Leveraging Causal Inference for Explainable Automatic Program Repair

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Abstract—Deep learning models have made significant progress in automatic program repair. However, the black-box nature of these methods has restricted their practical applications. To address this challenge, this paper presents an interpretable approach for program repair based on sequence-to-sequence models with causal inference and our method is called CPR, short for causal program repair. Our CPR can generate explanations in the process of decision making, which consists of groups of causally related input-output tokens. Firstly, our method infers these relations by querying the model with inputs disturbed by data augmentation. Secondly, it generates a graph over tokens from the responses and solves a partitioning problem to select the most relevant components. The experiments on four programming languages (Java, C, Python, and JavaScript) show that CPR can generate causal graphs for reasonable interpretations and boost the performance of bug fixing in automatic program repair.

Index Terms—Automated Program Repair, Program Analysis, Sequence-to-sequence Model, Causal Inference, Interpretability

I. INTRODUCTION

The goal of automatic program repair (APR) techniques is to automatically correct bug(s) in a piece of existing troublesome source code. Many researches have been devoted to applying machine learning techniques to APR [1]. Given the similarity between a program repair task and generic natural language processing (NLP) tasks such as sequence-to-sequence (Seq2Seq) learning and machine translation [2], there has been a lot of work on applying machine learning for program repair [3], [4], [5] and [6] in recent years. Similar techniques have been applied to code related tasks [7], [8], [9].

Although deep learning based Seq2Seq models have achieved overwhelming success in APR tasks, there still remains a lot of potential for improvement [10], [11]. One major concern is the interpretability of the deep Seq2Seq models, which is caused by the complicated nature of model architectures [12], [13]. The interpretability of deep models is often categorized into two types: 1.) model interpretability, which attempts to make the deep neural architecture itself interpretable and transparent, and 2.) prediction interpretability, which aims to explain particular predictions of the deep model [14]. Once a deep APR model has achieved these two aspects of interpretability, it becomes trustworthy, transparent, and controllable, which surely makes deep models more useful for practical deployment.

To improve the interpretability of APR models, this paper introduces causal inference, which has shown great promise in discovering causal relations in deep learning [15]. Simply combining APR with causal inference can lead to a few significant challenges. This paper aims to address three important unsolved issues about how to use causal inference in APR models. Because transparency in the deep APR models is often very restrictive and challenging to achieve [16], the first issue is how can we alleviate this difficult situation in real application. The second issue is how to define the causal graph in the APR task. The third issue is what kind of performance can be achieved by APR model combined with causal inference.

For the first issue, in this work we concentrate on prediction interpretability rather than model transparency. From the machine learning community, prediction interpretability can be sought more easily with existing methods, like Monte Carlo Dropout, Ensemble or Bayesian deep neural networks [17]. In a typical APR problem, the inputs are the original code and comments, the output is the predicted repaired code. To tackle the second issue, we can define the causal graph since we are focusing on the interpretable relationship between input and output. In a causal graph, the context is the input of code and comments, the outcome is the predicted repaired code, and the confounder is the data disturbance, i.e., the data augmentation. For the third challenge, we alter the potential confounder, which is one kind of text data augmentation, and observe the effect of APR with causal inference.

Specifically, we propose to utilize data augmentation strategy to discover the causal relations between the input source (that is, the code and comments) and the corrected bugs, which can improve the prediction interpretability of APR models. Data augmentation methods are used to disturb the original inputs, which are then fed into the deep Seq2Seq model to infer the causal relation between the input and output tokens in the similar manner as [15]. [15] utilized a Variational auto-Encoder (VAE) for data disturbance, which is computationally costly and hard to control. Our method is called CPR, short for Causal Program Repair, which leverages text data augmentation and easy to implement in comparison with VAE based method.

Our main contributions can be listed as follows:

• We proposed to utilize data augmentation strategy for the input perturbations required for causal analysis of APR

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Therefore, we discuss the related research in the following two subsections.

A. Sequence-to-Sequence Models in Automatic Code Repair

There are many existing works that attempt to use machine translation techniques to automatically fix bugs. Here are the most notable methods in this area. [18] formulates the patches generation as a Seq2Seq translation problem and proposes to use a neural machine translation (NMT) model with attention-based Encoder-Decoder. To evaluate the performance of various APR methods, [19] presents BEARS, a project for collecting and storing bugs into an extensible bug benchmark for automatic repair studies in Java. SequenceR [4] leverages a Seq2Seq model by combining an encoder and a decoder architecture, where recurrent neural networks (RNNs) with LSTM gates are used for both the encoder and decoder. [10] propose an APR framework using formal specification and expression templates.

Using a RNN encoder-decoder, [20] investigates the application of NMT for candidate patches generation. Applying NMT techniques and ensemble learning, CoCoNuT [6] can automatically repair programs of multiple languages in a end-to-end manner. [21] proposes a new NMT-based APR technique, called CURE, which leverages pre-training, subword tokenization and an efficient code-aware search strategy. [22] proposes a real-time code fix mechanism by semantic code suggestions, which is shown to improve the speed of repairing faulty programs. More details on APR can be found in [23].

B. Causal Inference

There is a very large body of work that attempts to address the issue of "explanation", but it is actually quite biased due to the different definitions of "explanation" that are of interest. In the field of machine learning, the area where interpretability is probably most valued is in medical applications, where the credibility of a predictive model depends heavily on its interpretability [24]. With the advent of the deep learning trend, recent work has enhanced each of the two aspects of interpretability: model transparency [25] and model functionality [26]. For a broad survey of interpretability in deep learning, we refer the reader to the survey [27].

Model interpretability methods based on causal inference (counterfactual samples) have been increasingly applied to various scenarios. Among them, the sample-based explanation approach aims to explain the decision and judgment process of the model by finding sample examples, [14], [28] proposes a model that justifies the prediction results using fragments of the input. One of the most typical approaches is the counterfactual explanations that interpret the model’s decisions by making minimal changes to the features on the existing samples and obtaining the expected counterfactual results, and collecting these samples with minor changes. [29] relies on local perturbations of the instance to explain the predictions of the black-box classifiers. A generic counterfactual generator with sequential control of perturbation types and positions is further proposed by [30], which can generate diverse sets of realistic counterfactuals that can be useful in various distinct applications.

III. PROPOSED METHOD

Comparing the Fig. 1(a), (b) and (c), we can transition from NMT to APR with causal inference, which is Fig. 1(c). Comparing Fig. 1 (a) and (b), the process of APR is similar to NMT. Both input source text and target text, and the expected text is inferred through the Seq2Seq model. According to Fig. 1(b), we propose an APR framework with causal analysis, as illustrated by Fig. 1(c).

As demonstrated in Fig. 2(a), we define a causal graph. In causal inference, capital X represents the treatment, capital A represents the potential confounder, and capital Y represents the outcome. In the APR problem, capital X is the input of code and comments, capital A indicates the data augmentation, and capital Y is the output of predicted repaired code. Based on the data augmentation, potential confounder A will influence X and Y, so we define the causal graph like the Fig. 2(a). To identify the input and output causality, we need to know the predict interpretability after we’ve defined the causal graph. Changing the input through data augmentation methods, we may figure out how the input influences the output, as shown in Fig. 2(b).
**TABLE I**

| Dataset     | Model       | Parameters | Language | Bugs number | fixed w/o CI | fixed with CI (CPR) |
|-------------|-------------|------------|----------|-------------|---------------|---------------------|
| Defects4J   | SequenceR   | 38M        | Java     | 393         | 12            | 20                  |
| Defects4J   | FConv       | 23M        | Java     | 393         | 12            | 21                  |
| Defects4J   | CodeBERT    | 675M       | Java     | 393         | 14            | 23                  |
| QuixBugs    | SequenceR   | 38M        | Java     | 40          | 7             | 13                  |
| QuixBugs    | FConv       | 23M        | Java     | 40          | 8             | 11                  |
| QuixBugs    | CodeBERT    | 675M       | Java     | 40          | 13            | 17                  |
| QuixBugs    | SequenceR   | 38M        | Python   | 40          | 6             | 13                  |
| QuixBugs    | FConv       | 23M        | Python   | 40          | 9             | 14                  |
| QuixBugs    | CodeBERT    | 675M       | Python   | 40          | 12            | 19                  |
| ManyBugs    | SequenceR   | 38M        | C        | 69          | 11            | 16                  |
| ManyBugs    | FConv       | 23M        | C        | 69          | 9             | 15                  |
| ManyBugs    | CodeBERT    | 675M       | C        | 69          | 13            | 18                  |
| BugAID      | SequenceR   | 38M        | JavaScript | 12        | 4             | 6                   |
| BugAID      | FConv       | 23M        | JavaScript | 12        | 3             | 3                   |
| BugAID      | CodeBERT    | 675M       | JavaScript | 12        | 6             | 7                   |

(a) The causal graph in APR task.
(b) The input and output connections.

Fig. 2. The causal graph in APR task.

Our approach formalizes this framework through a pipeline (sketched in Fig. 1(c)) that consists of three main components, each of which is described in detail in the following section: a perturbation model for locally exercising $F$, a causal inference model for inferring associations between inputs and predictions, and a selection step for partitioning and selecting the most relevant sets of associations.

1) Synonym Replacement (SR): Select $m$ words randomly from the original sentence that does not include stop words. Then alter these words with one of closeness meaning chosen at random.
2) Random Insertion (RI): Find a most similar meaning for a random word in the original sentence (not include stop words). Insert that most similar word into a stochastic position in the sentence. Repeat $m$ times.
3) Random Swap (RS): Casually select two words from the original sentence and switch their positions in $m$ times.
4) Random Deletion (RD): With probability $p$. Delete words from the original sentence randomly.

For sentence perturbation, we use Back-Translation (BT): Translating an existing example $x$ in language A into another language B and then translating it back into A to obtain an augmented example $\hat{x}$.

Long sentences will perform more word perturbation since they include more words than short ones. To fair comparison, we vary the number $m$ for word perturbation based on the sentence length $l$ with the formula $m = \lfloor \alpha l \rfloor$, where $\alpha$ is a parameter that indicates the percent of the changed words in a sentence (we use $p = \alpha$ for RD). Furthermore, we generate $m_{\text{dist}}$ disturbed sentences for each original sentence.

To perturb the comment texts, the data augmentations operate the level of the words, and the symbols like $\{, :, \text{ or } ==$ e.t.c. Symbols are also an essential part of a programming language.

This data augmentation strategy achieves similar outcomes but is considerably easier to employ because it does not involve the training of a language model and the usage of external datasets. We argue that it can be easily ported to other similar models.
IV. EXPERIMENTAL SETUP

A. Datasets

To train the ARP models in different programming languages, we collected corresponding training datasets for different programming languages based on the open-source datasets. For Java, we use Defects4J [32] and QuixBugs [33]. For Python, we use Python’s version of QuixBugs. For C, we used the ManyBugs datasets from prior work [34]. In order to compare with the Java, Python, and C program language, we select 12 JavaScript examples connected with ordinary bug problems in prior work (BugAID) [35].

Fig. 4. We inferred dependency graphs before (left) and after (right) explanation selection for the prediction. Our framework generates dependency estimates and explanation graphs. The green circles mean the buggy code, the yellow circles mean the comments text, and the blue circles mean debugged code. (a) Raw Dependencies, (b) Explanation Graph.

B. Settings

Training. In order to ensure the completeness of comparison, the details of training parameters are given here. Following Fig. 1(c), we have two parts that need to train and infernece, the APR model and the explainable graph. First, we use hyperband [36] to tune hyper-parameters. We restrict the range of hyper-parameters to appropriate values. The size of embedding is 64 to 512, the dimensions of convolutional layer is 32 to 256, the number of convolutional layers is 1 to 10, the size of hidden units of LSTM is 128 to 512, the size of Transformer heads is 4 to 8, the size of hidden units of Transformer is 128 to 512. The learning rate is 0.1, 0.01, 0.001, and 0.0001. Then we train APR models for one epoch on the different training sets with various hyper-parameters for tuning. We are ranking the hyper-parameters sets based on their perplexity. Perplexity is a typical metric in NLP that quantifies how well a model generates a sequence. We make it stop at convergence or until 20 epochs and ranking the the top-k (default k=5) models. In inference mode, we employ beam search with a beamwidth of 784.

Explainable graph. We equally chose a data disturbance method to generate the disturbed input based on the proposed data augmentation strategy. For the explainable graph step, we use the robust clustering method of [37], [38] to generate the graph in the experiment. These bilateral clustering methods do not take uncertainty into account.

Infrastructure We use the LSTM, and Transformer is running on Pytorch [39]. The implementations of FConv is provided by fairseq-py [40]. Our methods were trained and evaluated on an Intel Xeon E5-2695 with 4 NVIDIA V100 GPUs.

Performance The average time it takes to train the APR models for one epoch during tuning is 51 minutes. Sequentially for the SequenceR, FConv, and CodeBERT, it takes 93, 67, and 253 hours to train the model until convergence. During inference stage, producing 1000 patches for each bug brings 9 seconds.

C. Evaluation and Results

The performance with causal inference Table I displays the number of bugs fixed by the different approaches with or without causal inference. For all datasets, causal inference is used to improve the effect of debugging code. We test in four languages, and both models have been improved using causal inference. On the BugAID dataset, which is for JavaScript language, We observed an intriguing result. The bugs number for all three models is relatively less, and for FConv, the causal inference is not working. For SequenceR and CodeBERT, the effect of improvement is not obvious. We believe that the main reason is that the amount of data is too small.

Table II depicts the different consequences of different data disturbance approaches in our framework. The RI, RS, and RD approaches would degrade the performance of APR with causal inference. In the FConv model with the RD method, its performance is almost the same as that of a model without causal influence. Likewise, the CodeBERT with the RS method, which reduces the number of fixed codes to 12, achieves the same performance without causal influence. When using the APR model with causal inference, the SR and BT methods are the best choices. It demonstrates that the SR and BT methods have the best effect in the APR model with causal inference. It helps when the APR model is with the explainable graph because the SR and BT methods can maintain the original meaning of comments.

Fig. 5 shows the input and output’s interpretable relation with explanation graphs. The connected blue circle with more gray lines from green circles is more relevant. The density of gray lines might show whether or not the error code corresponds to the proper code. As shown in Fig. 5, the incorrect part of the buggy code is most connected to the correct part in the repaired code.

The explanation graph in data perturbation. Fig. 5 shows the explanation graph when using data augmentation. In Fig. 5 (a), (b), and (c), the buggy code is all connected to the most relevant input. Especially in Fig. 5(b), the incorrect symbol is connected to the correct symbol, where the second blue circle is the right answer. In Fig. 5 (d), the debugged code deletes the wrong parts compared to the buggy code. Since the solution is to delete the buggy code, the input is rarely connected to the output.

Fig. 6 (b), (c), (d), (e), and (f) illustrate the circumstance when the data augmentation is implemented for the comment


| Dataset      | Model       | Parameters | Language | Bugs number | Data augmentation | fixed w/o CI | fixed with CI (CPR) |
|--------------|-------------|------------|----------|-------------|------------------|--------------|---------------------|
| QuixBugs     | SequenceR   | 38M        | Python   | 40          | SR               | 10           | 13                  |
| QuixBugs     | SequenceR   | 38M        | Python   | 40          | RI               | 8            | 10                  |
| QuixBugs     | SequenceR   | 38M        | Python   | 40          | RS               | 7            | 11                  |
| QuixBugs     | SequenceR   | 38M        | Python   | 40          | RD               | 8            | 11                  |
| QuixBugs     | SequenceR   | 38M        | Python   | 40          | BT               | 9            | 12                  |
| QuixBugs     | FConv       | 23M        | Python   | 40          | SR               | 11           | 14                  |
| QuixBugs     | FConv       | 23M        | Python   | 40          | RI               | 8            | 11                  |
| QuixBugs     | FConv       | 23M        | Python   | 40          | RS               | 9            | 12                  |
| QuixBugs     | FConv       | 23M        | Python   | 40          | RD               | 9            | 10                  |
| QuixBugs     | FConv       | 23M        | Python   | 40          | BT               | 12           | 14                  |
| QuixBugs     | CodeBERT    | 675M       | Python   | 40          | SR               | 14           | 18                  |
| QuixBugs     | CodeBERT    | 675M       | Python   | 40          | RI               | 11           | 15                  |
| QuixBugs     | CodeBERT    | 675M       | Python   | 40          | RS               | 9            | 12                  |
| QuixBugs     | CodeBERT    | 675M       | Python   | 40          | RD               | 9            | 13                  |
| QuixBugs     | CodeBERT    | 675M       | Python   | 40          | BT               | 13           | 19                  |

![Fig. 5. Dependency estimates and explanation graph generated by our framework.](image)

![Fig. 6. Dependency estimates and explanation graph generated with data disturbances.](image)

V. Conclusion

Our data augmentation approach combined with a model-agnostic framework for prediction interpretability can produce reasonable, related explanations. We formulate the explanation problem of APR model in causal inference. Our methods can be generalized to a variety of settings in which inputs and outputs can be expressed as sets of features. Also, we used data augmentation sampling for data disturbances. Experiments...
with various data augmentation methodologies suggest that the APR model can be utilized as a causal inference tool.

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