016a; Alon et al., 2019) mostly relies on large corpora of code that can be used as training and test sets, allowing deep learning methods to reason about source code properties. The trained models are then incorporated into software engineering tools to assist the developers in their programming tasks. However, the real-world usage of such code models is still limited due to the quality of them. In this paper, we hypothesize that the quality of the dataset used to train the code model contributes significantly to the quality of the source code model, i.e., high-quality dataset is critical for building a good machine learning model (Shome et al., 2022; Koh & Liang, 2017; Pruthi et al., 2020). However, we observe that source code data used for training code models is collected using some heuristic, and people tend to assume that the label of such data is correct, despite the fact that there can be a lot of noise in the data.

In other domains, such as computer vision, there is a huge effort to manually label large-scale image datasets, such as CIFAR-10 (Krizhevsky et al., 2009), Fashion MNIST (Xiao et al., 2017), ImageNet (Deng et al., 2009), and others. However, performing the same to obtain high-quality code datasets is challenging, due to the fact that source code data requires specific programming expertise to understand the program in order to label correctly. For example, labeling the defect prediction dataset from Devign (Zhou et al., 2019), required 600 man-hours from 4 professional security researchers. In fact, not many research groups have the capability of manually labeling the code data, due to limited human and financial resources. People typically rely on heuristics to collect data like as commit messages, tags offered by code competition websites, etc. Numerous aspects must be investigated to assess the quality of the data. For example, even if a human spent time labeling source code data, determining whether the labeling step was effective is difficult, e.g., how can we be sure that a buggy (or defect) code snippet labeled by a human really contains a bug and not just code changes due to a program requirement change?

We find that the majority of code learning research focuses on improving performance from a model-centric standpoint. This means that a dataset remains constant while new models are proposed to achieve better performance on such dataset. In this paper, we approach code learning models from a data-centric standpoint, which means that the model remains constant, we improve the quality of the dataset on which such model will be trained on. Improving a dataset can have various implications. One can identify and exclude noisy labels from such dataset, or if we know what the correct labels should be, we can correct them. By identifying noisy samples, we hope to improve the dataset’s quality, thus improving the source code model’s performance. A method for automatically identifying noisy examples in datasets is required. To achieve this, we adapt the data-influence methods commonly used in deep learning research to ex-
plain the black-box neural network models. These methods work by calculating the influence of a training example on a model prediction. It will track how the loss on the test point changes throughout the training process whenever the training example of interest is used. Finally, these methods will provide an influence score. This score indicates whether a sample is noisy (or mislabeled). We adapt a set of state-of-the-art data-influence methods, including Influence Function (Koh & Liang, 2017) and TraCIn (Pruthi et al., 2020), with the aim of automatically identifying noisy samples in the code corpus. The noisy examples can be removed or corrected, and the remaining data is used to retrain a new model in the hopes of improving performance.

It should be noted that different tasks in software engineering are also formulated differently, such as classification-based (code classification, bug triage, etc.), detection-based (bug detection, malware detection, etc.), and generation-based (code summarization, code generation, etc.). As a result, developing a technique that works well for identifying noisy samples for all tasks is non-trivial. In this work, we concentrate on classification-based tasks, including code classification and defect prediction. For these two tasks, our evaluation shows that the data-influence methods can successfully identify a large number of noisy samples in the training dataset. Retraining the models on good training samples, for instance, results in better performance in terms of accuracy score. Our findings shed some light on the data-centric approach to code learning.

2. Related Work

Detecting noisy labels has long been a research topic in other domains, such as computer vision. The most well-known approaches are similarity-based (Pezeshkpour et al., 2021) and gradient-based (Pezeshkpour et al., 2021; Yeh et al., 2018; Pruthi et al., 2020; Barshan et al., 2020; Koh & Liang, 2017). These techniques work mainly by using similarity metrics to quantify the influence made by individual training points on specific test predictions. However, we discover that very little effort has been spent in the domain of software engineering to detect noisy labels in code corpora. (Allamanis, 2019) proposes a simple de-duplication step on source code corpora to determine whether or not the quality of the source code models improves after de-duplication. Another line of research looks into how changes to the input code affect the quality of the source models (Bui et al., 2019; Rafiqul Islam Rabin et al., 2020; Yefet et al., 2020). To the best of our knowledge, we are the first to use a data-influence based method to solve the problem of automatically detecting noisy code samples.

3. Problem Formulation

In this section, we define our problem and introduce some background on data-influence methods. We focus on gradient-based methods: Influence Function (IF) (Koh & Liang, 2017) and TraCIn (Pruthi et al., 2020) as they are currently state-of-the-art techniques.

Let \( M(\cdot; \theta) \) be a source code model trained on a training set \( Z_{\text{train}} \). Assume that \( Z_{\text{train}} \) contains some noise, our goal is to identify the set of noisy samples \( Z_{\text{noise}} \subset Z_{\text{train}} \). By removing or correcting \( Z_{\text{noise}} \), we get a new training set \( Z_{\text{clean}} \). Retraining \( M \) on \( Z_{\text{clean}} \) results in a new model \( M_{\text{clean}} \).

\( Z_{\text{test}} \) needs to be kept hidden until the testing phase to ensure the validity of our process, i.e., \( M_{\text{clean}} \) is expected to perform better on \( Z_{\text{test}} \) than \( M \) so \( Z_{\text{test}} \) must not be exposed during the noisy sample detection process. Therefore, we use the validation set \( Z_{\text{val}} \) as the anchor to detect noise. We use \( M \) to select from \( Z_{\text{val}} \) a set of correctly labeled samples. A sample is considered correct if the prediction from the model \( M \) match its label with high confidence. We call this set of correctly labeled samples \( Z_{\text{gold}} \).

Now, we describe the process to compute the influence score (IF) (Koh & Liang, 2017) to detect noise.\(^1\)

We want to know the influence of a sample \( Z_{\text{train}}(i) \) on the model \( M \). The brute-force approach is to remove \( Z_{\text{train}}(i) \) from \( Z_{\text{train}} \) to get a dataset \( Z_{\text{train}−i} \), train the model on this data set to get a model \( M(\cdot; \theta−i) \), and compute the influence of \( Z_{\text{train}}(i) \) as follows:

\[
S(Z_{\text{train}}(i), Z_{\text{gold}}) = \mathcal{L}(Z_{\text{gold}}; \theta−i) − \mathcal{L}(Z_{\text{gold}}; \theta)
\]  

(1)

where \( \mathcal{L} \) is the loss function, that takes in a dataset and the model \( M \). A negative score means the loss decreases if \( Z_{\text{train}}(i) \) is removed from the training set, i.e. \( Z_{\text{train}}(i) \) has a bad influence on the model \( M \). This brute-force algorithm is intractable for large datasets so (Koh & Liang, 2017) proposed the influence function to estimate this influence. The effect of removing \( Z_{\text{train}}(i) \) on \( Z_{\text{gold}}(j) \) is computed as:

\[
S_{IF}(Z_{\text{train}}(i), Z_{\text{gold}}(j)) = \left\langle \nabla_{\theta} \mathcal{L}(Z_{\text{gold}}(j); \theta), H^{-1} \nabla_{\theta} \mathcal{L}(Z_{\text{train}}(i); \theta) \right\rangle
\]  

(2)

where \( H \) is the Hessian of the loss function and \( \nabla_{\theta} \mathcal{L}(Z_{\text{gold}}(j); \theta) \) is the gradient of the loss at \( Z_{\text{gold}}(j) \) with respect to \( \theta \).

\(^1\)TracIn (Pruthi et al., 2020) follows the same principle. We do not present TracIn details in this work due to page constraints. Readers are encouraged to read the original paper to check the details of TracIn’s formula.
Towards Using Data-Centric Approach for Better Code Representation Learning

Table 1. Results on identifying the mislabeled samples. We take top $k\%$ samples with the lowest influence score and calculate the percentage of mislabeled samples in that set.

| Method       | POJ 104 | Devign |
|--------------|---------|--------|
|              | $k = 1$ | $k = 3$ | $k = 5$ | $k = 10$ | $k = 1$ | $k = 3$ | $k = 5$ | $k = 10$ |
| ASTNN        | IF      | 94.20 ± 3.72 | 90.36 ± 2.78 | 84.88 ± 2.26 | 59.71 ± 0.32 | - | - | - | - |
|              | TracIn  | 91.09 ± 5.06 | 86.20 ± 4.80 | 79.96 ± 1.29 | 55.97 ± 1.14 | - | - | - | - |
| CodeBERT     | IF      | 64.15 ± 1.07 | 29.25 ± 0.52 | 31.50 ± 1.28 | 14.92 ± 1.33 | 55.15 ± 3.86 | 43.34 ± 3.48 | 31.47 ± 1.39 | 22.77 ± 1.06 |
|              | TracIn  | 72.36 ± 2.39 | 57.31 ± 1.53 | 49.30 ± 1.33 | 35.36 ± 1.15 | 53.36 ± 5.77 | 35.90 ± 2.26 | 28.54 ± 1.00 | 21.39 ± 0.28 |
| BiLSTM       | IF      | 21.60 ± 2.80 | 19.19 ± 1.58 | 16.87 ± 0.90 | 14.21 ± 0.78 | 48.46 ± 5.68 | 32.98 ± 2.22 | 28.05 ± 1.16 | 21.89 ± 0.39 |
|              | TracIn  | 19.68 ± 0.87 | 15.86 ± 0.68 | 14.02 ± 0.92 | 11.17 ± 0.18 | 50.75 ± 2.00 | 33.40 ± 0.69 | 27.98 ± 1.20 | 21.76 ± 0.54 |

Figure 1. Evaluation Pipeline

A negative influence score $S_{IF}(Z_{train}^{(i)}, Z_{gold}^{(j)})$ shows that the angle between the gradients of $Z_{train}^{(i)}$ and $Z_{gold}^{(j)}$ is obtuse. Therefore, moving $\theta$ in the direction of $-\nabla_{\theta} L(Z_{train}^{(i)}; \theta)$ may increase the loss at $Z_{gold}^{(j)}$, which means that $Z_{train}^{(i)}$ is likely to be mislabeled.

4. Evaluation

To evaluate this problem on different methods in section 3, we consider two classification-based tasks: code classification and defect prediction. We first describe the original datasets and the source code models used for these classification-based tasks. Section 4.1 describes the workflow to generate synthetic data and section 4.2, 4.3 are our results.

Datasets: For code classification, we use the POJ 104 dataset (Mou et al., 2016b). This dataset consists of 52,000 C programs for 104 classes, each class will have 500 programs. For defect prediction, we use the Devign dataset (Zhou et al., 2019). Devign dataset includes 21,854 vulnerable C functions collected from open source projects, where the labels are manually labels by the software security experts. This task aims to determine whether a source code snippet that may cause vulnerability or not.

Source Code Models: The objective of this study is to demonstrate that the data-centric strategy can improve the performance of existing source code models, whether they are strong or weak. Here we present our choices that match with this goal.

1. Code classification: We choose ASTNN (Zhang et al., 2019), CodeBERT (Feng et al., 2020) and BiLSTM (Hochreiter & Schmidhuber, 1997). ASTNN is one of the state-of-the-art method that could achieve $\approx 98\%$ accuracy on POJ-104 dataset. CodeBERT (Feng et al., 2020) can perform moderately on this task as it could achieve $\approx 95\%$ according to our experiments.

2. Defect prediction: We follow CodeXGLUE benchmark to choose CodeBERT (Feng et al., 2020) and BiLSTM (Hochreiter & Schmidhuber, 1997). According to this benchmark, CodeBERT performs well while BiLSTM is usually chosen as one of the worst baseline for this task.

We take the public code artifacts from ASTNN ², CodeBERT ³ and BiLSTM to reproduce the results reported in the original work.

4.1. Evaluation Pipeline

It should be noted that our original datasets (POJ-104 and Devign) may or may not contain noisy data. We need datasets that contain “real” noisy data for evaluating methods. To address this issue, we present an evaluation pipeline for creating synthetic noisy data from original datasets and perform our evaluation on such pipeline. By this way, we can have a dataset that contains both clean and noisy data. Our goal is to develop a framework for identifying noisy samples from the training set of the chosen classification tasks utilizing data-influence methods. Figure 1 shows an

²https://github.com/zhangj111/astnn
³https://github.com/microsoft/CodeBERT
overview of our pipeline:

1. Initially, we have the original training set. To make it noisy, we randomly select a subset of $P\%$ of total samples of each class from such set. Then we change the label of these samples randomly. Now we have the training set $Z_{train}$ that contains both clean and noisy data.

2. We train the model on $Z_{train}$, result in model $M$. We use $M$ to randomly select $N$ correctly predicted samples from the validation set $Z_{val}$, resulting in $Z_{gold}$.

3. For each of the samples in training set $Z_{train}$, we compute the influence score with all samples in $Z_{gold}$. The score that represents for each training sample is:

$$S(Z_{train}^{(i)}, Z_{gold}) = \sum_{j=1}^{N} S(Z_{train}^{(i)}, Z_{gold}^{(j)})$$

4. The top $k\%$ samples with the lowest score, that is $Z_{noise}$, are determined to be noisy. We then remove or correct $Z_{noise}$ from $Z_{train}$ to create the new training set $Z_{clean}$. On $Z_{clean}$, the model is retrained from scratch using the same hyperparameters (including the same random initialization).

Our goal is to demonstrate the performance of data-influence methods in finding the mislabeled samples and the improve of the model’s performance after detecting noise. In our evaluation, we choose $P = 10\%$ and $N = 500$.

4.2. Results

In all experiments, we use accuracy score as the evaluation metric. We also run 3 different random seeds for random initialization and report the mean and standard deviation of accuracy in Table 1, 2, 3.

Table 1 shows the performance of IF and TracIn in identifying the noisy examples on the synthetic noisy data $Z_{train}$. In practice, we do not know how many percent of the samples in the dataset are noisy, so we choose different values of $k$. With ASTNN on POJ-104, both IF and TracIn can detect more than 55% noisy samples in top $k = 10\%$ samples with the lowest score, and when $k = 1\%$, such techniques can detect more than 91% noisy samples. On the other hand, the results of CodeBERT and BiLSTM on POJ-104 are lower for any $k$. Same phenomenon is applied to CodeBERT and BiLSTM on detecting noisy samples in Devign. This shows that the capability of the data-influence techniques also depends on the strength of source code models on a specific task. In general, the results in Table 1 support our hypothesis that data-influence methods are effective at detecting noise in code corpus.

Table 2 shows the performance after removing or correcting such noises detect in Table 1. Note that column Test ACC is the accuracy when training the model on the synthetic noisy dataset $Z_{train}$ and evaluate on the test dataset $Z_{test}$. We assume that $k\%$ samples detect in Table 1 are noisy (regardless if they are really noisy or not). Then, we do 2 separate steps to get the $Z_{clean}$. First, we remove the detected noisy samples. Second, instead of removing, we correct the detected noisy samples with the assumption that we know the correct labels. For the later, we can do this because we know the correct labels when making the training data become noisy. So in this case, $Z_{clean}$ has 2 versions, one is by removing the noise, and the other is by correcting the noise. Then we train the models on $Z_{clean}$ to get $M_{clean}$ and evaluate on $Z_{test}$. As shown in Table 2, we get some improvements in term of accuracy when correcting the noise for ASTNN on POJ-104 for any $k\%$, we also see the improvements when removing the noise. CodeBERT and BiLSTM produce identical results for code classification.
tion and defect prediction. In general, when removing or correcting noise, there is always an improvement in accuracy. This indicates that there is a strong probability of improvement when using data-influence techniques to detect noise.

4.3. Detect Noise In Practical Use Case

In the preceding section, we demonstrated that our method performs well with synthetically generated noisy data. Now we will evaluate our method in a more realistic scenario. We hypothesize that, between the two datasets POJ-104 and Devign, Devign may contain more "real noises” than POJ-104. The primary reason is that modern code classification techniques typically achieve greater than 95% accuracy on POJ-104, and ASTNN can even achieve 98% accuracy. With such remarkable performance, it is unlikely that POJ-104 contains any noises. Conversely, it is challenging to achieve good results on the Devign dataset. The SOTA techniques achieve only around 63% accuracy. We believe there is a high chance that this dataset contains noise that degrades performance (beside the other reason of model design). With such reason, we use Devign to demonstrate in this case with the assumption that Devign might contain noises and we attempt to detect noises in Devign.

We train the models on original Devign data with CodeBERT and BiLSTM and evaluate on the test data. Column Test ACC in table 3 shows the performance of the models that are trained on the original dataset. We then calculate the score for all training instances with the same procedure in our evaluation pipeline. After selecting $Z_{noise}$ that includes the top 1% samples with the lowest score, we remove or correct the label of $Z_{noise}$. Because this is a binary classification task, correcting the label in this case is trivial, i.e., change 0 to 1 and vice versa. After removing or correcting the noise, we retrain the models and evaluate on $Z_{test}$. The results are shown in table 3. We also include Random - a baseline randomly selecting a 1% sample set as $Z_{noise}$. When noises are removed, either for CodeBERT or BiLSTM, there are improvements in terms of ACC. This supports our hypothesis that the Devign dataset may contain noise, and that removing such noise will improve accuracy. However, the performance does not improve when correcting such noise, as shown in the column "correcting" in Table 3. In our future research, we will delve deeper into the causes of this phenomena.

| Method | Test ACC after removing noise | Test ACC after correcting noise |
|--------|-------------------------------|-------------------------------|
| IF     | 63.31 ± 0.10                 | 62.12 ± 0.92                 |
| TracIn | 63.40 ± 0.20                 | 62.67 ± 0.33                 |
| Random | 61.73 ± 0.05                 | 61.03 ± 0.10                 |
| IF     | 61.79 ± 0.49                 | 60.49 ± 1.39                 |
| TracIn | 62.13 ± 0.40                 | 61.40 ± 0.84                 |
| Random | 61.09 ± 0.22                 | 60.37 ± 0.14                 |

To begin, we mostly rely on synthetic noisy datasets to perform the evaluation. Further investigation of various datasets from various sub-domains is required to determine the limitations so that we can perform further analysis. Second, we only concentrate on classification-based tasks while we can do the same for many other tasks. For example, the dataset for the generation-based task, including code summarization, is typically collected by extracting the method body from code snippets collected on Github, and then extracting the comments of such methods. However, not all of the developers’ comments reflect the functionality of the given code snippet; this can also be interpreted as noise and should be carefully examined too. Third, the data-influence methods are mostly used for classification-based tasks, although there have been some attempts to extend them to other generation-based tasks in NLP. We need further improvement on these techniques to detect noisy data that can work on multiple types of tasks as well.

6. Conclusion

We present a novel data-centric perspective for enhancing the quality of source code models by using data-influence methods. Despite the fact that our results are preliminary for classification-based tasks, we have evidence that our methods will work in certain circumstances. In the future, we intend to pursue our research in three directions: (1) Identifying more noisy datasets to analyze and providing insights on the noises of such datasets; (2) Improving the methods to detect noisy data; and (3) Applying the methods to a broader range of software engineering tasks, such as code summarization, bug detection, and code translation.

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Towards Using Data-Centric Approach for Better Code Representation Learning

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Towards Using Data-Centric Approach for Better Code Representation Learning

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