A Closer Look into Transformer-Based Code Intelligence Through Code Transformation: Challenges and Opportunities

Yaoxian Li, Shiyi Qi, Cuiyun Gao, Yun Peng, David Lo, Zenglin Xu, and Michael R. Lyu

Abstract—Transformer-based models have demonstrated state-of-the-art performance in many intelligent coding tasks such as code comment generation and code completion. Previous studies show that deep learning models are sensitive to the input variations, but few studies have systematically studied the robustness of Transformer under perturbed input code. In this work, we empirically study the effect of semantic-preserving code transformation on the performance of Transformer. Specifically, 24 and 27 code transformation strategies are implemented for two popular programming languages, Java and Python, respectively. For facilitating analysis, the strategies are grouped into five categories: block transformation, insertion / deletion transformation, grammatical statement transformation, grammatical token transformation, and identifier transformation. Experiments on three popular code intelligence tasks, including code completion, code summarization and code search, demonstrate insertion / deletion transformation and identifier transformation show the greatest impact on the performance of Transformer. Our results also suggest that Transformer based on abstract syntax trees (ASTs) shows more robust performance than the model based on only code sequence under most code transformations. Besides, the design of positional encoding can impact the robustness of Transformer under code transformation. Based on our findings, we distill some insights about the challenges and opportunities for Transformer-based code intelligence.

Index Terms—Code intelligence, code transformation, Transformer, robustness.

1 INTRODUCTION

Over the past few years, deep neural networks (DNNs) have been continuously expanding their real-world applications for source code intelligence tasks [1], [2], [3], [4]. Due to the format similarity between source code and text [5], Transformer [6], an attention-based neural network architecture for learning textual semantics [7], is now widely used for source code representation learning [1], [2], [3], [4], and becomes a state-of-the-art architecture in several code intelligence tasks, including code completion, code summarization and code search, demonstrate insertion / deletion transformation and identifier transformation show the greatest impact on the performance of Transformer. We firstly design and implement 27 and 24 semantic-preserving code transformation strategies for Java and Python languages respectively, and group them into 5 types of strategies according to the scope of influence under semantic-preserving transformation, and (2) different code transformation strategies have different impacts on Transformer. Therefore, we aim at investigating whether Transformer can maintain performance under semantic-preserving code transformation, and the impact of different transformation strategies.

In this work, we empirically study the effect of semantic-preserving code transformation on the performance of Transformer. We firstly design and implement 27 and 24 semantic-preserving transformation strategies for Java and Python languages respectively, and group them into 5 types of strategies according to the scope of influence under the transformation: block transformation, insertion / deletion transformation, grammatical statement transformation, grammatical token transformation, and identifier transformation.
When applying the transformed code on three popular code intelligence tasks: code completion (CC), code search (CS), and code summarization (CoSum). For studying whether involving syntax information such as Abstract Syntax Trees (ASTs) is beneficial for improving the robustness of Transformer under code transformation, we classify the Transformer-based code intelligence models into two types according to the input: Seq-based Transformer and AST-based Transformer. The seq-based Transformer only considers sequences of code tokens as input; while AST-based Transformer also involves parsed ASTs as input.

Besides, the positional encoding is an essential component in Transformer [28], and has been proven effective in Transformer-based code models [3]. Therefore, in this work, we also study the impact of different positional encoding strategies on the robustness of Transformer models under code perturbation. Specifically, two widely-used positional encoding strategies, including absolute positional encoding [6] and relative positional encoding [30], are chosen for analysis. We aim at answering the following research questions in the work.

**RQ1:** How do different code transformations impact the performance of Transformer? (Seq-based Transformer)

**RQ2:** Is AST helpful for reducing the impact of code transformations on the performance of Transformer? (AST-based Transformer)

During answering each research question, we also consider different positional encoding strategies. We achieve some findings and summarize the key findings as below.

- **Code transformations such as insertion / deletion transformation and identifier transformation present the greatest impact on the performance of both seq-based and AST-based Transformers.**
- **Transformer based on ASTs shows more robust performance than the model based on only code sequence under most code transformations.**
- **The relative position encoding can improve the robustness of seq-based Transformer under most code transformations, but has no much benefit for the robustness of AST-based Transformer.**

Based on the findings, we derive some insights about the challenges and opportunities that would benefit future research. For example, future work is expected to better exploit ASTs to boost the robustness of Transformer models under code transformation. Besides, we also encourage future work to explore more effective attention approach or engage additional external knowledge to eliminate the distraction of insertion / deletion transformation. Furthermore, future work should eliminate the impact of identifiers during code representation learning, instead of relying on the semantics of identifiers.

The main contributions of this paper are summarized as follows:

- **We empirically study the effect of semantic-preserving code transformation on the performance of Transformer for three popular code intelligence tasks.**
- **We design and implement 27 and 24 code transformation strategies for Java and Python languages, respectively.**
- **We study how different aspects can impact the performance of Transformer, including the input and positional encoding strategy.**
- **We achieve some findings and implications that would benefit future research in the robustness of Transformer-based code intelligence tasks.**

The rest of this paper is organized as follows. We present the background of Transformer and code intelligence tasks in Section 2. The technical details of our code transformation strategies are presented in Section 3. The evaluation and study design are shown in Section 4. Then we present the experimental results and potential findings in Section 5. Based on the findings, we conclude some implications and future directions in Section 6. We discuss threats to validity in Section 7. Finally, we give the review of the literature related to our research in Section 8 and conclude the work in Section 9, respectively.

2 BACKGROUND

2.1 Transformer and positional encoding

Transformer employs the typical encoder-decoder structure [6], and is composed of stacked Transformer blocks. Each block contains a multi-head self-attention sub-layer
followed by a fully connected positional-wise feed-forward network sub-layer. The sub-layers are connected by residual connections [31] and layer normalization [32]. Different from the encoder, the decoder has attention sub-layers that use the key and value matrices from the encoder. Positional encoding is an essential component in Transformer [28], and has proven effective in code intelligence tasks [33]. We then introduce the two popular positional encoding strategies, including absolute positional encoding [30] and relative positional encoding [30], as below.

**Absolute positional encoding.** The original Transformer is supplemented by positional encoding to accommodate for the input’s sequential nature. It transposes the sequence of input vectors \( X = (x_1, x_2, ..., x_n) \) into the sequence of output vectors \( Z = (z_1, z_2, ..., z_n) \), where \( x_i, z_i \in R^{d_{model}} \). When doing self attention, Transformer first projects the input vector \( X \) into three vectors: the query \( Q \), key \( K \) and value \( V \) by trainable parameters \( W^Q, W^K, W^V \). The attention weight is calculated using dot product and softmax function. The output vector is the weighted sum of the value vector:

\[
e_{ij} = \frac{(x_i W^Q)(x_j W^K)^T}{\sqrt{d}}, \tag{1}
\]

\[
\alpha_{ij} = \frac{\exp{e_{ij}}}{\sum_{k=1}^n \exp{e_{ij}}}, \tag{2}
\]

\[
z_i = \sum_{j=1}^n \alpha_{ij}(x_j W^V), \tag{3}
\]

where \( d \) is the dimension of each vector, and is used to scale the dot product.

**Relative positional encoding.** To encode the pairwise positional relationships between input elements, Shaw et al. [30] propose the relative position encoding which models the relation of two elements through their distance in the input sequence. Formally, the relative position embedding between input element \( x_i \) and \( x_j \) is represented as \( a_{ij}^Q, a_{ij}^K, a_{ij}^V \in R^d \). In this way, the self attention calculated in Equ. (1) and Equ. (3) can be rewritten as:

\[
e_{ij} = \frac{(x_i W^Q)(x_j W^K + a_{ij}^K)^T}{\sqrt{d}}, \tag{4}
\]

\[
z_i = \sum_{j=1}^n \alpha_{ij}(x_j W^V + a_{ij}^V). \tag{5}
\]

Relative position representations take the relative distance into calculating attention rather than absolute position, which perform more effectively and flexibly.

### 2.2 Code intelligence task

**Code completion task.** Code completion is commonly used in modern integrated development environments (IDEs) for facilitating programming [33]. Developers use the code completion technique to predict expected code elements, such as class names and methods, based on given code surrounding the point of prediction [34]. Common code completion techniques include token-level completion and statement-level completion [34]. In our experiment, we focus on the token-level completion, and the task is to predict the next code token \((n_i)\) based on the previous code tokens \([n_0, n_1, ..., n_{i-1}]\).

**Code summarization task.** The task of code summarization is to generate a natural language summary (e.g., a documentation) for given source code [3]. Code summary can help developers to understand the function and purpose of code without requiring the developers to read the code itself, which can save them time from comprehending the details of that code [36]. For a dataset containing a set of programs \( C \) and targeted summaries \( S \), the task of code summarization is to generate the summary consisting of a sequence of token \( s = (s_0, s_1, ..., s_m) \) by maximizing the conditional likelihood \( \hat{s} = \arg \max_s P(s|c) \) for the given code \( c = (c_0, c_1, ..., c_n) \) from \( C \), where \( s \) is the corresponding summary in \( S \).

**Code search task.** The goal of code search is to find the most semantically-related code from a collection of code based on a given natural language query [37]. In our experiment, we focus on neural code search [38], [39], which learns the joint embeddings of natural-language query and code snippet [40]. The task of neural code search is to return the expected ranking order of code snippets for the given natural language.

### 3 Code transformation

To verify the robustness of Transformer under input perturbations, we have implemented 24 and 27 semantic-preserving code transformation strategies for Python and Java languages, respectively. The semantic-preserving code transformation is implemented on AST, and consists of three phases: (1) we parse the source code into its AST using the standard compiler tool (e.g., tree-sitter in our experiments); (2) we directly modify the structure of AST to the target code formation; (3) we convert the modified AST to a transformed source code. This process also needs to make sure the transformed code can be compilable and executable.

Table 1 presents all the transformation strategies and corresponding descriptions. To conduct a thorough investigation of the impact of transformed code on Transformer, we classify the code transformation strategies into five types according to the scope of influence under the transformation:

- Block transformation;
- Insertion / deletion transformation;
- Grammatical statement transformation;
- Grammatical token transformation;
- Identifier transformation.

For instance, the `bool to int transformation` converts the Boolean value from True/False to 1/0 and only affects the changed Boolean token, hence it belongs to grammatical token transformation.

**Block transformation (denoted as \( T_B \).** This type refers to the code transformation that impacts the code at block level, as shown in Figure 2 (b). The example illustrated in Figure 2 (b) is a block transformation, where the if-statement

1. https://tree-sitter.github.io/tree-sitter/
is transformed to the equivalent while-statement. The type contains seven code transformation strategies in total.

**Insertion / deletion transformation** (denoted as $T_{ID}$). This type of transformation is implemented at the statement level. The transformation generally adds new statements or deleting existing ones without impacting other statements in the program. During implementation, only sub-trees are added or deleted at the AST level, as depicted in Figure 2(c). For example, the remove unused variable transformation will remove the variable declaration statement if the variable is never used again, and such change will not affect other statements in the program. This type consists of 7 code transformation strategies.

**Grammatical statement transformation** (denoted as $T_{GS}$). This type of transformation is also operated at the statement level. Different from $T_{ID}$, $T_{GS}$ changes the statements in the original code, as depicted in Figure 2(d). For example, the change the unary operator replaces the statement $i++$ by $i=i+1$. This type has 10 code transformation strategies.

**Grammatical token transformation** (denoted as $T_{GT}$). This type of transformation changes the original code at the token level, and includes six code transformation strategies. As illustrated in Figure 2(e), the transformation only affects the type and value of associated AST nodes, with the structure unchanged. Note that the type of transformation does not involve identifiers. For instance, the bool to int transformation converts the Boolean operator from True/False to 1/0.

**Identifier transformation** (denoted as $T_{I}$). This type of transformation is also implemented at token level but mainly operates on identifiers, as illustrated in Figure 2(f). The type includes two transformation strategies, including function rename transformation and variable rename transformation. For example, the the variable rename transformation renames the identifiers (variable name) with placeholders such as var1 and var2. Additionally, some strategies cannot be implemented for both languages considering the language-specific characteristics. For example, the Python language does not support the increment and decrement operators, so the change the unary operator transformation strategy is only allowed in Java. The Java language treats Boolean as a unique data type with two distinct values: True and False, so the bool to int transformation strategy is only applicable for Python.

**4 EXPERIMENTAL SETUP**

**4.1 Datasets and pre-processing**

Following the prior work \cite{41}, we choose the Java and Python datasets from CodeSearchNet \cite{37} for evaluation. CodeSearchNet is a collection of large datasets with code-document pairs from open source projects on GitHub, which is widely-used in code intelligence tasks \cite{42}, \cite{43}. Detailed data statistics are illustrated in Table 2. The subject data consist of 165K / 5K / 11K training / validation / test code snippets for Java and 252K / 14K / 15K for Python, respectively. For facilitating analysis, we parse the code snippets into ASTs, and traverse the ASTs into sequences of tokens as input in depth-first-search order following \cite{3}.

**4.2 Implementation**

In this work, we consider three code intelligence tasks: code completion, code summarization, and code search. We elaborate on the detailed implementation of the three tasks in the following.
In our experiments, we implement a Transformer architecture for code summarization and code search tasks. Our Transformer models include 6 layers, 6 heads with the layers of our models to be 512. We set the maximum distance of relative attention to 32 for all tasks. We train Transformers using Adam with a starting learning rate of 0.0001 and a batch size of 32 / 32 / 128 with the epoch number being 15 / 20 / 100 for code completion, summarization, and search respectively. We train all models on 4 GPUs of Nvidia Tesla V100 with 32G of memory.

**Evaluation set.** As illustrated in Table 1 not all the transformation strategies are applicable for both programming languages. For example, the `bool to int` strategy is only allowed in Python. During analyzing the impact of each code transformation strategy on models’ performance, we only evaluate on the transformable code instead of all the code in the test set. Besides, to minimize the performance bias, we run each experiment for three times and report the average results.

| No. Transformation strategy | Description of transformation | Java | Python |
|----------------------------|--------------------------------|------|--------|
| B-1 For statement          | replace the for statement by equivalent while statement | ✓    | ✓      |
| B-2 While statement        | replace the while statement by equivalent for statement | ✓    | x      |
| B-3 Elseif to elseif       | convert elseif to else if, for example, if(x==1){ }else{if(x==2){ } } becomes if(x==1){ } else if(x==2){ } | ✓    | ✓      |
| B-4 Else if to elseif      | convert else if to elseif, for example, if(x==1){ } else if(x==2){ } becomes if(x==1){ } else if(x==2){ } | ✓    | ✓      |
| B-5 If to else             | use logical not operator to change the condition of if statement and exchange the block of if and else, for example, if(x==0){ block1 }else{ block2 } becomes if(!x==0){ block1 } else{ block2 } | ✓    | ✓      |
| B-6 Change if statement    | if the condition of if statement has logical operator(e.g. & &), it will split the if statement | ✓    | x      |
| B-7 Create new function    | move the variable initialization statement to generate a new function, and then call the function, for example, z = x+y becomes def func(x,y): return x+y z=func(x,y) | ✓    | ✓      |

| Insertion / deletion transformation. | |
|--------------------------------------|------|------|
| ID-1 Add comments                    | insert comments not related to the source code | ✓    | ✓    |
| ID-2 Add junk code                   | add code that is not related to the source code | ✓    | ✓    |
| ID-3 Add return statement            | add a return statement at the end of the source code that returns the default value | ✓    | ✓    |
| ID-4 Import library                  | import libraries unrelated to source code | ✓    | ✓    |
| ID-5 Delete comment                  | remove all the comments from source code | ✓    | ✓    |
| ID-6 Delete print                    | replace the print statement by empty statement, for example, replace print by pass | ✓    | ✓    |
| ID-7 Remove unused variable          | remove the variable declaration statement if the variable is never used | ✓    | ✓    |

**Grammatical statement transformation.**

| GS-1 Change return statement        | if the return statement returns an integer literal, we will declare a variable, and return the variable | ✓    | ✓    |
| GS-2 For move in variable declaration| move the variable declaration into for statement. For instance, int i; for(i=0;i<10;i++) becomes for(int i=0;i<10;i++) | ✓    | x    |
| GS-3 For move out variable declaration| move the variable declaration out of for statement | ✓    | ✓    |
| GS-4 Change variable declaration    | move the variable declaration and initialization, for example, int i=0 becomes int i=i=0 | ✓    | ✓    |
| GS-5 Add logical operator           | add the logical not operator and use opposite comparison operator, for example, x<y becomes !y>y=x | ✓    | ✓    |
| GS-6 Change comparison operator     | use the opposite comparison operator, for example, x<y becomes y>x | ✓    | ✓    |
| GS-7 Change argument assignment operator| change the argument assignment operator to assignment operator, for example, x+i=1 becomes x+=i=1 | ✓    | ✓    |
| GS-8 Change the unary operator      | change the increment or decrease operator. For instance, x++ becomes x=x+1 | ✓    | x    |
| GS-9 Add curly bracket              | add a curly brace to a single statement and then generate a new compound statement | ✓    | ✓    |
| GS-10 Delete curly bracket          | if the compound statement has only a single statement, delete curly of the compound statement | ✓    | ✓    |

|Grammatical token transformation. | |
|----------------------------------|------|------|
|GT-1 Bool to int                 | replace True or False by 1 or 0 | x    | ✓    |
|GT-2 Int to bool                 | replace 1 or 0 by True or False | x    | ✓    |
|GT-3 Upper integral type         | replace the integral type by a higher type, for example, replace int by long | ✓    | ✓    |
|GT-4 Upper floating type         | replace the integral type by floating type or replace float by double | ✓    | ✓    |
|GT-5 Change input API            | change the API for reading input | x    | ✓    |
|GT-6 Change output API           | change the API for writing output | ✓    | ✓    |

**Identifier transformation.**

| I-1 Function rename              | rename the function name and class name | ✓    | ✓    |
| I-2 Variable rename              | rename the variable name | ✓    | ✓    |

**Table 2: Statistics of experimental data.**

| Language | Train | Valid | Test |
|----------|-------|-------|------|
| Python   | 251,820 | 13,914 | 14,918 |
| Java     | 164,923 | 5,183  | 10,955 |

**Code completion.** We use the set up, metrics and implementation of Transformer according to [8]. Besides, we split code sequence whose length is over 500 following [5].

**Code summarization.** In our experiments, we select [10] as Transformer implementation except that we do not split sub-token following Chirkova et al. [5].

**Code search.** In our experiments, we implement a Transformer architecture for code search task based on [44]. We process the dataset following the strategy of Evangelos et al. [44]. For example, we filter the non-ASCII tokens and replace symbols by their English names (e.g., the symbol + in code token is replace by `addoperator`).

**Hyper-parameters.** The hyper-parameters setting in our experiments follows Transformer implementations [5], [10], [44] and we list the major hyper-parameters for code completion, code summarization, and code search tasks.
4.3 Evaluation metrics

4.3.1 Code summarization

We evaluate the source code summarization performance using three metrics: BLEU, METEOR and ROUGE-L.

**BLEU** is a widely-used metric in natural language processing and software engineering fields to evaluate the quality of generated texts, e.g., machine translation, code comment generation, and code commit message generation. It computes the frequencies of the co-occurrence of n-grams between the ground truth and the generated sequence to judge the similarity:

\[
\text{BLEU-N} = b(y, \hat{y}) \cdot \exp \left( \sum_{n=1}^{N} \beta_n \log p_n(y, \hat{y}) \right),
\]

where \( b(y, \hat{y}) \) indicates the brevity penalty, and \( p_n(y, \hat{y}) \) and \( \beta_n \) represent the geometric average of the modified n-gram precision and the weighting parameter, respectively.

**ROUGE-L** is commonly used in natural language translation [46], and is a F-measure based on the Longest Common Subsequence (LCS) between candidate and target sequences, where the LCS is a set of words appearing in the two sequences in same order.

\[
\text{ROUGE-L} = \left( 1 + \beta^2 \right) \frac{R_{lcs} P_{lcs}}{R_{lcs} + \beta^2 P_{lcs}},
\]

where \( R_{lcs} = \frac{\text{LCS}(X,Y)}{\text{len}(Y)} \) and \( P_{lcs} = \frac{\text{LCS}(X,Y)}{\text{len}(X)} \). \( X \) and \( Y \) denote candidate sequence and reference sequence, respectively. \( \text{LCS}(X,Y) \) represents the length of the longest common sub-sequence between \( X \) and \( Y \).

**Meteor** is an evaluation metric proposed based on BLEU [47]. It introduces synonym, stem, and other information to replace the precise matching in BLEU, and strengthens the role of recall in automatic evaluation.

4.3.2 Code search and code completion

For code search and code completion tasks, we use MRR as the evaluation metric. MRR is the average of the reciprocal rank of results of a set of queries. The reciprocal rank of a query is the inverse of the rank of the first hit result.

\[
\text{MRR} = \frac{1}{N} \sum_{n=1}^{N} \frac{1}{\text{rank}_i},
\]

where \( N \) is the total number of targets (tokens for code completion and code snippet for code search) in data pool and \( \text{rank}_i \) represents the position of the \( i \)-th true target in the ranking results.

5 RESEARCH QUESTIONS AND RESULT ANALYSIS

Our experimental study aims to answer the following research questions:

**RQ1**: How do different code transformations impact the performance of Transformer? (Seq-based Transformer)

**RQ2**: Is AST helpful for reducing the impact of code transformations on the performance of Transformer? (AST-based Transformer)

RQ1 aims at discovering which types of code transformation show greatest impact on the robustness of Transformer. RQ2 aims at analyzing whether AST is beneficial for improving the robustness of Transformer under different code transformations. During answering both RQs, we also consider the impact of different positional encoding strategies.

5.1 Answer to RQ1: Impact on seq-based Transformer

In this section, we compare the performance of Transformer before and after different code transformations for three different tasks. Table 3 Table 4 and Table 5 present the overall results of code completion, code search and code summarization, respectively.

5.1.1 Different types of code transformation on code sequence

In the section, we analyze the effects of different types of code transformation on the performance of seq-based Transformer. We observe that seq-based Transformer’s performance is affected to varying degrees by different types of code transformations. We elaborate on the detailed impact of different types of code transformation in the following.

**Block transformation (T_b)**. As shown in Table 3-5, we observe that Transformer demonstrates robust performance under block transformation on all code intelligence tasks. For example, the MRR values for the code completion task just decrease by 0.81% and 0.65% for Java and Python, respectively (seen in Table 3).

**Insertion / deletion transformation (T_id)**. From Table 3-5, we observe that insertion / deletion transformation has a substantial impact on Transformer on all code intelligence tasks. For example, the decrease of Transformer on the code search task is from 23.34% to 26.77% (seen in Table 4). When generating Java’s code summary, the BLEU, ROUGE-L, and METEOR values decrease by 5.31%, 7.85%, and 10.84%, respectively (seen in Table 5).

**Grammatical statement transformation (T_cs)**. We find that seq-based Transformer shows robust performance under grammatical statement transformation. For instance, the impact of this type of code transformation on the code search task is 0.30% and -0.87% for Java and Python (seen in Table 4), respectively.

**Grammatical token transformation (T_gt)**. From the experimental results, we observe that the grammatical token transformation has a slight influence on all tasks. For example, the MRR score has a decrease of 1.02% and 3.19% respectively for Java and Python on the code completion task, respectively (seen in Table 5).

**Identifier transformation (T_id)**. We observe that this type of code transformation has a substantial impact on all code intelligence tasks. For instance, the MRR score has a decrease of 42.21% and 38.22% for Java and Python under identifier transformation in code search task, respectively (seen in Table 4).

Finding 1: Transformer’s performance is affected to varying degrees by different types of code transformations.
TABLE 3: Results of code transformation on the performance of seq-based Transformer for the code completion task. Column “Pos.” represents the position encoding strategy, while “abs.” and “rel.” represent the absolute/relative position encoding, respectively. Column “w. t.” and “w/o t.” represent the results with and without code transformation. Different rows represent the results of different types of code transformation, while the bottom portion $T_{all}$ presents the average results. The red color indicates the degree of decrease.

| Type   | Pos. | MRR (Java) w/o t. | MRR (Java) w. t. | MRR (Python) w/o t. | MRR (Python) w. t. |
|--------|------|-------------------|------------------|---------------------|-------------------|
| $T_{b}$ | abs. | 0.7243            | 0.7185           | 0.6581              | 0.6539            |
|        | rel. | 0.7243            | 0.7390           | 0.6708              | 0.6672            |
| $T_{d}$ | abs. | 0.5925            | 0.5929           | 0.5999              | 0.5677            |
|        | rel. | 0.5999            | 0.5677           | 0.5580              | 0.5376            |
| $T_{c}$ | abs. | 0.7201            | 0.7082           | 0.6488              | 0.6377            |
|        | rel. | 0.7304            | 0.7186           | 0.6614              | 0.6502            |
| $T_{r}$ | abs. | 0.7180            | 0.7107           | 0.6509              | 0.6301            |
|        | rel. | 0.7277            | 0.7191           | 0.6637              | 0.6565            |
| $T_{i}$ | abs. | 0.7169            | 0.6485           | 0.6594              | 0.6139            |
|        | rel. | 0.7255            | 0.6544           | 0.6703              | 0.6163            |
| $T_{a}$ | abs. | 0.6944            | 0.6631           | 0.6331              | 0.6007            |
|        | rel. | 0.7036            | 0.6777           | 0.6448              | 0.6250            |

TABLE 4: Results of code transformation on the performance of seq-based Transformer for the code search task. The red and green colors indicate the degree of decrease and increase, respectively.

| Type   | Pos. | MRR (Java) w/o t. | MRR (Java) w. t. | MRR (Python) w/o t. | MRR (Python) w. t. |
|--------|------|-------------------|------------------|---------------------|-------------------|
| $T_{b}$ | abs. | 0.3630            | 0.3611           | 0.3853              | 0.3834            |
|        | rel. | 0.3601            | 0.3614           | 0.3808              | 0.3779            |
| $T_{d}$ | abs. | 0.3249            | 0.2379           | 0.2802              | 0.2148            |
|        | rel. | 0.3452            | 0.2599           | 0.2730              | 0.2080            |
| $T_{c}$ | abs. | 0.4208            | 0.4221           | 0.3891              | 0.3857            |
|        | rel. | 0.4350            | 0.4367           | 0.3861              | 0.3838            |
| $T_{r}$ | abs. | 0.4403            | 0.4397           | 0.3761              | 0.3368            |
|        | rel. | 0.4496            | 0.4485           | 0.3629              | 0.3248            |
| $T_{i}$ | abs. | 0.4363            | 0.2521           | 0.4093              | 0.2529            |
|        | rel. | 0.4428            | 0.2586           | 0.4050              | 0.2516            |
| $T_{a}$ | abs. | 0.3971            | 0.3426           | 0.3680              | 0.3147            |
|        | rel. | 0.4066            | 0.3530           | 0.3616              | 0.3092            |

Based on the above analysis, we achieve that seq-based Transformer shows robust performance under block transformation, grammatical statement transformation and grammatical token transformation, but suffers from obvious performance degradation under insertion / deletion transformation and identifier transformation. For example, in code completion task, the decreases of MRR score for Java under insertion / deletion transformation and identifier transformation are 10.62% and 9.54%, respectively, while the decreases caused by block transformation, grammatical statement transformation and grammatical token transformation are 0.81%, 1.66%, and 1.02%, respectively.

Finding 2: The insertion / deletion transformation and identifier transformation present greatest impact on the performance of seq-based Transformer.

During experimentation, we also find that inserting junk code at different locations (ID-2 front / middle / end) has different impact on the performance of seq-based Transformer. ID-2 middle represents the cases where the junk code is inserted inside the given code, and it is also the default implementation of ID-2 in other code transformation experiments. ID-2 front / end represents the junk code inserted before and after the given code, respectively. The results of inserting junk code at different locations for the code search and summarization tasks are shown in Table 6. We observe that Transformer’s performance degrades more evidently when junk code is inserted at the front of the given code than when it is inserted randomly or at the end. For example, on the code search task, the decrease of the ID-2 front / middle / end on seq-based Transformer are 42.67% / 25.31% / 15.95% for Java respectively, while the decrease for Python are 88.19% / 14.78% / 10.56%, respectively.

Finding 3: Inserting junk code at the front of the given code can affect Transformer’s performance more than inserting junk code at other locations.

5.1.2 Absolute position v.s. relative position

The section looks into whether position encoding impacts Transformer’s performance under code transformation. From Table 3, we find that Transformer with relative position encoding (Transformer_rel) shows more robust performance better compared to that with absolute position encoding (Transformer_abs) on three code intelligence tasks. For example, the overall MRR score of Transformer_abs has a decrease of 4.50% and 5.12% for Java and Python on the code completion task, while the decrease of Transformer_rel is 3.67% and 3.07%, respectively. More specifically, we find that the influence of relative position encoding is more obvious under insertion / deletion transformation than other types of code transformation. For example, the Transformer_abs and Transformer_rel’ MRR values under insertion / deletion transformation decrease by 10.62% and 5.37% for Java and 12.45% and 3.65% for Python, respectively, while the decreases under grammatical statement transformation are are 1.66% and 1.61% for Java and 1.72% v.s. 3.65% for Python, respectively ($T_{d}$ and $T_{c}$) in Table 3. The robustness improvement may be attributed to that the relative position encoding enhances the relationship between the tokens with the adjacent preceding tokens [30], making Transformer’s predictions more accurate on code completion.

Finding 4: Seq-based Transformer with relative position encoding shows more robust performance compared to that with absolute position encoding under most code transformations.

To sum up, seq-based Transformer shows robust performance under block transformation, grammatical statement transformation and grammatical token transformation. However, insertion / deletion transformation and identifier transformation have substantial impact on Transformer’s performance. Besides, the relative position encoding can improve the robustness of seq-based Transformer under most code transformations.

5.2 Answer to RQ2: Impact on AST-based Transformer

In this section, we compare the performance of AST-based Transformer before and after different code transformations for three different tasks. Tables 7, 8 and 9 present
5.2.1 Different types of code transformation on ASTs

In this section, we analyze the effects of different types of code transformation on the performance of AST-based Transformer. We observe that insertion / deletion transformation and identifier transformation have substantial impact on AST-based Transformer. For example, the decrease of that under grammatical statement transformation and grammatical token transformation are 0.55% and 0.75%, respectively. We elaborate on the detailed impact of ASTs on different types of code transformation in the following.

Block transformation ($T_B$) has a minor impact on AST-based Transformer’s performance as Table 7 shows. And AST-based Transformer shows more robust performance than seq-based Transformer. For example, when it comes to generating Python's code summary, the values of BLEU,
**TABLE 8**: Results of code transformation on the performance of AST-based Transformer for the code search task. The red and green colors indicate the degree of decrease and increase, respectively.

| Type     | MRR (Java) w/o. t. | MRR (Java) w.t. | MRR (Java) w/o. t. | MRR (Java) w.t. | MRR (Python) w/o. t. | MRR (Python) w.t. | MRR (Python) w/o. t. | MRR (Python) w.t. |
|----------|------------------|----------------|------------------|----------------|----------------------|------------------|------------------|------------------|
| T_A      | 0.3594           | 0.3599         | 1.14             | 0.3590         | 0.3997               | 0.3997           | 0.18             | 0.10             |
| T_B      | 0.3698           | 0.3702         | 1.09             | 0.3697         | 0.3953               | 0.3953           | 0.10             |
| T_D      | 0.3368           | 0.3220         | 4.41             | 0.2898         | 0.2258               | 0.2275           | 0.19             |
| T_G      | 0.3625           | 0.3462         | 4.49             | 0.2847         | 0.2168               | 0.2385           | 0.29             |
| T_C      | 0.3978           | 0.3980         | 0.04             | 0.4111         | 0.4097               | 0.4075           | 0.35             |
| T_T      | 0.4225           | 0.4220         | 0.13             | 0.4057         | 0.4046               | 0.4046           | 0.29             |
| T_G      | 0.4388           | 0.4366         | 0.49             | 0.3924         | 0.3448               | 0.3448           | 0.14             |
| T_T      | 0.4617           | 0.4607         | 0.21             | 0.3910         | 0.3415               | 0.3415           | 12.67            |
| T_I      | 0.4287           | 0.2428         | 43.36            | 0.4245         | 0.2644               | 0.2644           | 37.71            |
| T_T      | 0.4439           | 0.2558         | 42.83            | 0.4235         | 0.2678               | 0.2678           | 36.77            |
| T_R      | 0.3923           | 0.3519         | 10.31            | 0.3834         | 0.3285               | 0.3285           | 14.32            |
| T_M      | 0.4121           | 0.3706         | 10.08            | 0.3801         | 0.3252               | 0.3252           | 14.46            |

ROUGE-L, and METEOR decrease by 0.06%, 0.09%, and 0.44% on AST-based Transformer, while the decreases on seq-based Transformer are 0.90%, 0.53%, and 1.87%, respectively.

**Finding 5**: Compared to seq-based Transformer, AST-based Transformer demonstrates more robust performance under most code transformations.

5.2.2 **Absolute position v.s. relative position on ASTs**

This section looks into whether position encoding has an impact on the AST-based Transformer’s performance under code transformation. From Table 7-9, we find that relative position encoding does not make obvious improvement on AST-based Transformer’s robustness under code transformations. For example, the decrease in overall MRR score on Java’s code completion task is 2.61% and 2.60% for absolute and relative position encoding, while the decrease on Python is 1.95% and 1.87%, respectively. Similar results can be seen on the code search task (10.31% v.s. 10.08% for Java and 14.32% v.s. 14.46% for Python).

**Finding 6**: Relative position encoding does not evidently improve the robustness of AST-based Transformer under code transformation.

6 **DISCUSSION**

The experiments in Section 5 have demonstrated that insertion/deletion transformation and identifier transformation have a substantial impact on the robustness of Transformer. In this section, we discuss the Transformer’s robustness from three perspectives: the input-ASTs, insertion/deletion transformation, and identifier transformation.

6.1 **Effect of ASTs on the models’ robustness**

Based on the experimental results in Section 5.2, we observe that AST-based Transformer performs just marginally better than seq-based Transformer under different code transformations. Besides, the relative position encoding does not obviously improve the robustness of AST-based Transformer. Moreover, AST-based Transformers still cannot well understand the underlying semantic information of transformed code (e.g., insertion/deletion transformation and identifier transformation). The results indicate that exploiting ASTs for learning robust code semantics is still challenging.
TABLE 9: Results of code transformation on the performance of AST-Based Transformer for the code summarization task. The above part presents the results of Transformer with absolute/relative position encoding strategies (“abs.” and “rel.”) for Java, and the below part presents results for Python. The red and green colors indicate the degree of decrease and increase, respectively.

| Type | Pos. | BLEU | ROUGE-L | METEOR |
|------|------|------|---------|--------|
|      | w/o. t. | w. t. | w. t. | w. t. |
| T_b  | abs. rel. | 11.89 | 11.89 | 21.85 | 6.91 |
| T_d  | abs. rel. | 11.03 | 11.05 | 19.01 | 7.53 |
| T_g  | abs. rel. | 12.70 | 12.84 | 23.06 | 7.67 |
| T_c  | abs. rel. | 13.25 | 13.26 | 24.99 | 8.66 |
|      | abs. rel. | 12.50 | 12.17 | 22.23 | 7.21 |

| Type | Pos. | BLEU | ROUGE-L | METEOR |
|------|------|------|---------|--------|
|      | w/o. t. | w. t. | w. t. | w. t. |
| T_b  | abs. rel. | 12.51 | 12.50 | 18.89 | 4.85 |
| T_d  | abs. rel. | 11.11 | 11.05 | 19.66 | 5.94 |
| T_g  | abs. rel. | 10.72 | 10.59 | 15.90 | 4.16 |
| T_c  | abs. rel. | 13.41 | 13.31 | 21.36 | 5.68 |
|      | abs. rel. | 12.64 | 12.19 | 18.54 | 5.68 |

TABLE 10: Impact of different insert locations of junk code on AST-based Transformer. CS and CSM represent code search and code summarization tasks, respectively. The “Loc.” represents the insert locations, and middle / front / end represent inserting junk code to the given code at the middle / at the front / at the end, respectively. The red color indicates the degree of decrease.

| Loc. | Pos. | MRR (Java) w/o. t. | MRR (Java) w. t. | MRR (Python) w/o. t. | MRR (Python) w. t. |
|------|------|-------------------|------------------|----------------------|---------------------|
|      |      | abs. rel. | imp. (%) | abs. rel. | imp. (%) | abs. rel. | imp. (%) | abs. rel. | imp. (%) |
| front | abs. rel. | 0.4184 | 0.3565 | 14.79 | 0.4364 | 0.0601 | 86.23 |
|      | rel. | 0.4242 | 0.3448 | 18.72 | 0.4200 | 0.0389 | 97.04 |
| middle | abs. rel. | 0.4184 | 0.3821 | 8.66 | 0.4364 | 0.3750 | 14.06 |
|      | rel. | 0.4242 | 0.3826 | 9.81 | 0.4200 | 0.3564 | 13.13 |
| end | abs. rel. | 0.4184 | 0.4009 | 4.17 | 0.4364 | 0.3981 | 8.78 |
|      | rel. | 0.4242 | 0.4026 | 5.10 | 0.4200 | 0.3860 | 8.09 |

| Loc. | Pos. | BLEU | BLEU |
|------|------|------|------|
|      | w/o. t. | w. t. |
| front | abs. rel. | 13.94 | 12.66 |
|      | rel. | 13.82 | 12.47 |
| middle | abs. rel. | 13.94 | 12.75 |
|      | rel. | 13.82 | 12.68 |
| end | abs. rel. | 13.94 | 12.86 |
|      | rel. | 13.82 | 12.80 |

6.2 Effect of insertion / deletion transformation
From the experimental results in Section 5.1 and 5.2, we observe that the insertion / deletion transformation has a substantial impact on all tasks. The results indicate that inserting some junk data (e.g., comments, code snippets, or libraries) can greatly bias Transformer-based code intelligence models. This may be because that the models fail to attend to the important part in the transformed code.

One way to address the issue is to propose more effective attention models for identifying the useful part in the input code. Another way is to incorporate external knowledge such as API documentation to eliminate the distraction of insertion / deletion transformation. For example, if Transformer-based models can recognize noisy part in the input based on the external information, the robustness of the models would be improved under the insertion / deletion transformation.

Implication 2: Transformer needs more effective attention approach or additional external knowledge to eliminate the distraction of noisy information in the input code.

6.3 Effect of identifier transformation
Since identifiers are an important part to express the naturalness of code, their importance has been studied in many works [49], [50]. Based on the experimental results in Section 5.1 and 5.2, we observe that the identifier transformation have a substantial impact on both seq-based and AST-based Transformer. The results demonstrate the importance of
identifiers for code intelligence tasks, and that it is hard for Transformer to learn the code semantics under identifier transformation.

Identifiers could help models for better code understanding [51], [52]. However, most existing code intelligence models rely on identifiers rather than underlying semantic information, resulting in models being vulnerable to identifier transformation. For example, some identifier-based adversarial attack strategies [53], [54] for code intelligence have been proposed in recent years. Future work is encouraged to explore how to effectively understand the code semantics under identifier transformation.

**Implication 3:** Future work is expected to well exploit the underlying semantics of identifiers rather than completely rely on the literal meanings of the identifiers.

### 7 Threats to Validity

In this section, we describe the possible threats we may face in this study and discuss how we mitigate them.

**Internal validity** is mainly about the data prepossessing and training models. To reduce the threats, we conduct experiments based on the released code scripts, and the default training hyper-parameters for all models. Besides, we run each experiment for three times and compute the average results for all tasks.

**Construct validity** is mainly about the suitability of our evaluation metrics. To reduce this risk, we select the most widely-used metrics for different tasks to evaluate the impact. For example, we use BLEU [45], ROUGE-L [46] and Meteor [47] to evaluate the impact of different transformations on code summarization task.

**External validity** is mainly concerned with dataset we use. In our experiments, we select Java and Python datasets from CodeSearchNet. However, CodeSearchNet has some problems that will affect our experiments. For example, some instances of code in CodeSearchNet cannot be parsed into an abstract syntax tree. To reduce the threats, we filter the datasets following the previous work [55]. To further reduce the threats, we plan to collect more open-source projects to reproduce our experiments.

### 8 Related Work

#### 8.1 Code Intelligence Task

**Code completion task.** The success of deep learning boosts a series of code completion works based on deep learning models [56], [57]. For example, Alon et al. [58] proposed a structural language model based on Transformer, which leverages the syntax to model the code snippet as a tree to complete code. Liu et al. [59] pretrained a language model with a Transformer-based architecture and fine-tuned it for code completion. Kim et al. [60] proposed TravTrans, a Transformer-based approach that leverages ASTs for code completion.

**Code summarization task.** In recent years, many works that applied deep learning models in code summarization achieved great success and became more and more popular [60], [61]. For instance, Iyer et al. [62] proposed an LSTM-based model with attention to generate code summaries for source code. Wei et al. [63] and Zhang et al. [64] further introduced retrieved information for summarizing source code with the help of most similar code snippets. Alon et al. [64] sampled and encoded random AST paths into LSTMs to generate summaries of source code. Ahmad et al. [10] utilized Transformer on code summarization for better mapping the source code to their corresponding natural language summaries.

**Code search task.** The goal of code search is to find the most semantically related code from a collection of code based on a given natural language [57]. The traditional code search techniques are mainly based on information retrieval [65], [66], while the most popular approaches in recent years are based on deep neural networks [38], [39]. Sachdev et al. [67] proposed a neural code search engine which used a basic word-embedding for a code corpus. Gu et al. [6] proposed an RNBN-based code search model to represent source code and natural language queries through joint embedding. Fan et al. [40] utilized a self-attention network to construct a code representation network for building the semantic relationship between code snippets and queries. Besides, large-scale pre-train models such as Codebert [4] and GraphCodeBERT [68] also demonstrated good performance on the code search task.

#### 8.2 Code Transformation

Code transformations are widely used for compiler optimizations [69], [70], testability transformation [71], [72], [73], refactoring [74], [75], etc. In recent years, there have been an amount of works in the field of code intelligence that employs code transformation.

**Data augmentation.** Yu et al. [76] applied a source-to-source transformation strategy to increase the generalization capacity of deep learning models based on program-level data augmentation, and Wang et al. [77] incorporated curriculum learning into program-level data augmentation in order to optimize the efficiency of fine-tuning pre-trained models. Bui et al. [78] proposed a self-supervised contrastive learning framework to generate transformed code snippets and identify semantically-equivalent code snippets from large-scale unlabeled data of source code, which could generate additional dataset for fine-turning the pre-training models.

**Adversarial attack.** Quiring et al. [79] used semantics-preserving code transformations to generate adversarial examples and present a black-box attack that seeks examples by Monte-Carlo tree search. Li et al. [80] leveraged code transformations to attack DL-based detectors and decouple feature learning and classifier learning to present a static analysis-based vulnerability detector. Zhang et al. [81] applied reinforcement learning to select semantics-preserving samples and proposed a black-box attack approach against CNN malware detection models.

**Others applications.** Chen et al. [82] suggested a symbolic execution acceleration framework by machine-learning based compiler optimization tuning based on code transformation. Wu et al. [83] proposed an automating CUDA synchronization framework for bug detection at the LLVM-bitcode level via program transformation.
8.3 Robustness of code intelligence

Given the increased research interest in code intelligence, some works on the robustness of source code representation models are proposed [53, 54, 64, 55, 56, 57].

Yefet et al. [64] proposed an adversarial attacks generation approach for code via gradient based optimization, and it was effective in generating both targeted and non-targeted attacks. Rabin et al. [55] defined the generalizability in neural program models and studied the generalizability of method name prediction models using six semantic-preserving changes. Ramakrishnan et al. [57] proposed an adversarial-training method for neural models of code to enhance the robustness. Zhang et al. [53] defined the robust and non-robust features of DNNs, and proposed an identifier renaming algorithm (namely Metropolis-Hastings Modifier) for adversarial example generation on source code. Yang et al. [54] designed a black-box attack approach that was aware of natural semantics when generating adversarial examples of code, which was better than that of Zhang et al. [53]. Bielik et al. [86] refined the representation of source code and applied adversarial-training to improve robustness of neural models while preserving high accuracy.

9 CONCLUSION AND FUTURE WORK

In this study, we have empirically investigated the robustness and limitations of Transformer on code intelligence. We implement 27 and 24 code transformation strategies for Java and Python languages respectively and apply the transformed code to three code intelligence tasks to study the effect on Transformer. Experimental results demonstrate that insertion / deletion transformation and identifier transformation have the great impact on Transformer’s performance. Transformer based on ASTs shows more robust performance than the model based on only code sequence under most code transformations. Besides, the robustness of Transformer under code transformation is impacted by the design of positional encoding. Based on the findings, we summarize some future directions for improving the robustness of Transformer on code intelligence.

In the future, we plan to investigate the robustness of pre-trained models under code transformation. Moreover, we plan to collect more open-source projects to reproduce our experiments and to support more programming languages in our code transformation.

REFERENCES

[1] M. White, M. Tufano, C. Vendome, and D. Pashyvanyk, “Deep learning code fragments for code clone detection,” in 2016 31st IEEE/ACM International Conference on Automated Software Engineering (ASE). IEEE, 2016, pp. 87–98.
[2] X. Hu, G. Li, X. Xia, D. Lo, and Z. Jin, “Deep code comment generation,” in 2018 IEEE/ACM 26th International Conference on Program Comprehension (ICPC). IEEE, 2018, pp. 200–2010.
[3] X. Gu, H. Zhang, and S. Kim, “Deep code search,” in 2018 IEEE/ACM 46th International Conference on Software Engineering (ICSE). IEEE, 2018, pp. 933–944.
[4] Z. Feng, D. Guo, D. Tang, N. Duan, X. Feng, M. Gong, L. Shou, B. Qin, T. Liu, D. Jiang et al., “Codebert: A pre-trained model for programming and natural languages,” arXiv preprint arXiv:2002.08155, 2020.
[5] N. Chirkova and S. Troshin, “Empirical study of transformers for source code,” in Proceedings of the 29th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering, 2021, pp. 703–715.
[6] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, “Attention is all you need,” in Advances in neural information processing systems, 2017, pp. 5998–6008.
[7] T. Wolf, J. Chaumond, L. Debut, V. Sanh, C. Delangue, A. Moi, P. Cistac, M. Funtowicz, J. Davison, S. Shleifer et al., “Transformers: State-of-the-art natural language processing,” in Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, 2020, pp. 38–45.
[8] S. Kim, J. Zhao, Y. Tian, and S. Chandra, “Code prediction by feeding trees to transformers,” in 2021 IEEE/ACM 43rd International Conference on Software Engineering (ICSE). IEEE, 2021, pp. 150–162.
[9] M. Ciniselli, N. Cooper, L. Pascarella, A. Mastropalo, E. Aghajani, D. Pashyvanyk, M. Di Penta, and G. Bavota, “An empirical study on the usage of transformer models for code completion,” IEEE Transactions on Software Engineering, 2021.
[10] W. U. Ahmad, S. Chakraborty, B. Ray, and K.-W. Chang, “A transformer-based approach for source code summarization,” in Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (ACL), 2020.
[11] S. Gao, C. Gao, Y. He, J. Zeng, L. Y. Nie, and X. Xia, “Code structure guided transformer for source code summarization,” arXiv preprint arXiv:2104.08340, 2021.
[12] B. Berabi, J. He, V. Raychev, and M. Vechev, “Tfx: Learning to fix coding errors with a text-to-text transformer,” in International Conference on Machine Learning. PMLR, 2021, pp. 780–791.
[13] X. Gao, R. K. Saha, M. R. Prasad, and A. Roychoudhury, “Fuzz testing based data augmentation to improve robustness of deep neural networks,” in 2020 IEEE/ACM 42nd International Conference on Software Engineering (ICSE). IEEE, 2020, pp. 1147–1158.
[14] X. Xie, L. Ma, F. Juefei-Xu, M. Xue, H. Chen, Y. Liu, J. Zhao, B. Li, J. Yin, and S. See, “Deephunter: a coverage-guided fuzz testing framework for deep neural networks,” in Proceedings of the 28th ACM SIGSOFT International Symposium on Software Testing and Analysis, 2019, pp. 146–157.
[15] C.-Y. Ko, Z. Lyu, L. Weng, L. Daniel, N. Wong, and D. Lin, “Popqorn: Quantifying robustness of recurrent neural networks,” in International Conference on Machine Learning. PMLR, 2019, pp. 3468–3477.
[16] S. Garg and G. Ramakrishnan, “Bae: Bert-based adversarial examples for text classification,” arXiv preprint arXiv:2004.01970, 2020.
[17] N. Carlini and D. Wagner, “Towards evaluating the robustness of neural networks,” in 2017 cs symposium on security and privacy (sp). IEEE, 2017, pp. 39–57.
[18] D. Jakubovitz and R. Giryes, “Improving dnn robustness to adversarial attacks using jacobian regularization,” in Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 514–529.
[19] Y. Tian, K. Pei, S. Jana, and B. Ray, “Deeptest: Automated testing of deep-neural-network-driven autonomous cars,” in Proceedings of the 40th international conference on software engineering, 2018, pp. 303–314.
[20] T. S. Borkar and L. J. Karam, “Deeppcorrect: Correcting dnn models against image distortions,” IEEE Transactions on Image Processing, vol. 28, no. 12, pp. 6022–6034, 2019.
[21] J. Ebrahimi, A. Rao, D. Lowd, and D. Dou, “Hotflip: White-box adversarial examples for text classification,” arXiv preprint arXiv:1712.06751, 2017.
[22] A. Svyatkovskiy, S. K. Deng, S. Fu, and N. Sundaresan, “Inteledge compose: Code generation using transformer,” in Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering, 2020, pp. 1433–1443.
[23] Z. Tang, C. Li, J. Ge, X. Shen, Z. Zhu, and B. Luo, “Ast-transformer: Encoding abstract syntax trees efficiently for code summarization,” in 2021 36th IEEE/ACM International Conference on Automated Software Engineering (ASE). IEEE, 2021, pp. 1193–1195.
[24] Z. Li, Y. Wu, B. Peng, X. Chen, Z. Sun, Y. Liu, and D. Paul, “Setransformer: A transformer-based code semantic parser for code comment generation,” IEEE Transactions on Reliability, 2022.
[25] Z. Sun, Q. Zhu, Y. Xiong, Y. Sun, L. Mou, and L. Zhang, “Treegen: A tree-based transformer architecture for code generation,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 34, no. 05, 2020, pp. 8984–8991.
[26] X. Zheng, J. Zeng, Y. Zhou, C.-J. Hsieh, M. Cheng, and X.-J. Huang, “Evaluating and enhancing the robustness of neural network-based dependency parsing models with adversarial examples,” in Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, 2020, pp. 6608–6610.

[27] S. Ren, Y. Deng, K. He, and W. Che, “Generating natural language adversarial examples through probability weighted word saliency,” in Proceedings of the 57th annual meeting of the association for computational linguistics, 2019, pp. 1085–1097.

[28] G. Ke, D. He, and T.-Y. Liu, “Rethinking positional encoding in language pre-training,” in International Conference on Learning Representations, 2020.

[29] V. Shiv and C. Quirk, “Novel positional encodings to enable tree-based transformers,” Advances in Neural Information Processing Systems, vol. 32, 2019.

[30] P. Shaw, J. Uszkoreit, and A. Vaswani, “Self-attention with relative position representations,” arXiv preprint arXiv:1803.02155, 2018.

[31] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.

[32] J. L. Ba, J. R. Kiros, and G. E. Hinton, “Layer normalization,” arXiv preprint arXiv:1607.06450, 2016.

[33] A. Svyatkovskiy, S. Lee, A. Hadjitos, M. Riechert, J. V. Franco, and M. Allamanis, “Fast and memory-efficient neural code completion,” in 2021 IEEE/ACM 18th International Conference on Mining Software Repositories (MSR). IEEE, 2021, pp. 329–340.

[34] M. Izadi, R. Gismondi, and G. Gousios, “Codefell: Multi-tenant code completion by jointly learning from structure and naming sequences,” arXiv preprint arXiv:2202.06689, 2022.

[35] J. Zhang, X. Wang, H. Zhang, H. Sun, and X. Liu, “Retrieval-based neural source code summarization,” in 2020 IEEE/ACM 42nd International Conference on Software Engineering (ICSE). IEEE, 2020, pp. 1385–1397.

[36] A. LeClair, S. Haque, L. Wu, and C. McMillan, “Improved code summarization via a graph neural network,” in Proceedings of the 28th international conference on program comprehension, 2020, pp. 184–195.

[37] H. Husain, H.-H. Wu, T. Gazit, M. Allamanis, and M. Brockschmidt, “Codesearchnet challenge: Evaluating the state of semantic code search,” arXiv preprint arXiv:1908.09436, 2019.

[38] J. Cambroner, H. Li, S. Kim, K. Sen, and S. Chandra, “When deep learning meets code search,” in Proceedings of the 2019 47th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering, 2019, pp. 964–974.

[39] J. Gu, Z. Chen, and M. Monperrus, “Multimodal representation for neural code search,” in 2021 IEEE International Conference on Software Maintenance and Evolution (ICSME). IEEE, 2021, pp. 483–494.

[40] S. Fang, Y.-S. Tan, T. Zhang, and Y. Liu, “Self-attention networks for code search,” Information and Software Technology, vol. 134, p. 106542, 2021.

[41] M. R. Parvez, W. Ahmad, S. Chakraborty, B. Ray, and K.-W. Chang, “Retrieval augmented code generation and summarization,” in Findings of the Association for Computational Linguistics: EMNLP 2021, 2021, pp. 2719–2734.

[42] A. Mastropalao, S. Scalabrino, N. Cooper, D. N. Palacio, D. Poshyvanyk, R. Oliveto, and G. Bavota, “Using the study of text-to-text transfer transformer to support code-related tasks,” in 2021 IEEE/ACM 43rd International Conference on Software Engineering (ICSE). IEEE, 2021, pp. 336–347.

[43] J. Liu, Y. Liu, Q. Meng, M. Jiang, and J. Cleland-Huang, “Traceability transformed: Generating more accurate links with pre-trained bert models,” in 2021 IEEE/ACM 43rd International Conference on Software Engineering (ICSE). IEEE, 2021, pp. 324–335.

[44] E. Papathomas, T. Diamantopoulos, and A. Symeonidis, “Semantic code search in software repositories using neural machine translation,” in Icmla, “Task-specific neural code similarity detection using abstract syntax trees as graphs,” Proceedings of AAAIConference on Artificial Intelligence, 2021.

[45] J. Lacomis, P. Yin, E. Schwartz, M. Allamanis, C. Le Goues, G. Neubig, and B. Vasilescu, “Dire: A neural approach to decomplied identifier naming,” in 2019 34th IEEE/ACM International Conference on Automated Software Engineering (ASE). IEEE, 2019, pp. 628–639.

[46] H. Zhang, Z. Li, G. Li, L. Ma, Y. Liu, and Z. Jin, “Generating adversarial examples for testing robustness of source code prediction models,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 34, no. 01, 2020, pp. 1169–1176.

[47] Z. Yang, J. Shi, J. He, and D. Lo, “Natural attack for pre-trained models of code,” arXiv preprint arXiv:2201.08698, 2022.

[48] S. Lu, D. Guo, S. Ren, J. Huang, A. Svyatkovskiy, A. Blanco, C. Clement, D. Drain, D. Jiang, D. Tang et al., “Codexglue: A machine learning benchmark dataset for code understanding and generation,” arXiv preprint arXiv:2102.04664, 2021.

[49] A. Svyatkovskiy, Y. Zhao, S. Fu, and N. Sundaresan, “Pythia: Assisted code completion system,” in Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2019, pp. 2727–2735.

[50] Y. Wang and H. Li, “Code completion by modeling flattened abstract syntax trees as graphs,” Proceedings of AAAIConference on Artificial Intelligence, 2021.

[51] U. Alon, R. Sadaka, O. Levy, and E. Yahav, “Structural language models of code,” in International conference on machine learning. PMLR, 2020, pp. 245–256.

[52] F. Liu, G. Li, Y. Zhao, and Z. Jin, “Multi-task learning based pre-trained language model for code completion,” in Proceedings of the 35th IEEE/ACM International Conference on Automated Software Engineering, 2020, pp. 499–510.

[53] Y. Zhu and M. Pan, “Automatic code summarization: A systematic literature review,” arXiv preprint arXiv:1905.04352, 2019.

[54] Y. Wang, Z. Zhao, M. Yang, G. Xu, F. Wang, J. Yu, and P. S. Yu, “Improving automatic source code summarization via deep reinforcement learning,” in Proceedings of the 33rd ACM/IEEE International Conference on Automated Software Engineering, 2018, pp. 397–407.

[55] S. Iyer, I. Konstas, A. Cheung, and L. Zettlemoyer, “Summarizing source code using a neural attention model,” in Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), 2016, pp. 2073–2083.

[56] B. Wei, Y. Li, G. Li, X. Xia, and Z. Jin, “Retrieve and refine: exemplar-based neural comment generation,” in 2020 35th IEEE/ACM International Conference on Automated Software Engineering (ASE). IEEE, 2020, pp. 349–360.

[57] U. Alon, S. Brody, O. Levy, and E. Yahav, “code2seq: Generating sequences from structured representations of code,” in International Conference on Learning Representations, 2019.

[58] R. Sindhgatta, “Using an information retrieval system to retrieve source code samples,” in Proceedings of the 28th international conference on Software engineering, 2006, pp. 905–908.

[59] S. E. Sim, M. Umarji, S. Balsarian, C. V. Lopes, “How well do search engines support code retrieval on the web?” ACM Transactions on Software Engineering and Methodology (TOSEM), vol. 21, no. 1, pp. 1–25, 2011.

[60] S. Sachdev, H. Li, S. Luan, S. Kim, K. Sen, and S. Chandra, “Retrieval on source code: a neural code search,” in Proceedings of the 2nd ACM SIGPLAN International Workshop on Machine Learning and Programming Languages, 2018, pp. 31–41.

[61] D. Guo, S. Ren, S. Lu, Z. Feng, D. Tang, S. Liu, L. Zhou, N. Duan, A. Svyatkovskiy, S. Fu et al., “Graphcodebert: Pre-training code representations with data flow,” arXiv preprint arXiv:2009.08368, 2020.
[69] K. D. Cooper, A. Grosul, T. J. Harvey, S. Reeves, D. Subramanian, L. Torczon, and T. Waterman, “Exploring the structure of the space of compilation sequences using randomized search algorithms,” The Journal of Supercomputing, vol. 36, no. 2, pp. 135–151, 2006.

[70] J. Cavazos, G. Fursin, F. Agakov, E. Bonilla, M. F. O’Boyle, and O. Temam, “Rapidly selecting good compiler optimizations using performance counters,” in International Symposium on Code Generation and Optimization (CGO’07). IEEE, 2007, pp. 185–197.

[71] D. W. Binkley, M. Harman, and K. Lakhotia, “Flagremover: a testability transformation for transforming loop-assigned flags,” ACM Transactions on Software Engineering and Methodology (TOSEM), vol. 20, no. 3, pp. 1–33, 2011.

[72] P. McMinn, D. Binkley, and M. Harman, “Empirical evaluation of a nesting testability transformation for evolutionary testing,” ACM Transactions on Software Engineering and Methodology (TOSEM), vol. 18, no. 3, pp. 1–27, 2009.

[73] A. Baresel, D. Binkley, M. Harman, and B. Korel, “Evolutionary testing in the presence of loop-assigned flags: A testability transformation approach,” ACM SIGSOFT software engineering notes, vol. 29, no. 4, pp. 108–118, 2004.

[74] B. Daniel, D. Dig, K. Garcia, and D. Marinov, “Automated testing of refactoring engines,” in Proceedings of the 6th joint meeting of the European software engineering conference and the ACM SIGSOFT symposium on The foundations of software engineering, 2007, pp. 185–194.

[75] T. Mens and T. Tourwé, “A survey of software refactoring,” IEEE Transactions on software engineering, vol. 30, no. 2, pp. 126–139, 2004.

[76] S. Yu, T. Wang, and J. Wang, “Data augmentation by program transformation,” Journal of Systems and Software, p. 111304, 2022.

[77] D. Wang, Z. Jia, S. Li, Y. Yu, Y. Xiong, W. Dong, and X. Liao, “Bridging pre-trained models and downstream tasks for source code understanding,” arXiv preprint arXiv:2112.02268, 2021.

[78] N. D. Bui, Y. Yu, and L. Jiang, “Self-supervised contrastive learning for code retrieval and summarization via semantic-preserving transformations,” in Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval, 2021, pp. 511–521.

[79] E. Quiring, A. Maier, and K. Rieck, “Misleading authorship attribution of source code using adversarial learning,” in 28th {USENIX} Security Symposium ({{USENIX}} Security 19), 2019, pp. 479–496.

[80] Z. Li, J. Tang, D. Zou, Q. Chen, S. Xu, C. Zhang, Y. Li, and H. Jin, “Towards making deep learning-based vulnerability detectors robust,” arXiv preprint arXiv:2108.00669, 2021.

[81] L. Zhang, P. Liu, and Y.-H. Choi, “Semantic-preserving reinforcement learning attack against graph neural networks for malware detection,” arXiv preprint arXiv:2009.05602, 2020.

[82] J. Chen, W. Hu, L. Zhang, D. Hao, S. Khurshid, and L. Zhang, “Learning to accelerate symbolic execution via code transformation,” in 32nd European Conference on Object-Oriented Programming (ECOOP 2018). Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik, 2018.

[83] M. Wu, L. Zhang, C. Liu, S. H. Tan, and Y. Zhang, “Automating cuda synchronization via program transformation,” in 2019 34th IEEE/ACM International Conference on Automated Software Engineering (ASE). IEEE, 2019, pp. 748–759.

[84] N. Yefet, U. Alon, and E. Yahav, “Adversarial examples for models of code,” Proceedings of the ACM on Programming Languages, vol. 4, no. OOPSLA, pp. 1–30, 2020.

[85] M. R. I. Rabin, N. D. Bui, K. Wang, Y. Yu, L. Jiang, and M. A. Alipour, “On the generalizability of neural program models with respect to semantic-preserving program transformations,” Information and Software Technology, vol. 135, p. 106552, 2021.

[86] P. Bielik and M. Vechev, “Adversarial robustness for code,” in International Conference on Machine Learning. PMLR, 2020, pp. 896–907.

[87] G. Ramakrishnan, J. Henkel, Z. Wang, A. Albarghouthi, S. Jha, and T. Reps, “Semantic robustness of models of source code,” arXiv preprint arXiv:2002.03043, 2020.