WheaCha: A Method for Explaining the Predictions of Models of Code

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Attribution methods have emerged as a popular approach to interpreting model predictions based on the relevance of input features. Although the feature importance ranking can provide insights of how models arrive at a prediction from a raw input, they do not give a clear-cut definition of the key features models use for the prediction. In this paper, we present a new method, called WheaCha, for explaining the predictions of code models. Although WheaCha employs the same mechanism of tracing model predictions back to the input features, it differs from all existing attribution methods in crucial ways. Specifically, WheaCha divides an input program into “wheat” (i.e., the defining features that are the reason for which models predict the label that they predict) and the rest “chaff” for any prediction of a learned code model. We realize WheaCha in a tool, HuoYan, and use it to explain four prominent code models: code2vec, seq-GNN, GGNN, and CodeBERT. Results show (1) HuoYan is efficient — taking on average under twenty seconds to compute the wheat for an input program in an end-to-end fashion (i.e., including model prediction time); (2) the wheat that all models use to predict input programs is made of simple syntactic or even lexical properties (i.e., identifier names); (3) Based on wheat, we present a novel approach to explaining the predictions of code models through the lens of training data.

1 INTRODUCTION

Riding on the major breakthroughs in deep learning methods along with the ever-increasing public datasets and computation power, modern machine learning (ML) models, such as neural networks, have been increasingly applied to solve programming language tasks, and achieved remarkable success in a variety of problem domains: method name prediction [Alon et al. 2019a,b; Fernandes et al. 2019], program repair [Chen et al. 2019; Dinella et al. 2019], and program verification [Si et al. 2018; Yao et al. 2020]. Despite those accomplishments, neural networks mostly operate in a black-box manner, making it difficult to get insight into their internal mechanism of work. This lack of transparency has become an impediment to the use of learning-based program analysis tools, especially in security-critical settings (e.g., malware detection) as the degree to which their predictions can be trusted is rather unclear. From a scientific standpoint, improving the transparency of neural models is also essential to the soundness of science. Because their inability to provide explanations for their decisions not only weakens the validity but also hinders the openness of scientific discovery.

A Review of Attribution Methods. In the past few years, significant progress has been made in explaining the predictions of ML models. A prominent class of explainability techniques, called attribution methods, has sparked a lot of interest in the ML community. The idea is to assign an attribution score to each input feature w.r.t. a particular output of a network. In general, attribution methods can be classified into two categories: perturbation-based and backpropagation-based. The former refers to those that make perturbations to input features and observe the impact on later
neurons in the network. Zeiler et al. [2011] is a typical example in the image classification domain. In particular, it occludes different segments of an input image and visualizes the change in the activation of later layers. The strength of perturbation-based methods lies in their visibility, that is, one can directly visualize the marginal effect of any input feature via perturbation. Backpropagation-based methods exceed the perturbation-based in terms of efficiency. In particular, they can compute the attributions for all input features in a single forward and backward pass through the network.

As an early attempt, Simonyan et al. [2014] proposed using the gradient of the output w.r.t. pixels of an input image to compute a saliency map of the image. A key drawback of this approach is its inability to address the saturation problem, namely, gradients can be tiny at certain inputs that may yield significant activations within the network [Glorot and Bengio 2010; Shrikumar et al. 2017a]. Integrated Gradients [Sundararajan et al. 2017], a well-known explainability technique, offers a solution. Instead of computing the gradients at only the current value of the input, Sundararajan et al. [2017] propose to integrate the gradients as the inputs are scaled up from a pre-set starting value to their current value. We defer a detailed survey on the attribution methods to Section 5.

**Insights of WheaCha.** While the attribution methods can be readily applied to explain the predictions of learning-based program analysis tools, such as producing a ranking on the importance of different parts of the input program, they do not give a clear-cut definition of the critical features that models use for that prediction. Considering the ideal case in which there might exist a “sweet-spot” in the ranking that separates the critical features from the rest, then how to determine the “sweet-spot” is rather unclear. To address this shortcoming, this paper presents a new explanation method, WheaCha (Wheat and Chaff), for interpreting the predictions of models of code, a broad class of models that predict the properties of source code. Figure 1 shows one such task called method name prediction. We will use the program as our running example throughout the paper. Unlike the existing attribution methods that assign a relevance score to each input feature, WheaCha classifies an entire input into two kinds of features: the defining features, wheat, that are the reason models predict the label that they predict, and the remaining features, chaff. A natural question arises: how do we define wheat for an input program given a particular model prediction? Our insight is to observe how models react to a pair of complementary prediction samples derived from the original input. Technically, we formulate the following two constraints to quantify the influence of wheat. That is, the very same model must (1) preserve its prediction when the original input becomes wheat; and (2) change its prediction when the original input becomes chaff.

Below we illustrate these two constraints with our running example. Figure 2a shows that the expression, mItems.add(); alone preserves the prediction, addItem, seq-GNN makes for the original input, thus the first constraint is satisfied; Figure 2b shows that removing mItems.add(); from the input program changes seq-GNN’s prediction to retQueue, therefore the second constraint is also met. Compared to the existing attribution methods, WheaCha’s explanations allow end users to know precisely and definitively the features that models use for a prediction they make, and...
in turn evaluate the trustworthiness of the prediction more accurately. Considering the running example, WheaCha lets end users know exactly \( \text{mItems.add();} \); are the features seq-GNN uses to predict the label addItem, whereas, a ranking of the attribution score for each feature would have been vague (i.e., unclear how small an attribution score indicates feature irrelevance) and redundant (i.e., unnecessary to compare the attribution scores of features in the wheat, such as mItems vs. add, or those in chaff such as retQueue vs. log).

Using WheaCha’s explanations as the ground-truth, we find that the ranking produced by some of the most prominent attribution methods routinely underestimates the importance of wheat. Take seq-GNN’s prediction for the example program as an instance, Figure 3 shows that none of the top-five important tokens computed by Integrated Gradients [Sundararajan et al. 2017] is part of the wheat, the underlined expression in the program. This finding rebuts the aforementioned “sweet-spot” hypothesis, and confirms that existing attribution methods are unsuitable for wheat detection.

Identifying the wheat from an input program is a challenging task. With a token-based representation, a program composed of \( n \) tokens will yield a search space of \( 2^n \) candidates (i.e., every token may or may not be part of the wheat). Even after taking into account the syntactic and semantic constraints, the search space will not shrink dramatically. As a result, a brute-force search would be computationally intractable for any non-trivial program.

Our solution is based on the finding from Rabin et al. [2021a] — few simple code edits, albeit preserving the property of interest for input programs, frequently cause models to alter their predictions — we hypothesize that models heavily utilize small, local program features for predictions. To confirm our hypothesis, we conduct a preliminary study in which we test how models respond to new programs obtained via systematic reduction of the input programs. Quite surprisingly, we find that almost always an input program can be reduced to very few statements (i.e., \( \leq 3 \)) for which models make the same prediction as they do for the original program. This observation

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1 The reason that wheat does not compile is that seq-GNN, like most code models, does not require input programs to compile. In fact, WheaCha is general, capable of explaining models with or without compilation requirements.
indicates that a small code fragment may already contain the *wheat* that models need for making the correct prediction. Therefore, a more efficient approach is to first detect such code fragments, and then locate the *wheat* within them. At the technical level, we present “*Reduce and Mutate*”, a coarse-to-fine method for identifying the *wheat* that code models use for prediction. Given a program $P$ for which a model $M$ makes a prediction. First, we find a global minimum program $\bar{P}$ for $P$ that satisfies the first two above-mentioned constraints (*coarse-grained* search). Second, we mutate the expressions in $\bar{P}$’s statements to pinpoint the program properties $\tilde{P}$ that led to the satisfaction of the two constraints (*fine-grained* search). Although it looks like, at this point, we have found the *wheat* $\tilde{P}$ that $M$ uses to predict $P$, a core issue must be resolved: are $M$’s predictions for all intermediate programs that WheaCha uses to query $M$ (e.g., $\bar{P}$, $\tilde{P}$, etc.) still valid given the seemingly distribution shift between intermediate programs and original programs on which $M$ is trained (e.g., $P$). Inspired by ROAR [Hooker et al. 2019], we present a similar approach to tackle the potential out-of-distribution issue. The key idea is to retrain $M$ with additional data that resembles the intermediate programs. If WheaCha finds the same *wheat* $\tilde{P}$ — which are now clearly in distribution thanks to the retraining of $M$ — that retrained $M$ uses to predict $P$, we have confirmed that $\tilde{P}$ is indeed the *wheat* of $P$ that $M$ uses for prediction.

We realize our approach in a tool, called HuoYan, and use it to evaluate four pioneering code models: code2vec [Alon et al. 2019b], seq-GNN [Fernandes et al. 2019], GGNN [Allamanis et al. 2018], CodeBERT [Feng et al. 2020]. We choose them not only because they are prominent representatives of models of code, but more importantly, they reflect a wide variety of both model architectures and downstream tasks so that the effectiveness and generality of HuoYan can be thoroughly tested. Our evaluation results show (1) first, HuoYan is efficient — taking on average less than twenty seconds to compute the *wheat* for each evaluated model; (2) the *wheat* that all evaluated models use for prediction are simple as they never exceed fifteen tokens, many times down to the name of a single variable; (3) After training models on programs coming from a similar distribution to those with which WheaCha queried the models before, WheaCha almost always finds the same *wheat* that original and retrained models use for prediction. This is strong evidence that WheaCha’s approach is valid in light of the out-of-distribution issues; (4) Integrated Gradients and SHAP [Lundberg and Lee 2017], two among the most well-known attribution methods, do not precisely identify the *wheat* because those they assign higher scores frequently miss out on the *wheat*.

As an example use of *wheat*, we present a novel approach to explaining the predictions of code models. At the high-level, our approach answers a more fundamental question: which programs in the training set are most responsible for a model prediction? Ultimately, the weights of a model are derived from the training data. Hence our approach identifies the root cause for a prediction rather than interpreting the internal states of a model after its weights have been learned. At the technical level, given an unseen program $P$ for which a model $M$ predicts a label $L$, we rank $M$’s training programs with the label $L$ based on their distance to $P$, measured using their respective feature properties, and then present the top-$k$ closest programs as the explanations for the prediction $M$ made for $P$.

This paper makes the following contributions:

- A method for explaining predictions of models of code.
- A definition of the defining features (*i.e.*, *wheat*), the reason for which code models predict the label that they predict.
- A method for identifying the *wheat* that code models use for predictions.
- An implementation, HuoYan, which we use to evaluate code2vec, seq-GNN, GGNN, and CodeBERT. Results show that (1) HuoYan is efficient: taking on average less than twenty seconds to compute the *wheat*; (2) all models use simple syntactic or even lexical properties
We consider a machine learning model \( M \) from such that (1) \( \tilde{P} \) is a constituent of \( P \); \( \tilde{P} \)'s token sequence, denoted by \((t^P_m)_{m \in \mathbb{N}}\), is a subsequence of \( P \)'s denoted by \((t^P_m)_{m \in \mathbb{N}}\). Formally, \((t^P_m)_{m \in \mathbb{N}} = (t^P_m)_{k \in \mathbb{N}}\) where \((m_k)_{k \in \mathbb{N}}\) is a strictly increasing sequence of positive integers. (2) \( \tilde{P} \) is sufficient: \( M \) makes the same prediction for \( \tilde{P} \) as it does for \( P \) (i.e., \( \|M\| (P) = \|M\| (\tilde{P}) = L \)); (3) \( \tilde{P} \) is necessary: \( M \) makes a different prediction for \( P \setminus \tilde{P} \) than it does for \( P \) (i.e., \( \|M\| (P \setminus \tilde{P}) \neq \|M\| (P) \)) where \( P \setminus \tilde{P} \) denotes the operation that subtracts program \( \tilde{P} \) from \( P \) (Definition 2.2). Finally (4) \( \tilde{P} \) is minimum: there does not exist \( \tilde{P}' \) such that \( \tilde{P}' \) satisfies the above three requirements, and \(|\tilde{P}'| < |\tilde{P}| \) where \(|\cdot|\) denotes the length of a sequence.

Here we discuss the intuition behind Definition 2.1. First, the constituent requirement captures an obvious intuition, that is, the wheat must be part of an input program. Second, the sufficient requirement is also quite intuitive — as the wheat, they must single-handedly lead models to predict the same label as before without the rest of the input. However, the satisfaction of sufficient requirement alone does not suffice features to be the wheat. Consider the following example in Figure 4. Even though Figure 4a shows the statement, \log("Add item;")\,; manages to preserve the prediction, \texttt{addItem}, the model makes for the original input (i.e., the sufficient requirement is satisfied), it is not the reason for which seq-GNN makes this prediction because removing it from the input program barely influences seq-GNN. As displayed in Figure 4b, the probabilities at which seq-GNN predicts the top-five labels remain almost unchanged. Clearly, this prediction result suggests that seq-GNN does not even need \log("Add item;")\; let alone use it as the wheat to predict the example program. This is precisely the reason that Rabin et al. [2021b], which seeks exclusively the sufficient features as model interpretations, is flawed. In fact, our large-scale study shows that removing the features discovered by Rabin et al. [2021b] from input programs always never makes models alter their original predictions.

To address this issue, we design the necessary requirement: the removal of the wheat from the input program, which we call the subtraction operation (Definition 2.2), must lead models to predict different labels than they did for the original input.

**Definition 2.2. (Subtraction)** Given a program \( P \) and a set of statements \( \tilde{P} \), \( P \setminus \tilde{P} \) means for each statement \( S \) in \( \tilde{P} \), first locate the subtree, which is equivalent to the Abstract Syntax Tree (AST) of \( S \), from the AST of \( P \); then remove the located subtree from the AST of \( P \). Finally, serialize the resultant AST back to source code.
(a) A statement that satisfies the **sufficient** requirement.

```c
void addItem(int position) {
    log("Add item;");
}
```

(b) The same statement does not satisfy the **necessary** requirement.

```c
void addItem(int position) {
    List<Obj> mItems = retQueue();
    if (position > mItems.size())
        return;
    mItems.add(position, genItem());
    notifyItemInserted(position);
    log("Add item;");
}
```

Fig. 4. A statement that satisfies the **sufficient** but not **necessary** requirement.

Using only the **constituent**, **sufficient**, and **necessary** requirement, every input program is the **wheat** for itself — an uninteresting explanation for any model prediction. To address this issue, we impose the last constraint to ensure the precision of **wheat**. Specifically, we argue that $\tilde{P}$ should be the globally minimum sequence of tokens since it’s the most precise — covering the pattern that models have learned with the least amount of features (**i.e.** having the highest signal-to-noise ratio).

Given Definition 2.1, it is obvious that the **wheat** always exists for any input program for which models make a prediction. We left the proof to the supplemental material.

**Theorem 2.1** (Existence of Wheat). Given a prediction $L$ that $M$ makes for an input program $P$, the **wheat** $\tilde{P}$ that models use to predict the label of $P$ always exists.

### 3 METHODOLOGY

In this section, we first briefly describe a crucial weakness of models of code, which motivates a key idea of finding the **wheat**. Then, we give a detailed presentation of **Reduce** and **Mutate**, a simple yet efficient method for identifying the defining features. Next, we address the out-of-distribution issues, a potential validity concern about WheaCha’s approach. Finally, we present an application of the **wheat**.

#### 3.1 Background

While deep neural networks have been gaining increasing levels of interest in programming languages research, Rabin et al. [2021a] cautioned that some eminent code models are surprisingly unstable with their predictions. Simple, natural, and semantically-preserving transformations frequently cause models to alter their predictions. Here we use an example to demonstrate their finding. Figure 5a depicts the original method which is correctly predicted by code2vec to be factorial; Figure 5b depicts the transformed method, albeit semantically equivalent, is totally mishandled. None of the top-five predictions even remotely resemble the ground truth considering that all we changed is the order of the operands in a multiplication expression.

**Applicability of Delta Debugging.** Their finding suggests that models don’t evenly distribute their attention across the entire structure of input programs; instead, they focus on a small fragment of code. At first glance, Delta Debugging (DD) [Zeller and Hildebrandt 2002] seems to be a perfect approach to finding such code fragment from input programs. In particular, we can apply DD to remove the irrelevant code in reference to the **sufficient** and **necessary** requirement. It is worth mentioning a property that has to be satisfied in order for DD to be applicable is **Monotony** (Definition 6 in Zeller [1999]), meaning, in the software debugging setting, whenever an input causes a program to fail a test, others that include this input will also cause the program to
int f(int n) {  
if (n == 0)  
  return 1;  
else  
  return n * f(n - 1);  
}

(a) Prediction for the original method.

int f(int n) {  
if (n == 0)  
  return 1;  
else  
  return f(n - 1) * n;  
}

(b) Prediction for the transformed method.

Fig. 5. A simple, natural, semantically-preserving transformation causes code2vec to change its prediction.

Note that the probability of the top-one prediction is even higher on the transformed method.

fail. This property is crucial because it allows DD to remove partitions of the input that are unrelated to the cause of the failure. As a result, the search space still shrinks even when the failure-inducing faults can not be precisely located from the input. Conversely, without the monotony property, an irrelevant partition may not be removed from the input because its complement, albeit including the failure-inducing faults, can still have the program pass the test. We can easily redefine monotony in our settings to be whenever p satisfies both the sufficient and necessary requirement, then every super-sequence of p satisfies the two requirements as well, formally,

∀p ≤ P (M(p) = L ∩ M(P \ p) ≠ L ∧ p ≤ p′) ⇒ M(p′) = L ∩ M(P \ p′) ≠ L

where p ≤ P denotes p is a sub-sequence of P. It is rather clear that machine learning models do not guarantee to satisfy this property. Below, we use the running example to demonstrate seq-GNN’s non-satisfaction of the monotony property (Table 1), and in turn the ramifications of applying DD for wheat detection.

We skip the steps in which DD successfully reduces the example into the code fragment consisting of size(); return; and mItems.add(position). Since then DD can not make further reductions even though the fragment is clearly not the wheat. In fact, DD had an opportunity to remove either the statement size(); (at Step 6), the statement return; (at Step 7), or the parameter position (at Step 10) had the model satisfied the sufficient and necessary requirement and allowed DD to proceed. However, since predictions of seq-GNN are not monotonic, the resultant programs at all three steps turn out to violate the sufficient requirement. As a result,

Table 1. Reducing the running example using DD. Δ_i denotes partitions and ∇_i is the complement of Δ_i.
For simplicity, we use tokens to represent programs that are tested against the sufficient and necessary requirement at each step. The last column shows the requirement that partitions do not satisfy.

| Step | Partition | Tokens | Unsatisfied |
|------|-----------|--------|-------------|
| 1    | Δ_1       | size   | Both        |
| 2    | Δ_2       | return | Both        |
| 3    | Δ_3       | mItems | Both        |
| 4    | Δ_4       | add    | Both        |
| 5    | Δ_5       | position | Both      |
| 6    | ∇_1       | ✓      | ✓           |
| 7    | ∇_2       | ✓      | ✓           |
| 8    | ∇_3       | ✓      | ✓           |
| 9    | ∇_4       | ✓      | ✓           |
| 10   | ∇_5       | ✓      | ✓           |

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DD gets stalled and the final output is not minimal. For interested readers, we left DD’s complete procedure in reducing the example program to Section C in the supplemental material.

Although refining DD to deal with non-monotony subjects is a pathway forward, it is out of the scope of this work. Instead, we present a simple, efficient search strategy that first aggressively prunes the search space of the wheat (i.e., the goal of Reduce), and then precisely locate its constituent program properties from the remaining code fragment (i.e., the goal of Mutate).

3.2 Reduce

Because fragments that contain the wheat are usually small, the search can be made very efficient by testing out smaller code fragments first. Figure 6 illustrates the high-level steps of Reduce on the running example.

First, we flatten the input method into a list of statements (Step ①). We then traverse the fragments (i.e., combination of statements) in the ascending order of their size, starting with those that contain only one statement. We pick Stmt 1: List<Obj> mItems = retQueue(); as the first statement to check against the sufficient and necessary requirement. As depicted in Step ②, seq-GNN makes a different prediction for this statement 2, thus, the sufficient requirement is not met. We move on to the other statements. As shown at Step ③, Stmt. 2 also does not satisfy the sufficient requirement. We omit Stmt. 3 for its non-satisfaction of the sufficient requirement either. Next, we arrive at Stmt. 4: mItems.add(position, genItem());. In particular, we find that Stmt. 4 satisfies the sufficient requirement at Step ④ and necessary requirement at Step ⑤, we declare Stmt. 4 to be the fragment that contains the wheat. To avoid missing other candidates, we continue the traversal until reaching the last statement Stmt. 7 log("Add item;");, which violates the necessary requirement. Because future fragments to be explored will be non-minimum compared to Stmt. 4, the Reduce step completes with the lone output of Stmt. 4.

Algorithm 1 gives the details of the Reduce step. The goal of the Flatten function is to reduce an input program into a list of statements (line 2). The for loop at line 3 gradually increases the size of the subsets drawn from the Flatten function (line 2) while searching for the minimum code fragments. The CombineKStmt function at line 4 creates subsets of statements with size k.

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2To facilitate readers’ understanding, we highlight the predicted label within the shadowbox at each step in Figure 6 and 7.
**Algorithm 1** Find the minimum fragment of code.

1: procedure \textsc{FindMinimumFragment}(\textit{program, model})
2: statements $\leftarrow \text{Flatten}(\textit{program})$  
   $\triangleright$ traversing all subsets in the ascending of the
   cardinality; ‘-1’ excludes the entire set.
3: \textbf{for} \texttt{k} $\leftarrow$ 1 \textbf{to} statements.size - 1 \textbf{do}
   $\triangleright$ getting combinations of size \texttt{k}
4: \texttt{sets} $\leftarrow \text{CombineKStmt}(\texttt{statements, k})$
5: \texttt{fragments} $\leftarrow \emptyset$
6: \textbf{foreach} \texttt{set} $\in$ \texttt{sets} \textbf{do}
7: \quad \texttt{suff\_mth, nec\_mth} $\leftarrow \text{Reconstruct}(\texttt{set, program})$
8: \quad \textbf{if} \texttt{VerifyCodeFragment}(\texttt{suff\_mth, nec\_mth, model}) \textbf{then}
9: \quad \texttt{fragments} $\leftarrow \texttt{fragments} \cup \texttt{set}$
10: \quad \textbf{end if}
11: \textbf{end foreach}
12: \textbf{if} \texttt{fragments} $\neq \emptyset$ \textbf{then}
13: \quad \textbf{return} \texttt{fragments}
14: \textbf{end if}
15: \textbf{end for}
16: \textbf{end procedure}

programs: one for verifying against the \textit{sufficient} requirement (\textit{i.e.}, \texttt{suff\_mth}) and the other for verifying against the \textit{necessary} requirement (\textit{i.e.}, \texttt{nec\_mth}). In particular, \texttt{suff\_mth} is simply the current subset being explored, whereas \texttt{nec\_mth} is resulted from the subtraction of \texttt{suff\_mth} from \texttt{program} (Definition 2.2). Once the created subset is found out to be valid by \texttt{VerifyCodeFragment} function (line 8), we add it to the collection of all minimum subsets \texttt{fragments} (line 9). After we have traversed all combinations of \texttt{k} statements, we return \texttt{fragments} if it’s not an empty set (line 13), otherwise, we will continue to explore the code fragments with the size of \texttt{k+1}.

**Reduce vs. DD Regarding Non-monotony.** Since the code fragments that \textit{Reduce} identifies also include extra code that is irrelevant to the \textit{wheat}, \textit{Reduce} is affected by models’ non-monotony, the same way DD is affected. However, the degree to which non-monotony impacts \textit{Reduce} is in general less than that impacts DD. This is because the extra features included always stem from the same statement where the \textit{wheat} is, as a result, models, by and large, still behave monotonically (\textit{e.g.}, \texttt{seq-GNN} makes the same prediction for \texttt{mItems.add(position, genItem());} and \texttt{mItems.add()}). On the contrary, what DD encounters is that the extra code included along with the \textit{wheat} is significantly less constrained (\textit{i.e.}, it can be any statement or expression in the program) and come in larger quantities, making models far more likely to be non-monotonic.

### 3.3 Mutate

The features discovered in the \textit{Reduce} step lie at the level of statements (\textit{i.e.}, coarse-grained), thus they are likely to contain redundant elements. To pinpoint the fine-grained \textit{wheat}, we mutate the program discovered in the \textit{Reduce} step in an attempt to identify the minimal features that keep the \textit{sufficient} and \textit{necessary} requirement satisfied.

Since the number of tokens in the \textit{wheat} is not guaranteed to be so small as that of the statements in the minimum code fragment, the style of search adopted by the \textit{Reduce} step is likely to be
inefficient for the Mutate step. For this reason, we only remove the irrelevant part of the code fragment that does not cause the violation of either the sufficient or necessary requirement.

**Mutation as well as Reduction.** It is worth mentioning that a significant difference between the two steps is Mutate does not adopt solely a program reduction approach to identifying the fine-grained wheat. As an example, suppose a code fragment is already successfully reduced to a field access expression, `foo.bar`. We then attempt to further reduce the expression into a single identifier `foo`. If `foo` turns out to be invalid, we will mutate `foo` back into a field access expression, this time with an out-of-vocabulary field name instead of `bar` — `foo.oov`. Our rational is, even if `foo.bar` satisfies both the sufficient and necessary requirement, it is still possible that models use the type of the syntactic structure — field access expression — associated with the object `foo` rather than the specific name of its field — `bar` — as the wheat. To deal with features of this kind that are not explicitly presented, we mix the deletion and modification operations in the Mutate step to pinpoint both the explicit and implicit fine-grained features.

Figure 7 illustrates the procedure of the Mutate step. As depicted in Step ① and ②, it turns out that neither removing `mItems` nor mutating `mItems` into `oov` satisfies the sufficient requirement. Similarly, we find that the identifier `add` is also integral to seq-GNN’s prediction that can not be changed. Next, we move our attention to the first parameter position. It turns out that `mItems.add(genItem());` satisfies both the sufficient (Step ③) and necessary (Step ④) requirement, thus, we remove position from the code fragment. Regarding the subtraction operation (Definition 2.2) invoked for checking code against the necessary requirement, directly removing a subtree from an entire AST may result in dangling nodes that do not connect to any other node in the AST (e.g., the identifier position marked in dashed box in Figure 8c after we remove the AST of `mItems.add(genItem());` from that of the original program). In such cases, we simply connect the dangling nodes to the parent node of the root node for the deleted AST (e.g., connecting position to the method body as depicted in Figure 8d). Figure 8 gives a detailed illustration of this procedure. Subsequently, we succeed in removing the second parameter `genItem()` because `mItems.add();` also satisfies the sufficient (Step ⑤) as well as the necessary requirement (Step ⑥). Note that the comma that separates the two then parameters position and `getItem()` becomes a semicolon at Step ⑥ because both position and `genItem()` will be considered as standalone statements in the resultant program of the subtraction

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3 out-of-vocabulary words are those models have never encountered during training. Thus, replacing a token with an out-of-vocabulary word erases the influence of the replaced name on models. Throughout the paper, we use **Oov** to represent out-of-vocabulary words for simplicity and clarity.
Fig. 8. A illustration of the four-step process of subtracting `mItems.add(genItem);` from the original program. (1) Figure (a) presents the AST of the running example, and the AST of `mItems.add(genItem);` in the bottom left corner. For brevity, the ASTs are simplified. (2) Figure (b) highlights the overlapping nodes between the two ASTs. (3) Figure (c) emphasizes the resultant AST after the overlapping nodes are removed, as a result, `position` becomes a dangling node. (4) Figure (d) connects `position` to the body of the method as the completion of the subtraction operation.

of `mItems.add()` (Figure 14 in the supplemental material gives a detailed illustration). Finally, we conclude that `mItems.add()` is the *wheat* that seq-GNN uses for predicting the running example.

Algorithm 2 gives the details about how to pinpoint the *wheat* within the minimum code fragment discovered by the *Reduce* step. Technically, we perform a postorder traversal on the AST (line 4) of the minimum fragments. For each node operation in the AST, we consider the following two cases. If a node does not have any child node, then we first try deleting the node (line 22). If the resultant program no longer satisfies both the *sufficient* and *necessary* requirement, we will mutate the node into one with an out-of-vocabulary value (line 23). If a node has children nodes, it will be kept intact to preserve the status of its children (the if condition at line 21 will be evaluated to `false`). If by any chance a node happens to be irremovable (resp., immutable), we simply skip the deletion (resp., mutation) operation. This entire process is repeated until the AST of the code fragment can not be reduced any further (line 18 to 20). Considering some expressions, which can not be removed or mutated before, may become removable or mutable after others are dealt with first, thus, we compute a fixed point on the result of the *Mutate* function to make certain the final output will be minimal. (lines 12 to 15).

**Minimality** Although the result of Algorithm 2 may not satisfy the *minimum* requirement in Definition 2.1, it satisfies 1-minimality, or more precisely 1-tree-minimality [Misherghi and Su

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4Interested readers may refer to Section E in the supplemental material for the details of `DeleteNode` and `MutateNode` in Algorithm 2.
Algorithm 2 Find the wheat.

1: procedure FindFeatures(fragments, program, model)
2: \textproc{min\_root} \leftarrow \textproc{Parse}(program).\textproc{root}  \quad \triangleright \textproc{min\_root} is defined to track the minimal features
3: \textproc{fragments} is a list of the minimum fragments returned from the \textproc{Reduce} step
4: \textbf{foreach} \textproc{min\_mth} \in \textproc{fragments} \textbf{do}
5: \quad \textproc{root} \leftarrow \textproc{Parse}(\textproc{min\_mth}).\textproc{root}
6: \quad \textproc{MutateToFixpoint}(\textproc{root}, program, model)
7: \quad \textproc{min\_root} \leftarrow \textproc{Min}(\textproc{root}, \textproc{min\_root})  \quad \triangleright \textproc{return the minimum of two code features}
8: \textbf{end foreach}
9: \textbf{return} \textproc{min\_root}
10: \textbf{end procedure}

11: \textbf{function} MutateToFixpoint(root, program, model)
12: \quad \textproc{last\_root} \leftarrow \emptyset
13: \quad \textbf{while} \textproc{last\_root} \neq \textproc{root} \textbf{do}
14: \quad \quad \textproc{last\_root} \leftarrow \textproc{root}
15: \quad \quad \textproc{Mutate}(\textproc{root}, \textproc{root}, program, model)
16: \quad \textbf{end while}
17: \textbf{end function}

18: \textbf{function} Mutate(node, root, program, model)
19: \quad \textbf{foreach} child \in node.children \textbf{do}
20: \quad \quad \textproc{Mutate}(child, root, program, model)
21: \quad \end foreach
22: \quad \textbf{if} node.children.size == 0 \textbf{then}
23: \quad \quad \textbf{if not} \textproc{DeleteNode}(node, root, program, model) \textbf{then}  \quad \triangleright \textproc{removing node}
24: \quad \quad \quad \textproc{MutateNode}(node, root, program, model)
25: \quad \quad \textbf{end if}
26: \quad \textbf{end if}
27: \textbf{end function}

2006\] that DD no longer satisfies due to the non-monotony of machine learning models. In addition, we show in Section 4.5 that even without the guarantees in theory, \textproc{Reduce} and \textproc{Mutate} is in fact remarkably effective in finding the global minimum features in practice.

\textbf{Compilability} We can easily adjust \textproc{Reduce} and \textproc{Mutate} to accommodate code models that do require input programs to compile. For example, we can filter out uncompilable code with the help of existing compilers in both steps and only use those that compile to query the model.

\subsection{3.4 The Validity of WheaCha’s Approach in Light of the Out-of-distribution Issues}

Since the programs that WheaCha queries a model with at both \textproc{Reduce} and \textproc{Mutate} step differ from those that the model has seen in training, it seems that WheaCha violates one of the key assumptions in machine learning: the training and evaluation data come from the same distribution, in which case the predictions that the model makes for the query programs will be unsound, and the validity of WheaCha’s approach will be called into serious question. To address this issue, we draw from a seminal work in explainable ML, ROAR [Hooker et al. 2019], which proposes a
retraining approach for handling the distribution shift when evaluating the explainability methods. Their insight is that a commonly used strategy in estimating the feature importance — removing the supposedly informative features from the input and observing how the classifier degrades — comes at a significant drawback because a performance degradation might be caused by a shift in distribution instead of removal of information. In contrast, Hooker et al. [2019] first retrains the model on the modified data (e.g., in image classification domain, they replace the fraction of the pixels estimated to be most important by an attribution method with a fixed uninformative value for each training image) and then evaluates on test images, which are modified in the same manner, if a feature estimator can identify the important input pixels whose subsequent removal causes the sharpest degradation in accuracy. Since retraining makes certain that training and test data comes from a similar distribution, the removal of important features becomes the only plausible explanation for accuracy degradation. On the other hand, ROAR is not without limitations. For one, while the architecture is the same, the model used during evaluation is not the same as the model on which the feature importance estimates were originally obtained.

Inspired by Hooker et al. [2019]’s approach, we design a similar retraining procedure that not only tackles the out-of-distribution issue but also addresses the inherent limitation of ROAR. Denoting the model by $M$, its training set by $P$ and test set by $Q$, we describe the steps of our approach:

1. for each program $P \in P$, we perform Reduce and Mutate to generate new programs $P'$ — what WheaCha would have queried the model with for finding the wheat of $P$.
2. we manually label each program $P \in P$ before training $M$ on $P \cup P'$.
3. we deploy WheaCha to find the wheat that retrained $M$ uses to predict each program $Q \in Q$.
4. we compare the wheat that WheaCha finds for each program $Q \in Q$ before and after the retraining of $M$.

Using the wheat produced by step (3), albeit no longer out-of-distribution, creates the same problem: WheaCha is essentially explaining the predictions of the retrained model rather than the original model. Instead, we check the equivalence of the two sets of wheat at step (4), if they turn out to be identical, we declare that the wheat WheaCha finds for each test program $Q$ are indeed the wheat that $M$ uses for prediction; furthermore, the consistency between the two sets of wheat also indicates the retraining procedure does not fundamentally change the model behavior, therefore, WheaCha can explain predictions of a model in its original form (without retraining).

### 3.5 An Application of The Wheat

We utilize the revealed features code models use to explain their predictions. The idea is as follows. Given a Model $M$, and a program $P$ from $M$’s test set for which $M$ predicts $L$. First, we discover the wheat $M$ uses to predict $L$; Second, we do the same thing for all programs in $M$’s training set with the label $L$. Note that in a generative setting (e.g., code2vec, seq-GNN) where training set might not contain a method of label $L$, we consider all methods whose name is a subset of the words in $L$. Finally, we rank these training programs based on the distance between their and $P$’s revealed features. Our rationale is to find the training programs from which models extracted the wheat at the first place. Thus, our method explains the root cause of a prediction rather than interprets the internal state of models.

### 4 EVALUATION

We realize our method Reduce and Mutate in a tool, called HuoYan, which extracts the wheat that code models use for prediction. In this evaluation, we first deploy HuoYan to explain several prominent code models. Then we examine the validity of WheaCha’s approach. Next, we evaluate
if attribution methods can find the wheat that HuoYan finds. Finally, we evaluate the effectiveness of our wheat-based explanation to code models.

4.1 Evaluation Subjects

Models. We choose code2vec [Alon et al. 2019b] because it is among the first to predict method names in large-scale, cross-project settings. We choose seq-GNN since it’s the state-of-the-art model in method name prediction. GGNN [Allamanis et al. 2018] is selected because it is the first graph model applied in the programming domain for variable misuses detection. We also include CodeBERT [Feng et al. 2020], a bimodal pre-trained model for programming language and natural language. It achieves state-of-the-art performance on both natural language code search and code documentation generation, the latter of which is used in this evaluation.

Datasets. For all models except code2vec, we use the datasets on which they are evaluated when they are first proposed. That is Java-small for seq-GNN; a dataset of 2.9 million lines of real-world C# code for GGNN; and CodeSearchNet [Husain et al. 2019] for CodeBERT. To keep our engineering effort manageable, we only use Java programs in CodeSearchNet (496,688 in total), which should be sufficient for validating HuoYan’s effectiveness. Since Java-med, and Java-large share similar characteristics with Java-small except for their bigger size, and code2vec and seq-GNN target the same downstream tasks, we use Java-small, Java-med, and Java-large to evaluate both models. We have re-trained all models using their implementations open-sourced on GitHub. The performance of all re-trained models is either comparable or superior to the original (Table 11-13 in the supplemental material). Note that we only use programs in test sets as the evaluation subjects in case models over-fit to training sets.

Baseline. We use DD as a baseline method; in particular, we apply DD to remove code that is irrelevant to a prediction (determined by the sufficient or necessary requirement). In the end, we declare the program that can not be further removed as the wheat.

4.2 Performance of HuoYan

We evaluate the performance of WheaCha by the time HuoYan spends generating explanations end-to-end (i.e., including the time models spend on prediction). The results show that the two methods are neck and neck in practice even though DD is more efficient than HuoYan in terms of the worst-case complexity (i.e., quadratic time vs. exponential time). This is due to the size of the minimum code fragment HuoYan finds, which never exceeds three statements for over a million programs used in the evaluation. Furthermore, since the minimal fragment of three statements rarely occurs, DD would not display a significant upgrade. To conclude, HuoYan is efficient: taking on average less than twenty seconds to compute the wheat.

4.3 Makeup of the Wheat

Finding the Wheat We follow Algorithm 1 and 2 to identify the minimum code fragments and pinpoint the fine-grained features within these fragments. Table 3 gives the average number of
tokens the *wheat* is composed of. Overall, we find that none of the *wheat* that any evaluated model uses for prediction exceed fifteen tokens. This result indicates that existing code models use simple program properties for prediction. Additionally, the *wheat* generated with those properties, albeit not guaranteed to be the global minimum, still help end users to know the *wheat* that models use for predictions. Table 3 also gives a comprehensive, head-to-head comparison between HuoYan and DD. Clearly, HuoYan is better across the board. A deeper analysis reveals that for less than 9% of all test programs, DD manages to find the same *wheat* as HuoYan, while HuoYan finds smaller *wheat* for the remaining over 91%. In other words, DD never finds smaller *wheat* than HuoYan. This is a concrete piece of evidence that the degree to which non-monotony impacts HuoYan is significantly less than that impacts DD.

Fig. 9. Lexical *wheat*. Top (resp., bottom) figures are the original methods (resp., *wheat*).

Fig. 10. Syntactic *wheat*.

| Methods | code2vec | seq-GNN | GGNN | CodeBERT |
|---------|----------|--------|------|----------|
|         | Java-small | Java-med | Java-large | Java-small | Java-med | Java-large | C# Datasets | CodeSearchNet |
| Baseline | 14.21 | 17.13 | 16.24 | 12.30 | 14.84 | 10.04 | 14.22 | 13.63 |
| HuoYan   | 8.53 | 9.91 | 9.58 | 6.74 | 6.79 | 5.66 | 6.81 | 6.78 |

**Investigating the Substance of the Wheat.** We classify the *wheat* into three categories according to their constituent program properties: lexical, syntactic, and semantic.

- **Lexical:** If each statement in the *wheat* consists of a single identifier. Figure 9 depicts two examples, in both cases, the *wheat* consist of only one identifier.
- **Syntactic:** If there is at least one statement in the *wheat* composed of a syntactic expression (Figure 10).
- **Semantic:** seq-GNN and GGNN are the two models which take in semantic properties as model inputs. In particular, they use nine kinds of manually designed edges (described in Section G of
### Fig. 11. Semantic wheat. The bottom figure shows the AST of the wheat, in which dash arrows denote the semantic edges. For clarity, the AST is simplified.

the supplemental material), out of which seven can be deemed as semantic in nature, to enrich the original AST of input programs. Therefore, we define the wheat to be semantic if its AST is augmented with at least one semantic edge. Take the method `compare` in Figure 11 as an example, the three semantic edges — one `LastWrite` edge and two `ComputeFrom` edges — must be present in the AST of the wheat, otherwise the *sufficient* and *necessary* requirement are no longer satisfied at the same time. Thus, we classify this example as semantic. To determine whether seq-GNN and GGNN used semantic properties in their wheat, we first run Reduce and Mutate as usual, then we remove all semantic edges from the augmented AST of the obtained wheat. If the resulted tree no longer satisfies both the *sufficient* and *necessary* requirement, we categorize the wheat to be semantic.

Table 4 gives detailed statistics on the classification for each model. Clearly, for all evaluated models, the wheat primarily consists of lexical properties.

### Table 4. Types of the wheat that each model uses for prediction.

| Types     | code2vec                  | seq-GNN                  | GGNN                  | CodeBERT                  |
|-----------|---------------------------|--------------------------|-----------------------|---------------------------|
|           | Java-small | Java-med | Java-large | Java-small | Java-med | Java-large | C# Datasets | CodeSearchNet |
| Lexical   | 59.27%        | 51.34%    | 50.22%     | 77.60%        | 64.39%    | 71.25%     | 53.39%      | 49.17%        |
| Syntactic | 40.73%        | 48.66%    | 49.78%     | 21.73%        | 32.96%    | 26.24%     | 46.12%      | 50.83%        |
| Semantic  | –             | –         | –          | 0.67%         | 2.65%     | 2.51%      | 0.49%       | –             |

Proc. ACM Program. Lang., Vol. 1, No. CONF, Article 1. Publication date: January 2018.
Table 5. The number of programs that we add into each dataset for retraining.

|                       | Java-small | Java-med | C# Datasets | CodeSearchNet |
|------------------------|------------|----------|-------------|---------------|
| #original programs – training | 665,115    | 3,004,536| 130,101     | 454,451       |
| #added programs – training   | 336,938    | 1,106,288| 46,862      | 267,922       |
| #original programs – validation | 23,505     | 410,699  | 21,594      | 15,328        |
| #added programs – validation   | 11,908     | 151,222  | 7,778       | 9,036         |

4.4 Confirm the Validity of WheaCha in Light of the Out-of-distribution Issues

Based on the high-level steps introduced in Section 3.4, we present the technical details from two key aspects: data generation and labeling.

**Data Generation.** First, we perform the *Reduce* operation to generate code fragments for each program in the training set. Then, for each code fragment, we generate additional programs by randomly removing or mutating its constituent expressions. Such programs resemble the code produced out of the *Mutate* step.

**Data Labeling.** Given the amount of work, we attempt to recruit all undergraduate, master and PhD students from Math, Physics, Chemistry, Electronic Engineering, and Computer Science department at our university for the labeling task. In the end, we find 458 students in total and each student has at least one year of programming experience. We also hired 84 professional developers via Amazon Mechanical Turk. Here, we describe the set-up of this experiment in detail. First, for each generated program, we assign it the label of the program from which the *wheat* is derived. Second, we ask participants to confirm the assigned label for each generated program. Specifically, participants are required to assess based on their intuition if the assigned label correlates to the generated program. An example we gave to all participants is that the *wheat* of the running example correlates well to the label *addItem*, therefore, the label should be accepted for the *wheat* as a standalone program. To ensure the quality of labeling, we present every generated program with the assigned label to two participants, and we will only approve the program if both agree to accept the label, otherwise, the program is rejected. We also assign all rejected programs a new label that has not appeared in the original training set.

We randomly select either training or validation set to add each approved program. We keep the same ratio between the added training programs and validation programs as the original dataset. To keep the added data balanced, we also randomly sample a rejected program to accompany each approved program. Table 5 shows the number of programs we add including both the confirmed and rejected into Java-small, Java-med, C# Datasets, and CodeSearchNet. We disregard Java-large because it demands excessive human effort to label enough programs given the size of its training set (more than 15 million programs). In addition, Java-small and Java-med should already contain enough data points to validate model behavior, in turn, WheaCha’s approach.

**Results.** First, we validate the accuracy of all evaluated models on the augmented datasets. We find that all retrained models become more accurate even though the increase of accuracy is negligible (Table 14-16 in the supplemental material). We deploy WheaCha to explain the retrained models, and then compare the two sets of *wheat* before and after the retraining. It is worth mentioning we also set out to validate Sivand’s approach [Rabin et al. 2021b] using the same original and retrained models. Considering the manually labeled programs also resemble those with which Sivand would have queried the model, thus, in the same way we can evaluate if Sivand’s approach is still valid after the distribution shift between the training and test data is erased. Table 6 presents the results. Regarding WheaCha, we find that an overwhelming majority of the programs in every dataset has the same *wheat* before and after the retraining (the row designated by “Matched”), confirming that those are indeed the *wheat* models use for prediction with or without the seemingly
Table 6. The percentage of programs for which wheat are identical (designated by “Matched”), come from the same code fragment (designated by “Related”), or entirely different (designated by “Distinct”) before and after retraining for Sivand and WheaCha.

| Approach | Comparison | code2vec Java-small | code2vec Java-med | seq-GNN Java-small | seq-GNN Java-med | GGNN C# Datasets | CodeBERT CodeSearchNet |
|----------|------------|---------------------|-------------------|---------------------|------------------|-----------------|----------------------|
| Sivand   | Matched    | 46.2%               | 37.8%             | 44.9%               | 41.2%            | 38.4%           | 41.9%                |
|          | Related    | 23.9%               | 30.8%             | 32.5%               | 29.5%            | 26.4%           | 36.7%                |
|          | Distinct   | 29.9%               | 31.4%             | 22.6%               | 29.3%            | 35.2%           | 21.4%                |
| WheaCha  | Matched    | 92.5%               | 96.8%             | 94.8%               | 97.5%            | 93.9%           | 96.5%                |
|          | Related    | 3.6%                | 2.4%              | 2.1%                | 1.7%             | 4.3%            | 2.2%                 |
|          | Distinct   | 3.9%                | 0.8%              | 3.1%                | 1.0%             | 1.8%            | 1.3%                 |

distribution shift. “Related” represents the wheat models use before and after the retraining come from the same code fragment. They differ at the level of expressions, for example, using retrained models, WheaCha manages to reduce more features from the previous wheat at the Mutate step or vice versa. "Distinct" means retrained models use entirely different wheat than the original model. Apparently, this raises issues despite the tiny number of programs that falls into this category. To dig deeper, we discover that all such wheat met the sufficient and necessary requirement before, only to get discarded due to the violation of the minimum requirement. The reason that they become the wheat for retrained models is simple: the then wheat that original models use gets bloated after the retraining (i.e., Mutate operation could not reduce so many features as before), making wheat the minimum. Nevertheless, the “Distinct” (as well as the “Related”) scenario does not invalidate WheaCha’s approach considering the change of model behavior, to a minor degree, is to be expected after retraining. Overall, we conclude WheaCha’s approach is valid in light of the out-of-distribution issues.

On the contrary, Sivand’s explanations change significantly after the retraining. In particular, only around 40% of the wheat that retrained models use are the same as those that original models use. There is also a large number of programs on each dataset that falls into the “Distinct” category. Given that Sivand’s approach does not have a similar notion of minimality, “Distinct” wheat suggests a drastic change in Sivand’s explanations after retraining. Overall, the results strongly indicate the distribution shift heavily influences Sivand. This is yet another fundamental flaw of Rabin et al. [2021b] in addition to ignoring the necessary requirement when producing model explanations.

Discussion. A natural question arises: for the original models (without retraining) how is it possible for the wheat, which is far from the data that models have seen during training, still within the learned distribution? We believe it is because of the very intrinsic limitation of models’ that they only learn local, lexical/syntactic features from training programs. In other words, even with a whole program to learn, models still extract patterns from simple parts of the program which the wheat is likely to resemble, as a result, they lie in the distribution that models learned.

4.5 Can WheaCha Find the Global Minimum Features

In this experiment, we set out to confirm the minimality of the wheat found by HuoYan. As explained earlier, finding the global minimum wheat requires exhausting all subsequences of the token sequence of the input method. Therefore, to lessen the computational burden, we limit the evaluation data for this experiment to those methods that have either a small set of tokens or small wheat found by HuoYan (Table 7). We also diversify the data w.r.t. the size of programs and wheat to make our results unbiased. To confirm the global minimality of the wheat for the selected methods, we exhaust all subsequences of the token sequence of the input method up to the size of the wheat, specifically, we start from the subsequences of size one, and gradually increase to the size of the
Table 7. Statistics on the selected methods for the minimality experiment.

| Models      | #statements in methods | #tokens in wheat | #methods in total |
|-------------|-------------------------|------------------|-------------------|
|             | Min | Max | Mean | Median | Min | Max | Mean | Median |           |
| code2vec    | 1.0 | 12.0| 7.4  | 5.0    | 2.0 | 17.0| 9.4  | 8.0    | 21,324    |
| code2seq    | 1.0 | 15.0| 7.2  | 6.0    | 2.0 | 16.0| 10.1 | 9.0    | 18,105    |
| seq-GNN     | 1.0 | 12.0| 5.8  | 5.0    | 2.0 | 16.0| 8.2  | 7.0    | 19,751    |
| extreme     | 1.0 | 14.0| 8.1  | 6.0    | 2.0 | 15.0| 7.5  | 7.0    | 20,028    |

Table 8. Percentage of programs whose wheat are fully covered by explainability methods.

| Models      | Integrated Gradients (Top-N%) | Attention-based (Top-N%) | SHAP (Top-N%) |
|-------------|--------------------------------|--------------------------|---------------|
|             | 10% | 30% | 50% | 70% | 90% | 10% | 30% | 50% | 70% | 90% | 10% | 30% | 50% | 70% | 90% |
| code2vec    | 8.23 | 11.42 | 13.85 | 21.69 | 27.93 | 52.50 | 60.00 | 62.50 | 64.91 | 69.22 | 4.38 | 5.02 | 6.37 | 15.24 | 55.19 |
| seq-GNN     | 1.74 | 6.32 | 10.17 | 17.90 | 25.54 | 41.36 | 45.81 | 51.27 | 56.92 | 60.14 | 6.12 | 9.33 | 12.02 | 38.24 | 60.58 |
| GGNN        | 1.95 | 4.56 | 9.23 | 15.68 | 23.18 | 38.23 | 42.32 | 52.53 | 57.21 | 61.21 | 4.72 | 7.64 | 11.72 | 21.45 | 65.23 |
| CodeBERT    | 6.23 | 10.33 | 13.12 | 20.90 | 29.50 | 41.97 | 48.44 | 52.02 | 58.19 | 63.12 | 6.20 | 11.54 | 15.67 | 27.30 | 73.56 |

Note that this is also the way in which we verify the wheat for our running example. To cope with such a heavy computational burden, we exhaustively generate the test candidates for each program beforehand in a parallel fashion; then we place them into separate batches to fully exploit the potential of our GPUs (i.e., ≈10K test candidates per second per GPU). The whole experiment takes almost three months to complete.

We find that for 79,208 wheat that HuoYan identified, the brute-force search never finds a single instance where the wheat is smaller. Our results speak volume to the precision of our Reduce and Mutate method in finding the critical features that models use for prediction even if they are not guaranteed to be the global minimum.

4.6 Can Other Explainability Methods Find Wheat

In this experiment, we evaluate whether or not some of the most prominent attribution methods can also find the wheat that HuoYan finds. We choose Integrated Gradients [Sundararajan et al. 2017] and SHAP [Lundberg and Lee 2017], both of which have been widely used for explaining the predictions of image and natural language models. Worth noting that the two methods are typically contrastive (i.e., they account for deviations from a baseline), we design a baseline in which the embedding for each token (or node) is set to 0. This is the conventional approach followed by the explainability literature. Additionally, we choose the attention mechanism [Bahdanau et al. 2015], which makes models pay greater attention to certain factors (e.g., elements in an input) when processing the input data. Therefore, the features that are heavily attended to can be deemed as an explanation naturally. In theory, the three explainability methods may find the wheat that HuoYan does not, therefore, we only use the 79,208 programs whose wheat are already verified in Section 4.5.

First, we pick input features with top-N% highest attribution scores computed by the method. Then, we show the percentage of the programs that are fully covered by those input features (Table 8). Quite unexpectedly, the attention mechanism turns out to be the top performer in this experiment. Up to the features that receive the top-70% attribution scores, attention beats the other two methods by a significant margin across all evaluated models. Another interesting observation we made about the attention is it can already cover a good amount of programs when only using the top-10% of the input features and the increase of the coverage slows down when more features are selected. This indicates the important role the attention plays in helping models to learn the right features for prediction. As for the other two methods, SHAP’s advantage over Integrated Gradients only stands out after the 50% mark, otherwise, their numbers are in the same ballpark.
Overall, it’s evident that none of those explanation methods are good at finding the wheat. This is an expected outcome because the criteria by which WheaCha evaluates the importance of input features is fundamentally different than the above explanation methods. Specifically, WheaCha uses sufficient, necessary and Minimum requirement whereas the other three methods quantify the influence of features in mathematical terms (e.g., gradients, SHAP values, or attention scores).

4.7 Explaining the Predictions of Code Models

We conduct a user study to evaluate our technique for producing explanations for the prediction of all four models. As described in Section 3.5, our technique finds training methods similar to a test method based on the AST distance between their wheat. We also adopt a simple baseline that searches for training methods based on the AST distance of the entire method.

![Fig. 12. An example prediction produced by our technique and baseline.](image)

(a) A test method.  
(b) The closet found by our technique.  
(c) The closet found by baseline.

Fig. 12. An example prediction produced by our technique and baseline.

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![Fig. 13. Questionnaire used in the study.](image)

(1) The system finds training examples that have similar structure (or substructure) to the test example.  
(2) Given the similarity of the structure (or substructure), explanations that the system produce are accurate.  
(3) As a user of the model, I find the system helpful in provide an insight of how models work.  
(4) As a user of the model, I feel comfortable using this model along with the system providing the explanations.  
(5) As a designer of the model, I find the system helpful in debugging models’ mispredictions and improves their quality.

Fig. 13. Questionnaire used in the study.

**Procedure.** Each participant is given two sets of methods. One set contains 4 methods randomly selected from the test set of the three datasets, and each method is accompanied with 5 methods found to the closet by our technique on the corresponding training set. As an example, we show a test method (Figure 12a) accompanied by a training method (Figure 12b) that is the closest found by our technique. We highlight their wheat in the shadow box. Similarly, the other set presents the same content except that the 5 methods are found by the baseline approach. An example is shown in Figure 12c. After reviewing a set of methods, each participant is given a set of questions to answer. The questionnaire is depicted in Figure 13. For each question, participants are given 5 choices to make: strong disagree, disagree, neutral, agree, and strongly agree. Each choice is interpreted as a score starting from 1 for strongly disagree all the way to 5 for strong agree. We also conduct an
Table 9. Participants’ responses.

| Question | Our technique | Baseline |
|----------|---------------|----------|
| 1        | 4.7           | 2.1      |
| 2        | 4.5           | 1.8      |
| 3        | 3.9           | 1.8      |
| 4        | 3.1           | 1.2      |
| 5        | 3.6           | 1.5      |

interview after the study during which we encourage them to give any comments/suggestions that they may have.

**Participants.** We have recruited 32 data scientists from a high-tech company through an internal email thread and paid them $50 each for participating the study. Each participant has at least one year of Java programming experience. All of them have at least two years of experience in developing machine learning models at work. We have explained to each participant beforehand that our technique finds the training programs from which models learned their parameters for predicting the name of a particular test method, and they are asked to rate the quality of the explanations.

**Results.** Table 9 shows the results of the questionnaire. In particular, each row contains the average score to a question for our technique and baseline approach. It is clear that participants have rated our technique consistently higher than the baseline approach by a notable margin. In terms of the actual score, participants have given more than 3 to all questions indicating an overall positive attitude toward our technique. Specifically, for Questions 1 and 2, participants are very positive about the accuracy of the predictions found by our technique. For Question 3 and 5, participants also agree that the system would benefit both users and designers of the model by providing the rationale of model predictions. One participant even raises the possibility of performing re-training with examples generated based on the wheat to improve the model accuracy. Question 4 is the only one to which participants reacted a bit more negatively. Therefore, we focus on this question in our post-study interview.

The main message we received from participants who give particularly low scores to this question is that even though the system gives accurate explanations, they won’t be very helpful when models only seem to use almost random textual properties to predict. For example, one participant explained that once an explanation is given, albeit having a similar substructure of the test method, users still have to manually examine the rest of the program in order to decide if the explanation can really match the prediction of the test method. Therefore, having a model that learns the right features is also necessary.

As standard in user studies, we performed a t-test to evaluate the statistical significance of our results. The p-value of a two-tailed t-test (assuming potentially unequal variance) comparing our technique against the baseline approach is \(2 \times 10^{-6}\). This means the probability that our technique has no influence on classification accuracy is less than 1 in 100,000, indicating our results are statistically significant.

## 5 RELATED WORK

The work closest to ours is Rabin et al. [2021b], which discovers that input programs can be reduced to significantly smaller code snippets for which models still make the correct predictions. Our work in fact surpasses Rabin et al. [2021b] at many levels. Conceptually, we propose necessary
requirement that \textit{wheat} has to satisfy in addition to the \textit{sufficient} requirement. Technically, we show DD, which powers Sivand [Rabin et al. 2021b], suffers from models’ non-monotony. In contrast, our technique \textit{Reduce} and \textit{Mutate} is more precise in identifying the \textit{wheat} evidenced by our extensive evaluation. Empirically, we demonstrate the validity of WheaCha’s approach in light of out-of-the-distribution issues, whereas, Sivand is fundamentally flawed in dealing with the distribution shift between the training and query programs. Finally, we also present a novel application of the \textit{wheat} while Rabin et al. [2021b] have not demonstrated any utility of their method. For the remainder of this section, we survey two lines of related work: attribution methods and models of code.

5.1 Attribution Methods

In machine learning field, attribution methods are usually classified into two categories: Perturbation-based and backpropagation-based. The former generates explanations by iteratively probing a trained machine learning model with different variations of the inputs. As a few representatives, Zeiler et al. [2011] visualized the neural activations of individual layers of a deep convolutional network by occluding different segments of the input image and generating visualizations using a deconvolution network (DeConvNet). Zintgraf et al. [2017] use a conditional sampling based multi-variate approach to generate more targeted explanations on image classification CNNs. The Interpretability Randomization Test (IRT) and the One-Shot Feature Test (OSFT) introduced by Burns et al. [2020] focuses on discovering important features by replacing the features with uninformative counter-factuals. To derive a representation that is understandable by humans, LIME [Ribeiro et al. 2016] tries to find important contiguous superpixels (a patch of pixels) in a source image towards the output class. Lundberg and Lee [2017] present a unified framework, SHAP, which computes individual feature contributions towards that output prediction.

As for the backpropagation-based methods, Saliency maps [Simonyan et al. 2014] construct attributions by taking the absolute value of the partial derivative of the target output with respect to the input features. Gradient*Input [Shrikumar et al. 2016] was then proposed to improve the sharpness of the attribution maps. The attribution is computed by taking the (signed) partial derivatives of the output with respect to the input and multiplying them with the input itself. Integrated Gradients [Sundararajan et al. 2017], similarly to Gradient*Input, computes the partial derivatives of the output with respect to each input feature. However, while Gradient*Input computes a single derivative, evaluated at the provided input $x$, Integrated Gradients computes the average gradient while the input varies along a linear path from a baseline $\hat{x}$ to $x$. Layer-wise Relevance Propagation (LRP) introduced by Bach et al. [2015] is used to find relevance scores for individual features in the input data by decomposing the output predictions of the DNN. DeepLIFT [Shrikumar et al. 2017b], similar to LRP, assigns each unit $i$ an attribution that represents the relative effect of the unit activated at the original network input $x$ compared to some other reference input.

5.2 Models of Code

Machine learning methods have been applied to a variety of programming language tasks such as method name prediction [Alon et al. 2019a,b; DeFreez et al. 2018a,b; Fernandes et al. 2019; Wang and Su 2020], bug detection [Allamanis et al. 2018; Wang et al. 2020], program repair [Chen et al. 2019; Dinella et al. 2019; Sakkas et al. 2020], and type inference [Allamanis et al. 2020; Wei et al. 2019]. Below we survey a few notable representatives. GGNN is the first to learn program embeddings from graph representations of source code. code2vec and code2seq are among the first in predicting method names in large-scale, cross-projecting settings. DeFreez et al. [2018b] is the first to use static program traces to learn function embeddings. Wang et al. [2018] is the first to embed programs with their executions. Chen et al. [2019] and Dinella et al. [2019] utilize sequence and graph models for program repair. Yao et al. [2020] and Si et al. [2018] are the noteworthy efforts in inferring
loop invariant with deep learning models. CodeBERT [Feng et al. 2020] learns general-purpose representations that support downstream natural language-programming language applications.

6 Conclusion

In this paper, we present WheaCha, an explanation method for models of code. Conceptually, we formalize the defining features that models use for predicting the label of input programs. Technically, we develop Reduce and Mutate and its implementation HuoYan, which we use to explain code2vec, seq-GNN, GGNN, and CodeBERT. We found that (1) HuoYan is efficient and effective in finding wheat; (2) through retraining, we confirm the validity of WheaCha amid the distribution shift between training and queried programs; (3) all models use simple syntactic or even lexical properties for prediction; (4) some of the most popular attribution methods routinely miss out on the wheat; (5) we present an example application of the revealed features: providing explanations for predictions of code models. Through a user study, we have shown the usefulness of our wheat-based explanation method.

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A DEFINITION OF SUBSEQUENCE

A subsequence of \(<a>\) is a sequence \(<b>\) defined by \(b_k = a_{n_k}\), where \(n_1 < n_2 < \ldots\) is an increasing sequence of indices [John Philip and West 1997].

For example, if \(a_n = 2n - 1\) and \(n_k = k^2\), then \(b_k = 2k^2 - 1\) [John Philip and West 1997].

\[
\begin{array}{|c|cccccccc|}
\hline
n & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 \\
a_n & 1 & 3 & 5 & 7 & 9 & 11 & 13 & 15 & 17 \\
k & 1 & 2 & 3 &  &  &  & &  & \\
b_k & 1 & 7 & & & 17 & \\
\hline
\end{array}
\]
THE EXISTENCE OF WHEAT

Theorem B.1 (Existence of Wheat). Given a prediction $L$ that $M$ makes for an input program $P$, the wheat $\tilde{P}$ that models use to predict the label of $P$ always exists.

Proof. Assume otherwise, so that the wheat $\tilde{P}$ does not exist for $P$.

Because the body of $P$, $B_P$, satisfies constituent, sufficient, and necessary requirement in Definition 2.1. It has to be the minimum requirement that $B_P$ violates, meaning, there exists a set of statements(expressions) $P'$ that also satisfies all but the minimum requirement, and $|(t_{n_P})_{n \in \mathbb{N}}| < |(t_{n_{B_P}})_{n \in \mathbb{N}}|$. Since $P'$ is not the wheat either, we can infer that $P'$ is also not minimum.

Because the domain that contains all sets of statements(expressions) whose token sequence is a subsequence of $P$'s is finite, and the size of the candidate programs will monotonically decreases (i.e., $|(t_{n_P}^{B_P})_{n \in \mathbb{N}}| < |(t_{n_{B_P}}^{B_P})_{n \in \mathbb{N}}|$, $|(t_{n_P}^{B''_P})_{n \in \mathbb{N}}| < |(t_{n_{B''_P}}^{B''_P})_{n \in \mathbb{N}}|$, and so on), there will be a global minimum set of statements(expressions) $\tilde{P}$ that satisfies all requirements in Definition 2.1, which implies that $\tilde{P}$ is the wheat for $P$. This contradicts the assumption that $\tilde{P}$ does not exist for $P$. \qed
EXAMPLES OF DELTA DEBUGGING

The motivating example includes nineteen tokens. At the first step, we split the program into two partitions: the first partition ($\Delta_1$) contains the first nine tokens (List, Object, mItems, =, retQueue, if, position, >, mItems) and the second one ($\Delta_2$) has the last ten tokens (size, return, mItems, add, position, genItem, notifyItemInserted, position, log, "add item"). We proceed with $\Delta_2$ since it satisfies the sufficient and necessary requirement. Then, we split $\Delta_2$ into two partitions, and demonstrate the subsequent steps in Table 10.

Table 10. An example from sequence GNN model without the monotonicity. $\Delta_i$ denotes partitions and $\nabla_i$ is the complement of $\Delta_i$. For simplicity, we use tokens to represent programs that are tested against the sufficient and necessary requirement at each step. The last column shows the requirements that partitions do not satisfy, but pass means the partitions satisfy both requirements.

| Step | Partition | Tokens | Results |
|------|-----------|--------|---------|
| 1    | $\Delta_3$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Pass |
| 2    | $\Delta_4$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Necessary |
| 3    | $\Delta_5 = \nabla_6$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Both |
| 4    | $\Delta_6 = \nabla_5$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Both |
| 5    | $\Delta_7$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Both |
| 6    | $\Delta_8$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Both |
| 7    | $\Delta_9$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Both |
| 8    | $\Delta_{10}$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Both |
| 9    | $\nabla_7$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Sufficient |
| 10   | $\nabla_8$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Sufficient |
| 11   | $\nabla_9$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Sufficient |
| 12   | $\nabla_{10}$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Sufficient |
| 13   | $\Delta_{11}$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Both |
| 14   | $\Delta_{12}$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Both |
| 15   | $\Delta_{13}$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Both |
| 16   | $\Delta_{14}$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Both |
| 17   | $\Delta_{15}$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Both |
| 18   | $\nabla_{11}$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Sufficient |
| 19   | $\nabla_{12}$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Sufficient |
| 20   | $\nabla_{13}$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Sufficient |
| 21   | $\nabla_{14}$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Sufficient |
| 22   | $\nabla_{15}$ | ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | Sufficient |
D AN EXAMPLE OF THE SUBTRACTION OPERATION IN THE MUTATE STEP

Figure 14 gives a detailed illustration for subtracting mItems.add(); from the original program.

Fig. 14. A illustration of the four-step process of subtracting mItems.add(); from our example program. (1) Figure (a) presents the AST of the running example, and the AST of mItems.add(); in the bottom left corner. For brevity, the ASTs are simplified. (2) Figure (b) highlights the overlapping nodes between the two ASTs. (3) Figure (c) emphasizes the resultant AST after the overlapping nodes are removed, as a result, position and getItem() become dangling nodes. (4) Figure (d) connects position and getItem() to the body of the method.
E THE FUNCTIONALITY OF DELETENODE AND MUTATENODE

Algorithm 3 gives a detailed illustration for DeleteNode and MutateNode functions. In the DeleteNode function, we first try removing the node, which comes from its first parameter, then check whether the resultant program satisfies both the sufficient and necessary requirement (Line 3). If it satisfies, we update the current program to the new one whose node is deleted (Line 4). Similarly, in the MutateNode function, we will mutate the node into one with an out-of-vocabulary value (Line 8) and update the program if the resultant program satisfies the two requirements (Lines 9 and 10). Both DeleteNode and MutateNode functions invoke the VerifyWheat function, which constructs two programs for checking against the sufficient and necessary requirements, respectively. The function returns True only when the resultant program satisfy both requirements, otherwise it returns False.

Algorithm 3 Delete and mutate AST nodes.

```
1: function DELETENODE(node, root, program, model)
2:     new_root_del ← root.Delete(node)                                ▶ remove node
3:     if VERIFYWHEAT(new_root_del , root, program, model) then
4:         Update(root, new_root_del)                                 ▶ update to the new program
5:     end if
6: end function

7: function MUTATENODE(node, root, program, model)
8:     new_root_mut ← root.Replace(node, oov)                         ▶ replace node with oov
9:     if VERIFYWHEAT(new_root_mut , root, program, model) then
10:        Update(root, new_root_mut)                                 ▶ update the program
11: end if
12: end function

13: function VERIFYWHEAT(node, root, program, model)
14:     program_suff ← Serialize(node)                               ▶ checking against the sufficient requirement
15:     if model.Predict(program_suff) != model.Predict(program) then
16:         return False                                               ▶ does not satisfy the sufficient requirement
17:     end if
18:     program_necc ← Subtract(root, node)                           ▶ checking against the necessary requirement
19:     if model.Predict(program_necc) == model.Predict(program) then
20:         return False                                               ▶ does not satisfy the necessary requirement
21:     end if
22:     return True
23: end function
```
F PERFORMANCE OF RE-IMPLEMENTED MODELS

We have re-implemented code2vec, Sequence GNN, GGNN and CodeBERT. Table 11, 12, and 13 show the performance of all re-implemented models is either comparable or superior to the originals.

Table 11. Compare reimplementations (bolded) to originals for code2vec and Seq-GNN.

| Models | Java-small | | | Java-med | | | Java-large | |
|--------|-------------|-------------|-------------|-------------|-------------|-------------|
|        | Precision   | Recall      | F1          | Precision   | Recall      | F1          | Precision   | Recall      | F1          |
| code2vec | 18.51       | 18.74       | 18.62       | 38.12       | 28.31       | 32.49       | 48.15       | 38.40       | 42.73       |
| code2vec | 19.23       | 17.72       | 18.44       | 40.32       | 28.89       | 33.66       | 48.90       | 37.26       | 42.29       |
| Seq-GNN | —           | —           | 51.4        | —           | —           | —           | —           | —           | —           |
| Seq-GNN | 49.94       | 47.35       | 48.61       | 58.46       | 45.73       | 51.32       | 61.82       | 50.32       | 55.48       |

Table 12. Compare reimplementations (bolded) to originals for GGNN.

| Models | C# Datasets Accuracy |
|--------|----------------------|
| GGNN   | 78.2                 |
| GGNN   | 78.0                 |

Table 13. Compare reimplementations (bolded) to originals for CodeBERT.

| Models | CodeSearchNet Smoothed BLEU score |
|--------|----------------------------------|
| CodeBERT | 17.65               |
| CodeBERT | 17.66               |
G ADDITION EDGES USED IN FERNANDES ET AL.

Below we give the list of edges Fernandes et al. [2019] incorporate into ASTs.

- **NextToken** connects each terminal node (syntax token) to its successor.
- **LastRead** connects a terminal node of a variable to all elements of the set of terminal nodes at which the variable could have been read last.
- **LastWrite** connects a terminal node of a variable to all elements of the set of syntax tokens at which the variable was could have been last written to.
- **ComputedFrom** connects a terminal node of a variable $v$ to all variable tokens occurring in $expr$ when $expr$ is assigned to $v$.
- **LastLexicalUse** chains all uses of the same variable.
- **ReturnsTo** connects return tokens to the method declaration.
- **FormalArgName** connects arguments in method calls to the formal parameters that they are matched to.
- **GuardedBy** connects every token corresponding to a variable (in the true branch of a if statement) to the enclosing guard expression that uses the variable.
- **GuardedByNegation** connects every token corresponding to a variable (in the false branch of a if statement) to the enclosing guard expression that uses the variable.

We exclude **NextToken** and **ReturnsTo** since they do not represent any semantic properties.
We have re-trained code2vec, Sequence GNN, GGNN and CodeBERT on the manually labeled datasets. Table 14, 15, and 16 show the performance of all re-trained models is negligibly higher than original models.

Table 14. Compare code2vec and Seq-GNN before and after the retraining (bolded numbers denotes the results of retrained models).

| Models   | Java-small | | | Java-med | | |
|----------|------------|------------|----------|------------|----------|
|          | Precision  | Recall     | F1       | Precision  | Recall    | F1       |
| code2vec | 19.23      | 17.72      | 18.44    | 40.32      | 28.89     | 33.66    |
| code2vec | 19.33      | 18.01      | 18.74    | 40.38      | 28.97     | 33.96    |
| Seq-GNN  | 49.94      | 47.35      | 48.61    | 58.46      | 45.73     | 51.32    |
| Seq-GNN  | 50.12      | 48.39      | 48.62    | 58.51      | 46.09     | 52.00    |

Table 15. Compare GGNN before and after the retraining (bolded numbers denotes the results of the retrained model).

| Models   | C# Datasets | Accuracy |
|----------|-------------|----------|
| GGNN     | 78.0        |          |
| GGNN     | 78.8        |          |

Table 16. Compare CodeBERT before and after the retraining (bolded numbers denotes the results of the retrained model).

| Models    | CodeSearchNet | Smoothed BLEU score |
|-----------|---------------|---------------------|
| CodeBERT  | 17.66         |                     |
| CodeBERT  | 17.91         |                     |