An Extensive Study on Pre-trained Models for Program Understanding and Generation

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ABSTRACT

Automatic program understanding and generation techniques could significantly advance the productivity of programmers and have been widely studied by academia and industry. Recently, the advent of pre-trained paradigm enlightens researchers to develop general-purpose pre-trained models which can be applied for a broad range of program understanding and generation tasks. Such pre-trained models, derived by self-supervised objectives on large unlabelled corpora, can be fine-tuned in downstream tasks (such as code search and code generation) with minimal adaptations. Although these pre-trained models claim superiority over the prior techniques, they seldom follow equivalent evaluation protocols, e.g., they are hardly evaluated on the identical benchmarks, tasks, or settings. Consequently, there is a pressing need for a comprehensive study of the pre-trained models on their effectiveness, versatility as well as the limitations to provide implications and guidance for the future development in this area. To this end, we first perform an extensive study of eight open-access pre-trained models over a large benchmark on seven representative code tasks to assess their reproducibility. We further compare the pre-trained models and domain-specific state-of-the-art techniques for validating pre-trained effectiveness. At last, we investigate the robustness of the pre-trained models by inspecting their performance variations under adversarial attacks. Through the study, we find that while we can in general replicate the original performance of the pre-trained models on their evaluated tasks and adopted benchmarks, subtle performance fluctuations can refute the findings in their original papers. Moreover, none of the existing pre-trained models can dominate over all other models. We also find that the pre-trained models can significantly outperform non-pre-trained state-of-the-art techniques in program understanding tasks. Furthermore, we perform the first study for natural language-programming language pre-trained model robustness via adversarial attacks and find that a simple random attack approach can easily fool the state-of-the-art pre-trained models and thus incur security issues. At last, we also provide multiple practical guidelines for advancing future research on pre-trained models for program understanding and generation.

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CCS CONCEPTS

• **Software and its engineering** → Reusability.

KEYWORDS

Code Representation, Deep Learning, Pre-Trained Language Models, Adversarial Attack

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1 INTRODUCTION

The research tasks of program understanding and generation, e.g., code summarization, code generation, code search, and defect prediction, have been increasingly studied for decades. Moreover, the advent of deep learning and machine learning techniques has strongly advanced the progress of such research domains [9, 25, 26, 50, 84]. Recently, a group of researchers have proposed natural language (NL)-programming language (PL) pre-trained models to provide general-purpose representations of the semantic connections between natural languages and program languages to support various program understanding and generation tasks once and for all [3, 16, 18, 21, 27]. In contrast to conventional deep learning techniques which require task-specific feature extraction or model selection, such NL-PL pre-trained models are usually derived from self-supervised language modeling tasks on large unlabelled program language corpora with simple modification and low-cost fine-tuning. Specifically, they tend to adopt the popular transformer [69] architectures, e.g., BERT [15] and GPT [55], for pre-training to facilitate the performance on program understanding and generation tasks. For instance, CodeBERT [18] is pre-trained on millions of program functions and natural language comments by two self-supervised tasks—Masked Language Modeling (i.e., randomly masking input tokens) and Replaced Token Detection [13] (i.e., randomly replacing input tokens) to predict the masked/replaced tokens for input tokens. After pre-training, the CodeBERT model is fine-tuned on different tasks. Moreover, the recently proposed CodeX[12], a GPT-based model pre-trained on massive code samples from Github, automatically fixed 28.8% of programming problems in the HumanEval[12] dataset on the automatic programming task.

Despite the effectiveness and versatility of the NL-PL pre-trained models shown in their original papers, their performance evaluations can nevertheless be susceptible to bias. Specifically, while there are many potential tasks which the NL-PL pre-trained models can be applied for [24, 54, 65, 66, 83], they hardly are applied for fully identical tasks for comprehensive performance comparison and analytics. Moreover, even for certain identical tasks they are evaluated upon, they sometimes adopt diverse benchmarks such that their performance can hardly be precisely compared either. Furthermore, many studies have addressed that general-purpose language models for NL are essentially defective. For instance, their efficacy can be hard to reproduce [6]. In addition, they are quite sensitive to noises and attacks under a set of behavioral tests [59]. Such facts altogether can indicate a strong need of an extensive study for the existing NL-PL pre-trained models.

In this paper, to our best knowledge, we conduct the first comprehensive study on the existing NL-PL pre-trained models to enhance the understanding of their strengths and limitations. Specifically, our objectives of the study include (1) validating the performance of different NL-PL pre-trained models, (2) comparing such models with the previous domain-specific state-of-the-art (SOTA) models, and (3) investigating the robustness of pre-trained models. Note that although the existing work, e.g., CodeXGLUE [43], also presents experimental studies on NL-PL pre-trained models, they hardly evaluate all studied models simultaneously on universal benchmarks and fail to provide insightful analyses on them.

To this end, we first determine to extensively study the effectiveness of the pre-trained models with expanded tasks and datasets which have not been explored by any previous work. In particular, we adopt eight mainstream pre-trained models, i.e., CodeBERT [18], CodeGPT [43], CodeT5 [71], CodeTrans [16], ContraCode [27], CoTexT [53] GraphCodeBERT [21], and PLBART [3] as our studied subjects mainly because they are publicly available SOTA models designed for a broad spectrum of the program understanding and generation tasks. We then evaluate all the studied pre-trained models on top of benchmark `CodeXGLUE` [43] because its inclusive datasets have been widely adopted by many of the studied models and it also presents deterministic training/testing data split for strengthening the fairness of their performance comparison. Meanwhile, we evaluate the effectiveness of the studied models against the non-pre-trained SOTA techniques of individual program understanding and generation tasks on top of an extended benchmark. Next, we further inspect the robustness of the studied models via adversarial attacks with multiple existing approaches and a simple random attack approach proposed in our paper.

Our study exposes multiple important and interesting insights for designing and developing future NL-PL pre-trained models. Specifically, we find that no pre-trained models can dominate the other models on all studied downstream tasks and their validity can be compromised. More specifically, while the performance of our studied pre-trained models can be generally replicated on their originally adopted benchmarks, subtle performance fluctuations can refute the performance comparison results of the studied models in their original papers. For instance, although PLBART reports performance superiority over CodeBERT, our study indicates that it cannot outperform CodeBERT for defect detection and code search. We also find that there hardly exists a dominating pre-trained model and pre-training with multiple objectives (e.g., the encoder-decoder-based models) potentially compromises the pre-training power for individual objectives. Moreover, by comparing with the domain-specific SOTA techniques, we find that the pre-trained models could enable prominent performance on multiple studied tasks, e.g., CodeGPT improves 10.18% and 63.94% on clone detection and code search over the datasets adopted in the original papers of the corresponding SOTA techniques. At last, we propose a new adversarial attack framework for evaluating the robustness of the pre-trained models and demonstrate for the first time that despite the presented excellent performance, the studied models can be easily attacked by a simple random attack approach. Interestingly, even though certain models, e.g., GraphCodeBERT, enhances the performance over existing models, e.g., CodeBERT, by injecting auxiliary information (i.e., DFG) for modeling, it is even more vulnerable to adversarial attacks. Accordingly, our study also reveals various practical guidelines for advancing NL-PL pre-trained models in the near future.

To summarize, our paper makes the following contributions.

- **Dataset.** For the commonly studied tasks, we collect an extensive dataset including a widely-used dataset `CodeXGLUE` and the datasets from domain-specific techniques such that each task is assigned with common and sufficient datasets for evaluating multiple NL-PL pre-trained models.
- **Study.** An extensive study with general-purpose NL-PL pre-trained models on the proposed datasets which contributes on (1) validating and calibrating performance of the original papers, (2) comprehensive and standardized experimental studies compared to the original papers, (3) adopting adversarial attacks for NL-PL pre-trained models to study their robustness for the first time.
- **Implications.** This work reveals multiple implications including (1) reliable and replicable experiments are essential before releasing pre-trained models since subtle performance fluctuations across multiple runs can easily override their performance comparisons; (2) proposing dominating general-purpose models can be challenging—surprisingly, state-of-the-art encoder-decoder-based models can compromise their encoder components and

perform even worse than pure encoder-based models for multiple program understand and generation tasks; (3) pre-trained models should be explored more since they tend to outperform conventional SOTA technologies on multiple downstream tasks; (4) as the first study for NL-PL pre-trained model robustness via adversarial attacks, we find that the existing pre-trained models (even the ones with special strategies for improving model robustness) are rather vulnerable.

Note that all our study data, code, and results are publicly available in [2].

2 BACKGROUND

2.1 Program Understanding&Generation Tasks

Automatic program understanding and generation could assist software development and significantly advance the productivity of programmers. Following prior work [43], we now briefly introduce typical program understanding and generation tasks.

2.1.1 Program Understanding Tasks. Program understanding refers to a set of tasks, e.g., classification and ranking, where models are required to first produce vectorized representations of programs and then perform downstream tasks such as prediction or similarity check.

Defect Detection [84]. This task detects whether a program contains vulnerabilities, e.g., resource leaks and unsafe references.

Clone Detection [50]. This task estimates similarity between two program fragments. Typically it can be realized by binary classification between code pairs and code retrieval respectively.

Code Search [24]. This task matches the semantics between natural language queries and programs.

2.1.2 Program Generation Tasks. A program generation task requires to produce/generate a sequence of tokens/words either in program languages (e.g., code generation, code repair, and code translation) or natural languages (e.g., code summarization):

Code Summarization [25]. This task generates a short paragraph describing the functionality of a code snippet such that programmers can promptly understand its function.

Code Repair [67]. This task aims to fix program bugs automatically.

Code Translation [9]. This task translates code from one program language to another.

Code Generation [26]. This task generates code by the given natural language description or under the assistance of the predefined policies or artificial intelligence techniques.

2.2 NL-PL Pre-Trained Models

A typical NL-PL pre-trained model refers to pre-training a large model on massive unlabelled corpora by self-supervised objectives, and fine-tuning the model on downstream tasks (i.e., program understanding and generation tasks) with task-specific loss. Many NL-PL pre-trained models [3, 18, 21, 27] have been proposed where their commonly adopted pre-trained schemes are presented in Figure 1. Note that following prior work (e.g., CodeT5 [71] and PLBART [3]), "Encoder" or "Decoder" essentially refers to the Transformer Encoder/Decoder component [69] for simplicity. In particular, the pre-training paradigm contains two stages—one for pre-training

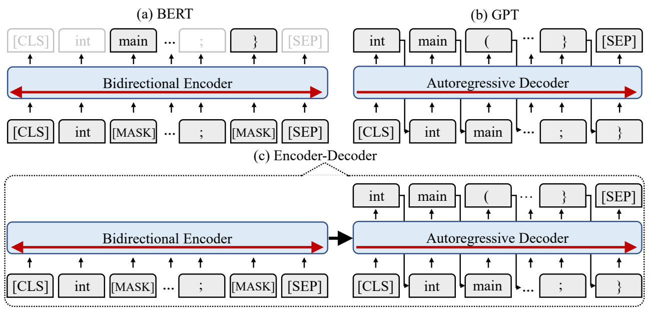


Figure 1: Illustration for pre-training and fine-tuning

```
int main() {
    printf("Hello, World!");
}
```

Figure 2: A Code example

and the other for fine-tuning. In the pre-training stage, models are trained by self-supervised objectives on large corpora. Here we take two popular pre-training tasks, Masked language Modeling [15] and Language Modeling [55] for illustration.

Let us know take Figure 2 as an example. Such code snippet will be first flattened by removing all the indents, line breaks, etc., for pre-processing, followed by inserting `[CLS]` and `[SEP]` in its front and end position to form an input sequence. Next, in Figure 1a, for the **encoder-based** models such as CodeBERT [18], GraphCodeBERT [21], and ContraCode [27], they randomly mask parts of the input sequence (e.g., '`main`', and '`{`' are replaced by the `[MASK]` token) where the objective of their models is to recover the masked tokens (Masked language Modeling). Meanwhile, in Figure 1b, the **decoder-based** model such as CodeGPT [43] is trained auto-regressively, i.e., each generated output will be extended into the original input sequence for subsequent token generation until it reaches an `[SEP]` (Language Modeling). The **encoder-decoder-based** models such as CodeT5 [71], CodeTrans [16], CoTexT [53] and PLBART [3] jointly train encoder and decoder for comprehensive modeling of the language. As illustrated in Figure 1c, the encoder first encrypts the polluted (masked) input and injects the features to the decoder which then reads the encoded features to autogressively generate output tokens along with recovering the masked input. Note that there can be more self-supervised tasks for pre-training models [13, 30]. However, they are not our main focus and thus not presented in this paper. Eventually, we can fine-tune the resulting pre-trained models on small datasets for specific tasks.

Although many NL-PL pre-trained models have been proposed and studied, they are hardly studied on common benchmarks and tasks which can render the evaluation results in their original papers rather biased. Moreover, they fail to comprehensively present performance comparisons with the domain-specific non-pre-trained SOTA techniques for validating their values. At last, limited research work has deeply studied their robustness. While existing work, e.g., CodeXGLUE [43], studies the performance of multiple models, it fails to comprehensively evaluate all of them on universal benchmarks and thus could not fully assess the studied models or draw insights/guidelines for developing/enhancing them.

Table 1: Pre-Trained Model Summarization

Models	CodeBERT	GraphCodeBERT	ContraCode	CodeGPT	PLBART	CodeTrans	CoTexT	CodeT5
Model Size	125M	125M	23M	124M	140M	220M	220M	220M
Architecture	RoBERTa (encoder)	RoBERTa (encoder)	Transformer-Encoder (encoder)	GPT2 (decoder)	BART (encoder-decoder)	T5 (encoder-decoder)	T5 (encoder-decoder)	T5 (encoder-decoder)
Pretrain Dataset	CodeSearchNet [24] 6.4M PL + 2.1M	CodeSearchNet [24] 2.3M PL + 2.3M	CodeSearchNet [24] 1.8M PL + 0.08M	CodeSearchNet [24] 1.1M/1.6M PL + few	self-collected 680M PL + 47M	CodeSearchNet [24] and [11, 47, 58, 75] 5.9M PL + 32.4M	CodeSearchNet [24] and BigQuery [1] 2.1M PL + 2.1M NL	CodeSearchNet [24] and BigQuery [1] 8.3M PL + 5.2M NL
Evaluation Tasks	Cloze Test Code Search Code Summarization	Clone Detection Code Repair Code Search Code Translation	Clone Detection Code Summarization Type Inference	Code Completion Code Generation	Clone Detection Code Generation Code Repair Code Summarization Code Translation Defect Detection	Code Generation Code Summarization Commit Message Generation	Code Generation Code Repair Code Summarization Defect Detection	Clone Detection Code Generation Code Repair Code Summarization Code Translation Defect Detection

3 THE EXTENSIVE STUDY

3.1 Subjects and Dataset

3.1.1 Subjects. After CodeBERT was proposed in EMNLP'20, the research on NL-PL pre-trained models (referred to as "pre-trained models" or simply "models" in later sections) has become a hot spot with multiple emerging models. While there can be many potential state-of-the-art pre-trained models to be studied, we choose to filter them for evaluating the models which are representative, publicly available, and designed for a wide range of program understanding and generation tasks for an extensive study. For example, CuBERT [31] only differs from CodeBERT in that CodeBERT additionally adopts the RTD (replaced token detection) [14] pre-training objective. Moreover, TransCoder [60] is only designed for the code translation task. Following prior work [18, 21, 71], we exclude them from our study. As a result, we select eight recently proposed pre-trained models as our studied subjects, i.e., CodeBERT, GraphCodeBERT, ContraCode (all as encoder-based models), CodeGPT (decoder-based model), CodeT5, CodeTrans, CoTexT and PLBART (all as encoder-decoder-based models).

CodeBERT [18]. Following the same architecture of BERT [15], i.e., the transformer-based encoder [69], CodeBERT employs Masked Language Modeling [15] (as in Section 2.2) and Replaced Token Detection [13] (i.e., randomly replacing tokens to train the model for detecting whether the tokens are replaced) as pre-training tasks.

GraphCodeBERT [21]. GraphCodeBERT, proposed in ICLR'21, adopts a transformer-based encoder architecture and incorporates code graph structure information (i.e., data flow graph) during pre-training with Edge Prediction (i.e., masking the variables in data flow edges) and Node Alignment (i.e., predicting variable alignment across source code and data flow) as pre-training tasks.

ContraCode [27]. Inspired by contrastive learning [68], ContraCode, proposed in April 2021, augments the training data by performing semantics-preserving transformations. In addition to the Masked Language Modeling objective, it employs InfoNCE [68] loss for contrastive training sample pairs for pre-training.

CodeGPT [43]. CodeGPT, proposed in NeurIPS'21, pre-trains a transformer-based decoder language model GPT [55] on programming languages. Its pre-training process follows the same scheme as illustrated in Figure 1b.

PLBART [3]. PLBART, proposed in NACCL'21, is a transformer-based encoder-decoder inspired by BART [33]. It follows the similar pre-training tasks of BART including Token Masking, Token Deletion, and Token Infilling.

CodeTrans [16]. CodeTrans, proposed in September 2020, is a transformer-based encoder-decoder following the model settings of T5 [56]. It adopts Span Masking [30] (i.e., randomly masking a span of tokens as a whole rather than single element in Masked Language Modeling) and Language Modeling (i.e., auto-regressive language generation) as its objectives to train the model.

CoTexT [53]. CoTexT, proposed in NLP4Prog'21, is also built on the same architecture as T5 [56]. It pre-trains the model with NL-PL data on top of original T5 checkpoints.

CodeT5 [71]. CodeT5, proposed in EMNLP'21, follows the same encoder-decoder architecture as T5 [56]. CodeT5 proposes a novel identifier-aware pre-training task to leverage code-specific structural information as well as a bimodal dual generation pre-training task for augmenting NL-PL alignment.

Table 1 summarizes the features of our studied subjects. While `CodeSearchNet` which contains six program languages with 2.3M PL-NL function pairs is widely employed as the pre-training corpus, different models actually adopt quite divergent training data subsets. For instance, CodeBERT only uses 2.1M PL-NL function pairs while ContraCode selects 1.8M program functions and only 80K natural language comments. Furthermore, we can clearly observe that in their original papers, they do not adopt the common dataset or tasks for evaluating their effectiveness, e.g., CodeBERT is originally evaluated on `CodeSearchNet` [24], while ContraCode incorporates varying data sources for type inference and code summarization [4, 22] and also collects a dataset for clone detection. Such facts indicate a pressing need to unify the evaluation protocols for a fair comparison between them.

3.1.2 Datasets. We first aim to adopt a commonly-used benchmark where the studied pre-trained models can be all extensively evaluated. In particular, we adopt the `CodeXGLUE` [43] dataset, a benchmark constructed by Microsoft for program understanding and generation tasks which collects 14 datasets from previous studies. Note that `CodeXGLUE` is selected because many of its inclusive datasets have already been adopted for the performance evaluation of multiple studied models in this paper. Moreover, it provides deterministic training/testing data split scheme for all the models to strengthen the fairness of their performance comparison. Specifically, we adopt `BigCloneBench` [65] and `POJ-104` [54] for clone detection, `Devign` [83] for defect detection, `Bugs2Fix` [66] for code repair, `CodeTrans` [43] for code translation, `CodeSearchNet-AdvTest` [24] for code search, and `CodeSearchNet-Java` [24] for code summarization. Such datasets are adopted by both our studied subjects in this paper and their original papers and thus can advance the replication of most original evaluations and further extend the study of all the pre-trained models.

Furthermore, for performing a fair comparison between pre-trained models and non-pre-trained SOTA models (illustrated later in Section 3.3.2), we include 4 datasets adopted for evaluating the SOTA models in their original papers in addition to our CodeXGLUE benchmark. As a result, the pre-trained models and the SOTA models can both be evaluated upon the originally adopted projects and the extended projects. In particular, we add the `Reveal` [10] dataset for defect detection, the `POJ-15` [17] dataset for clone detection, the `DGMS-Java` [34] dataset for code search, and `Rencos-Java` [79] for code summarization.

3.1.3 Metrics. Note that many studied pre-trained models have already been evaluated under a set of metrics in their original papers. We then retain all of them in our study for fair performance comparison. Specifically, we adopt *Accuracy* for defect detection, $F1$, *Precision*, *Recall*, and *Mean Average Precision* (*MAP*) for clone detection, and *Mean Reciprocal Rank* (*MRR*) for code search. We adopt *BLEU*-4 for code summarization. For code repair, code translation, and code generation, we adopt *BLEU*-4, *Accuracy*, and *CodeBLEU*. Note that while *Accuracy* can be adapted for diverse tasks, it essentially denotes the proportion of testing samples whose prediction/-generation results are precisely consistent with the target.

3.1.4 Implementation. We obtain the studied models from their corresponding publicly available repositories. We also employ the training/validation/test data splits and fine-tuning procedure for each dataset as in CodeXGLUE. Particularly for the understanding tasks, the models are appended with a Fully-Connected (FC) layer to project the embedding of tokens (e.g. [CLS], the last token) into classes. For the generation tasks, the encoder models (CodeBERT) are appended with a transformer decoder for generating code regressively while the decoder (CodeGPT) or encoder-decoder (PLBART) models directly generate code regressively. The newly added FC layers or decoders during fine-tuning are first initialized randomly and then trained (i.e., fine-tuned) in the corresponding datasets of each task respectively.

3.2 Research Questions

We investigate the following research questions in our study:

- **RQ1:** *How do pre-trained models perform for program understanding and generation tasks?* For this RQ, we extensively study the performance evaluation between all the adopted pre-trained models upon the `CodeXGLUE` benchmark [43].
- **RQ2:** *How do pre-trained models perform against non-pre-trained models?* For this RQ, we evaluate and compare the performance between pre-trained models and domain-specific non-pre-trained state-of-the-art (SOTA) models on multiple tasks.
- **RQ3:** *Are the pre-trained models robust?* For this RQ, we apply semantics-preserving adversarial attack techniques to investigate the robustness of the studied models.

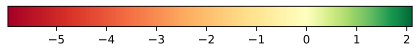
3.3 Results and Analysis

3.3.1 RQ1: How Do the Pre-trained Models Perform for Program Understanding and Generation Tasks? While the studied pre-trained models investigate diverse program understanding and generation tasks, we determine to evaluate the tasks which have been studied by more than one of our studied subjects, i.e., the listed tasks in Section 2.1, under the fine-tuning process provided in prior work CodeXGLUE [43] for extensively studying and comparing their performance. Note that considering the model randomness, we run all our experiments for 5 runs as recommended by prior work [52] and present the average results, while all our studied pre-trained models do not clearly indicate their number of runs in their original papers.

Table 2: Evaluation results on program understanding tasks

Task	Defect Detection	Clone Detection				Code Search
Dataset	Devign	BigCloneBench			POJ-104	AdvTest
Metrics	Acc	Precision	Recall	F1	MAP	MRR
CodeBERT	**63.68**	95.53	96.94	96.22	86.78	27.16
GraphCodeBERT	63.35	95.80	**96.99**	**96.38**	**89.97**	**30.79**
ContraCode	58.42	95.04	96.93	95.96	45.65	14.34
CodeGPT	63.49	95.33	96.93	96.09	71.22	26.06
PLBART	60.77	**96.30**	96.21	96.25	62.26	10.89
CodeTrans	63.03	90.56	95.80	92.93	61.88	22.26
CoTexT	61.48	90.96	95.74	93.29	58.72	17.19
CodeT5	63.62	92.44	95.60	93.98	55.50	24.65

Gap Color Bar



Tables 2 and 3 demonstrate the average experimental results in program understanding and generation tasks respectively on top of benchmark `CodeXGLUE`. Specifically, we adopt dataset `BigCloneBench` for evaluating clone detection as a classification problem [8, 17, 43], i.e., determining whether a pair of code snippets are cloned, where *Precision*, *Recall*, and $F1$ are used as the evaluation metrics. We also adopt dataset `POJ-104` for evaluating clone detection as a retrieval problem [43, 51], i.e., retrieving the cloned samples of a given code snippet from the whole testing set, where *MAP* is used as the evaluation metric. Moreover, for code repair, we adopt two datasets of different sizes (labeled as `small` with 58350 samples and `medium` with 65454 samples from [43]) in Table 3 for evaluating how they impact the studied models. We also evaluate bi-directional code translation tasks, i.e., translating from Java to C# and from C# to Java. Meanwhile, by comparing our evaluation results with the corresponding results presented in their original papers, we mark their numerical variations in terms of color gradients as illustrated by "Gap Color Bar" of Table 2, where the color gradients represent the difference magnitude of our study results subtracting the original results. For instance, the $F1$ score of GraphCodeBERT under clone detection drops 0.72 in our study and is represented as light yellow in Table 2. Moreover, the *BLEU*-4 score of CodeTrans under code summarization is increased by 0.20 in our study and represented as light green in Table 3. Note that the rest unmarked statistics refer to our extended evaluation results which are not included by their corresponding original papers.

We find that most of our results can be consistent with the original results. For instance, the $F1$ score is 96.38 in our study and 97.10 in the original paper of GraphCodeBERT for clone detection under `BigCloneBench`. Moreover, the *BLEU*-4 score is 20.39 in our study and 20.19 in the original paper of CodeTrans under code summarization. Meanwhile, the average absolute difference of our experimental results and the original results is 1.37%, indicating that our experimental results are not significantly different from the original results, and we can overall replicate the performance of the studied models as their original papers.

However, multiple performance comparison results in our study can be reversed compared with their original papers. Specifically, Figure 3 presents the average $F1$ and min-max variations across 5 runs of clone detection under `BigCloneBench`. We notice that

Table 3: Evaluation results on program generation tasks

Task	**Code Summarization**	**Code Repair**						**Code Translation**						**Code Generation**		
Dataset	**Java**	**Small**			**Medium**			**Java to C#**			**C# to Java**			**Concodel**		
Metrics	**BLEU-4**	**BLEU-4**	**Acc(%)**	**CodeBLEU**	**BLEU-4**	**Acc(%)**	**CodeBLEU**	**BLEU-4**	**Acc(%)**	**CodeBLEU**	**BLEU-4**	**Acc(%)**	**CodeBLEU**	**BLEU-4**	**Acc(%)**	**CodeBLEU**
CodeBERT	18.72	74.36	17.19	**78.73**	88.56	10.15	88.35	78.48	58.40	83.05	74.79	59.90	80.52	34.20	19.60	35.30
GraphCodeBERT	19.10	74.05	17.21	78.37	88.60	10.27	**88.38**	79.82	59.70	83.93	71.60	56.30	77.95	34.82	20.25	35.79
ContraCode	14.04	57.92	7.42	54.40	65.26	0.21	54.90	44.06	26.60	55.40	35.83	24.60	49.16	17.31	2.25	20.35
CodeGPT	14.77	71.97	19.64	75.74	86.71	12.12	86.28	82.83	63.30	86.65	78.73	65.80	83.69	33.51	19.80	34.54
PLBART	19.02	76.77	17.55	76.06	88.33	9.64	85.95	82.95	63.00	86.77	78.19	63.40	83.67	37.75	20.20	40.63
CodeTrans	**20.39**	72.09	**22.55**	74.69	86.99	**13.74**	86.31	82.71	63.20	86.70	79.22	66.40	84.95	33.45	**22.45**	34.45
CoTexT	19.37	77.62	20.27	77.53	84.06	7.45	82.54	77.15	59.50	79.70	72.66	60.70	77.66	32.14	20.60	38.33
CodeT5	20.38	**77.68**	21.25	77.87	**89.07**	13.57	86.70	**83.78**	**65.60**	**87.50**	**79.88**	**66.90**	**85.29**	**39.54**	21.40	**42.71**

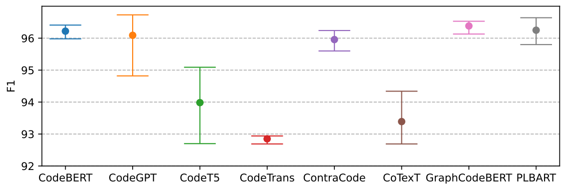


Figure 3: Min-max F1 variations of clone detection under `BigCloneBench`

the performance discrepancies of all the executions cause non-negligible impact on performance comparison among different models. For example, CodeGPT incurs the largest performance variance, i.e., it can outperform all the other pre-trained models in one run and underperform them in another run. Moreover, Although PLBART reports 0.7 $F1$ advantage over CodeBERT in its original paper, the min-max gap of PLBART in our study, i.e., 0.84 in Figure 3, may easily make such results untenable. Additionally, Table 2 presents that the defect detection accuracy of CodeBERT and PLBART is 63.68 and 60.77 respectively in our study while 62.08 and 63.18 respectively in the PLBART paper. Although such fluctuations appear to be minor/limited, they can easily reverse the performance comparison results and potentially compromise the strength of PLBART (and some other models).

Finding 1: The performance of all studied models can overall be replicated on their original benchmarks. However, subtle performance fluctuations can result in the untenable findings in their original papers, e.g., PLBART fails to outperform CodeBERT in defection detection and clone detection.

Program understanding tasks. We observe from Table 2 that the encoder-based CodeBERT and GraphCodeBERT can generally provide the optimal performance among all studied pre-trained models. Specifically, GraphCodeBERT outperforms CodeT5 by 24.91% and 62.11% for code search and clone detection under `POJ-104` respectively. On the other hand, for clone detection under `BigCloneBench` and defect detection, the encoder-decoder-based models achieve similar performance with CodeBERT and GraphCodeBERT, i.e., around 1% performance variance. Note that such results conceptually correspond to the findings in the research domain of natural language models [33, 56]—while encoder-based models can in general outperform encoder-decoder-based models in language understanding, their performance difference in certain tasks (e.g., Stanford Sentiment Treebank and Quora Question Pairs [33]) can be rather limited.

Program generation tasks. We observe from Table 3 that in general, the encoder-decoder-based pre-trained models can outperform other models on most program generation tasks. Specifically, CodeT5 and CodeTrans enable the optimal performance on code summarization, translation, and generation. Interestingly, we also find that on specific generation tasks, encoder-decoder-based models barely outperform encoder-based models. Specifically, for code repair, CodeBERT and GraphCodeBERT enable the optimal *CodeBLEU* under the `Small` and `Medium` dataset respectively (i.e., 78.73 and 88.38). For code generation, CodeBERT and GraphCodeBERT slightly outperform CodeTrans and CoTexT under *BLEU*-4, i.e., 34.20 and 34.82 v.s. 33.45 and 32.14. For code summarization, GraphCodeBERT performs similarly with PLBART and CoTexT, i.e., 19.10 v.s. 19.02 and 19.37.

We can summarize from such results above that encoder-based pre-trained models can achieve similar or even superior performance over encoder-decoder-based models on specific program generation tasks (e.g., code repair), i.e., the encoder-based models can be potentially as general-purpose as encoder-decoder-based models. Such fact seems to be overlooked by previous studies [3, 33, 56] which believe the encoder-decoder architecture is optimal for general-purpose pre-trained models. Note that for decoder-based CodeGPT, it fails to enable optimal performance on any task. We thus infer that only adopting decoder architecture is inadequate for building general-purpose pre-trained models.

Finding 2: Encoder-based pre-trained models can achieve similar or even superior performance over encoder-decoder-based models on specific program generation tasks.

Interestingly, Tables 2 and 3 both present that for the tasks evaluated via multiple metrics, the studied models incur quite fluctuating performance under all the adopted metrics. Especially for code repair, the optimal performance under the 3 metrics are achieved by 3 different models. Also, for program understanding tasks, CodeBERT, the first of its kind, still outperforms later proposed CodeT5 and PLBART which declare their performance gain on CodeBERT in their original papers.

We further attempt to analyze why there can hardly be a dominating pre-trained model for all the tasks. Recall that the encoder-based models like CodeBERT, GraphCodeBERT can in general outperform encoder-decoder-based models CodeT5, CoTexT, CodeTrans, PLBART for program understanding tasks, and vice versa for program generation tasks. To illustrate, we revisit Figure 1 where an encoder-based model employs a bi-directional architecture, i.e., each token is allowed to inspect the whole sentence for computing its context-aware representation. Therefore, such representation typically reflects rich information to understand a sequence and is favored for program understanding tasks. On the other hand, encoder-decoder-based models only take advantage of the informative encoder representations to advance its decoder to generate fluent and meaningful sequences, i.e., they do not fully explore the potential power of their program understanding capabilities. Consequently, the performance of encoder-decoder-based models on program understanding tasks are hindered by the generation objective, i.e., enhancing program generation performance is in fact at the cost of program understanding tasks. Note that such trade-off is also well recognized in the NLP domain [33, 56]. Accordingly, we derive that it is challenging or even impractical to develop an almighty model which rules all the tasks with current pre-training objectives, e.g., Masked Language Modeling and auto-regressive loss.

Finding 3: There exists no dominating pre-trained models. One main reason is that the current SOTA encoder-decoder models largely overlooked the fact that different training objectives (for program understanding and generation) can potentially compromise each other. We call for future research on more inclusive encoder-decoder models.

3.3.2 RQ2: How Do Pre-trained Models Perform against Non-pre-trained Models? Pre-trained models are expected with prominent performance because they can effectively capture rich knowledge (e.g., syntax and semantics) from massive pre-training data compared with non-pre-trained models (e.g., training corpora size by millions for pre-trained models in Table 1 v.s. by tens of thousands for non-pre-trained models in Table 4). Such data are implicitly encoded via a huge number of parameters, which can eventually facilitate a variety of downstream tasks [74]. For validating such initiative, it is essential to compare the performance between the pre-trained models and the domain-specific non-pre-trained SOTA approaches. To this end, we search the most recently published papers in top academic venues for identifying all the tasks which are presented that they can outperform a number of well-known previously published techniques. Accordingly, we also attempt for generalized SOTA techniques such that the performance comparison can be limited within the identical scope. Eventually, we adopt the following domain-specific SOTA techniques.

Reveal [10]: Chakraborty et al. conduct a study over deep-learning-based defect detection in TSE'21. They investigate the deficiency of the existing defect detection datasets and propose a more refined dataset. Meanwhile, they propose a graph neural network (GNN) approach Reveal which leverages program structure information, i.e., AST and CFG, and significantly outperforms the previous SOTA approaches in both precision (by 33.57%) and recall (by 128.38%).

FCDetector [17]: Fang et al. propose FCDetector to extract syntax and semantic information from source code for clone detection in ISSTA'20. In particular, FCDetector joins different functions in programs through caller-callee relationships and then applies its own fusion embedding techniques[17] to learn hidden syntactic and semantic features of the whole programs. It can significantly outperform previous SOTA approaches. Meanwhile, they also construct a smaller code clone dataset (with 15 label types) based on `POJ-104` which is named as `POJ-15` in this paper.

DGMS [37]: Ling et al. propose a code search approach DGMS in TKDD'21. DGMS leverages GNN and program structure information and also extracts structure information of natural language query for natural code search. Their evaluation results demonstrate that the DGMS model significantly outperforms SOTA models in *MRR* (up to 31.53%). Furthermore, we also adopt their code search dataset as one of our extended datasets for a fair comparison.

Rencos [79]: Rencos is a retrieval-based code summarization approach proposed in ICSE'20 which can take advantage of both neural and retrieval-based techniques. Previous studies [62, 79] have shown that Rencos outperforms other non-pre-training SOTA approaches. Meanwhile, we also adopt their code summarization dataset as one of our extended datasets for a fair comparison.

To the best of our knowledge, such approaches are so far the latest and highly regarded work in their domains. On the other hand, we could not find a proper non-pre-trained model for code generation, code repair, and code translation. In particular, the SOTA code generation approach NL2Code [73] relies on external knowledge, e.g., API documentation of specific program language, to generate code, and the SOTA code repair approaches [20, 44] require precise fault localization [40, 80] information, and thus can hardly be extended to the CodeXGLUE dataset. While we can trace back to earlier domain-specific techniques, i.e., CONCODE [26], CODE-TRANS [67], which adopt RNN-based seq2seq models, previous studies [21, 28, 60] have shown that pre-trained models using the transformer architecture can largely outperform them in program generation tasks. For code translation, the latest research work [60] also demonstrates that the pre-trained models can outperform non-pre-trained domain-specific techniques.

Table 4 presents the performance comparison results of pre-trained and non-pre-trained SOTA models. Note that we adopt `POJ-15` for evaluating clone detection as a classification problem corresponding to `BigCloneBench` in Table 2, while `POJ-104` is used for retrieval-based clone detection. By comparing the clone detection results under `BigCloneBench`, we observe that the performance of CodeBERT and GraphCodeBERT cannot be generalized to the extended `POJ-15` dataset. In particular, GraphCodeBERT achieves the optimal *MAP* of 89.97 under dataset `POJ-104` and achieves 96.38 $F1$ under dataset `BigCloneBench` for clone detection. However, its $F1$ score drops to 66.80 under the `POJ-15` dataset. Such dramatic performance degradation also occurs for CodeBERT (from 96.22 to 55.46), ContraCode (from 95.96 to 50.47), and CodeTrans (from 92.93 to 66.73). The above results may be due to the fact that the hyperparameters adopted directly from their original papers are not all optimal for our dataset, e.g., it is more suitable for above models under `BigCloneBench` rather than `POJ-15`. We thus infer that even for the pre-trained models which are supposedly general-purpose for various benchmarks may incur severe performance degradation, i.e., the pre-trained models are data-dependent.

Finding 4: General-purpose pre-trained models can incur dramatic performance variance.

We can observe that for most tasks, the pre-trained models can significantly outperform the domain-specific SOTA models. In particular, for defect detection, CodeBERT and CoTexT achieve the

Table 4: Pre-trained and non-pre-trained SOTA models evaluated on the extended datasets

Task	**Defect Detection**		**Clone Detection**				**Code Search**	**Code Summarization**	
Dataset	**CodeXGLUE**	**Reveal Dataset**	**POJ-104**	**POJ-15**			**DGMS Dataset**	**CodeXGLUE**	**Rencos Dataset**
Metrics	**Acc**		**MAP**	**Precision**	**Recall**	**F1**	**MRR**	**BLEU-4**	
CodeBERT	**63.68**	89.57	86.78	51.55	60.03	55.46	84.28	18.72	20.82
GraphCodeBERT	63.35	90.15	**89.97**	50.23	99.70	66.80	**89.01**	19.10	21.35
ContraCode	58.42	89.75	45.65	50.61	50.32	50.47	76.87	14.04	12.98
CodeGPT	63.49	89.79	71.22	**100.00**	**100.00**	**100.00**	86.51	14.77	20.85
PLBART	60.77	89.09	62.26	**100.00**	**100.00**	**100.00**	64.24	19.02	21.55
CodeTrans	63.03	89.62	61.88	50.08	99.97	66.73	80.57	**20.39**	18.17
CoTexT	61.48	**90.72**	58.72	50.40	99.06	66.86	85.83	19.37	24.80
CodeT5	63.62	85.97	55.50	53.76	92.38	67.97	83.16	20.38	26.55
Not Pre-trained SOTA	**Reveal**		**FCDetector**				**DGMS**	**Rencos**	
	56.97	87.23	27.49	95.69	86.32	90.76	52.77	15.32	**28.96**

optimal *Accuracy* of 63.68 and 90.72 respectively under `CodeXGLUE` and `Reveal`. Such performance can outperform the SOTA technique `Reveal` by 11.78% and 4.00% respectively.

For clone detection under `POJ-104` (illustrated in Section 3.3.1), GraphCodeBERT achieves a *MAP* of 89.97 and largely exceeds non-pre-trained SOTA model FCDetector which obtains 27.49. Meanwhile, for clone detection under `POJ-15` with the same setting as the FCDetector paper, CodeGPT and PLBART strongly outperform FCDetector by achieving 100 in terms of $F1$, Precision, and Recall. Note that `POJ-15` (introduced in FCDetector) is a smaller and simpler dataset compared with `BigCloneBench`, i.e., 1510 vs. 9126 code fragments. Moreover, `POJ-15` incurs a data leakage issue [61], i.e., part of the testing samples can be seen during training, while `BigCloneBench` incurs no such issue [43]. As a result, CodeGPT and PLBART can achieve excellent performance on `POJ-15` while others cannot due to the data-dependency issue (Finding 4).

Note that for code summarization, SOTA Rencos outperforms GraphCodeBERT by 35.64% under the dataset adopted in its original paper and underperforms it by 19.79% in the `CodeXGLUE` dataset. We assume such performance may be caused since Rencos can be quite data-dependent. Specifically, when summarizing target programs, Rencos first retrieves similar code snippets from the training dataset, and regards them as part of the input to its adopted neural network for code summarization. Therefore, it can achieve superior performance in the dataset which contains substantial duplicate samples across training and testing datasets.

To summarize, we infer that pre-trained models generally outperform non-pre-trained SOTA models in program understanding tasks. Since they enable powerful performance gain, establishing domain-specific SOTA techniques by gradually upgrading the existing ones can take a long way to go. Therefore, we recommend researchers to make more efforts in studying pre-trained models.

Finding 5: Pre-trained models could be more promising than non-pre-trained models and more research efforts should be devoted to this direction.

3.3.3 *RQ3: Are the Pre-trained Models Robust?*

Finding 4 reveals that pre-trained models can enable quite inconsistent performance under different datasets which implies the potential model robustness issues. Such issues can severely hinder the practical usage of pre-trained models especially when they can be easily manipulated/fooled. Take defect detection as an example, a shrewd developer may cheat the anti-defect system via semantics-preserving edit (demonstrated in Table 5) for avoiding additional code review process. Such tricks may increase the threats of program crashes or deadlocks. The cheating process can be considered as adversarial attack to the pre-trained models [63, 76]. Therefore, we determine to apply semantics-preserving adversarial samples to attack the pre-trained models for inspecting their robustness.

Algorithm 1: CodeAttack

```
Input: $P$, $k$, $n$, $search$, $transformation$
Result: $P'$
1  $best\_P' \leftarrow P$;
2  $sites \leftarrow$ Identify the sites that can be edited in $P$ by $AdvCG$;
3  $k\_sites \leftarrow search(sites, k)$;
4  for $site$ in $k\_sites$ do
5      $P\_list \leftarrow transformation(site, best\_P', n)$;
6      $best\_P' \leftarrow$ evaluate each $P'$ in $P\_list + best\_P'$ and get the
         best $P'$;
7      if $best\_P'$ can fool the model then
8          return $best\_P'$;
9      end
10 end
11 return $best\_P'$
```

However, to the best of our knowledge, there exists no adversarial attack approach specifically designed for NL-PL pre-trained models before this study. In particular, in programming language area, while the previous attacking approaches [63, 76] for programming languages employ one-hot embedding [76], all existing NL-PL pre-trained models adopt continuous vector embedding [48] which renders the one-hot embedding attacking inapplicable. As for adversarial attacks in natural languages, models are allowed to modify every word in sentence. Simply following such unconstrained operation in NL-PL pre-trained models may edit key words of programs, e.g., "for" and "while", and thus possibly break program semantics and fail program executions. To safely conduct adversarial attacks which preserve program semantics and syntax for pre-trained models, we propose a new framework based on AdvCG [63] (originally designed for non-pre-trained models to search and find sites which are safe to be modified in programs) and attacking approaches from NLP [19, 29, 35, 45, 46] (adversarial attack approaches that modify the sites with optimal perturbations). As illustrated in Algorithm 1, for a program P, we initialize the best perturbed P' as P (Lines 1). AdvCG is employed to analyze the code and identify sites that can be safely edited **without** changing the program semantics, e.g.,

Table 5: Evaluating robustness under defect detection and code summarization

Performance under adversarial attack	Defect Detection							Code Summarization						
	Original	BAE	BERT-Attack	LSH	Hard-Label	TextFooler	Random	Original	BAE	BERT-Attack	LSH	Hard-Label	TextFooler	Random
CodeBERT	63.68	26.91	27.06	48.44	29.63	22.90	**22.71**	18.72	4.06	2.64	11.59	**1.69**	2.36	2.30
GraphCodeBERT	63.35	18.03	9.93	39.55	**4.98**	9.18	6.47	19.10	3.08	1.79	11.68	**0.58**	1.44	1.31
ContraCode	58.42	9.26	7.29	25.06	**1.64**	4.61	3.75	14.04	4.55	4.03	8.96	**2.61**	3.52	3.37
CodeGPT	63.49	38.48	36.65	45.17	36.51	35.28	**34.76**	14.77	4.58	3.51	10.25	6.99	3.47	**3.40**
PLBART	60.77	18.33	15.17	34.54	18.88	12.86	**12.64**	19.02	2.88	1.53	9.89	**1.43**	1.70	1.57
CodeTrans	63.03	25.28	23.27	39.41	23.12	20.33	**18.92**	20.39	5.98	**4.23**	14.44	8.80	4.66	4.57
CoTexT	61.48	22.12	22.34	40.97	24.72	21.30	**20.37**	19.37	5.97	**4.82**	13.90	9.58	5.34	5.55
CodeT5	63.62	31.90	27.40	48.66	41.12	26.91	**26.13**	20.38	6.93	**4.42**	15.20	12.30	5.31	4.87
Avg num queries	/	128.51	106.22	27.29	925.51	133.37	130.46	/	145.32	121.54	22.65	814.53	157.56	156.51

Table 6: Attack approaches

Approach	Search Method	Transformation Method
BAE [19]	Word Importance Rank	Word Swap Language Model BAE
BERT-Attack [35]	Word Importance Rank	Word Swap Language Model BERT
LSH [46]	Word Importance Rank	Word Swap WordNet
Hard-Label [45]	Genetic Algorithm	Word Swap Embedding
TextFooler [29]	Word Importance Rank	Word Swap Embedding
Random	Random	Random
WIR-Random	Word Importance Rank	Random
Random+	Random	Random+

local variables and function parameters (Lines 2). Then, a search method is applied to select up to k sites which can potentially lead to optimal perturbation (Line 3). For each resulting candidate site, a transformation method, which replaces the original token in the site with another word, is employed n times and results in n perturbations of the program P (Lines 4-5). Such n perturbations are evaluated and the one which can best fool the pre-trained model is selected as new program P' for iterative operations (Lines 6-9). Note that the program semantics and syntax are ensured to be **unchanged** since all the modifications are performed only on safe sites identified by AdvCG which is widely used by attack approaches [57, 76] for programming languages.

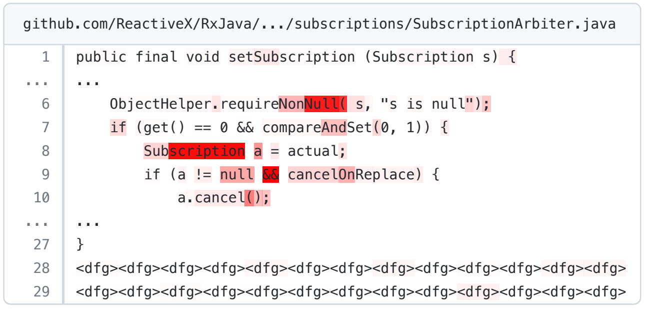
Note that the search method is designed to select the optimal K perturbations sites from a predefined set, and the transformation method is designed to perturb a given program while preserving its semantics based on the selection results from the search method. Table 6 summarizes the details of the search and transformation methods [19, 29, 35, 45, 46]. For the search methods, Word Importance Rank (WIR) [49] algorithm is employed to rank each site according to the output magnitude difference before and after renaming the site to "UNK" token, while Genetic Algorithm [45] finds the optimal combination of sites and transformations by mutation and crossover of different perturbations. For the transformation methods, all of them aim to find a suitable token to replace the original one in a given site. Word Swap Embedding [49] returns a synonym via extra embedding model. Word Swap WordNet [46] returns a synonym via a WordNet model. Word Swap Language Model BERT [35] returns a new token generated by an extra BERT model. An attack approach can be composed by different search methods and transformation methods, as described in TextAttack [49]. In addition, we also design a simple random attack approach (namely Random approach) by randomly selecting attack sites and then renaming each selected site with a random new word. Note that the random selection is also **semantics-preserving** following Lines 2-3 of Algorithm 1 as the safe sites have been selected and we only randomly select/replace them. We also design a WIR-Random approach (introduced later) to further study the effectiveness of different search methods.

Next, due to the page limit, we only present the attack results of defect detection for program understanding and code summarization for program generation to evaluate model robustness, since they are mostly studied by our studied models and also studied by previous adversarial attack study on program languages [63]. Table 5 presents the attack results. We can observe that the overall model performance degrade significantly via most attack approaches, e.g., the CodeBERT performance significantly drops 64.34% and 87.71% for defect detection and code summarization with the Random approach respectively. Such results indicate that pre-trained models are vulnerable against semantics-preserving edits.

Finding 6: We demonstrate for the first time that NL-PL pre-trained models are not robust. They are highly vulnerable against semantics-preserving adversarial samples.

In addition, CodeT5 and CodeGPT are relatively more robust than other pre-trained models. For instance, the performance of CodeT5 drops 58.93% for defect detection under the Random attack, less than 69.98% of CodeTrans and 66.87% of CoTexT which both build on the same T5 architecture. The superiority of CodeT5 could be caused by its unique identifier tagging pre-training task, i.e., identifying whether a code token is an identifier and advancing CodeT5 to ignore odd attack tokens. Meanwhile, CodeGPT enables optimal robustness under defect detection, e.g., dropping 45.25% under the Random attack. Such superiority may come from its special decoder-only architecture. Nevertheless, we still need more research to determine the impact of different models, pre-training tasks, and training data on the model robustness. Unfortunately, such issues are not intensively discussed in the existing literature. To our best knowledge, ContraCode is the only model that mentions and attempts to this issue via contrastive learning with semantics-preserving and non-semantics-preserving samples. However, its robustness even underperforms other models as in Table 5.

Interestingly, while GraphCodeBERT is expected to be more robust than CodeBERT since it includes additional DFG information for pre-training, it actually performs worse. Therefore, we further attempt to understand how GraphCodeBERT captures tokens and DFG by accessing its attention which can be derived by executing transformer. Such attention represents how the model considers the importance of each input token and can be widely visualized for model interpretability [32]. Specifically, we extract the attention weights of the first layer for the GraphCodeBERT model where such weights can indicate how much attention GraphCodeBERT pays to



```
github.com/ReactiveX/RxJava/.../subscriptions/SubscriptionArbiter.java
public final void setSubscription (Subscription s) {
...
    ObjectHelper.requireNonNull( s, "s is null");
    if (get() == 0 && compareAndSet(0, 1)) {
        Subscription a = actual;
        if (a != null && cancelOnReplace) {
            a.cancel();
...
}
<dfg><dfg><dfg><dfg><dfg><dfg><dfg><dfg><dfg><dfg><dfg><dfg><dfg>
<dfg><dfg><dfg><dfg><dfg><dfg><dfg><dfg><dfg><dfg><dfg><dfg><dfg>
```

Figure 4: GraphCodeBERT attention weight example

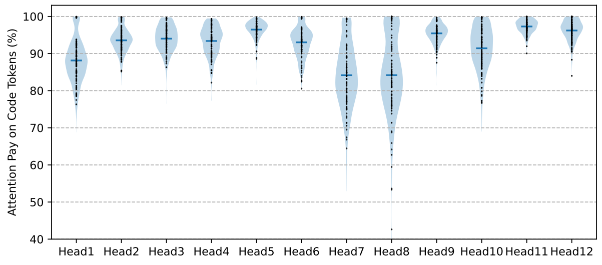


Figure 5: Attention paid on code tokens

the input. As presented in Figure 4, we mark the attention weights under colors, where darker red indicates more attention paid to the associated words. We can observe that, GraphCodeBERT pays more attention to program tokens, e.g., "`Null`" and "`scription`". Such words, which are part of this code snippet, can advance more to code search than other words. In fact, GraphCodeBERT does not pay much attention to the inclusive DFG information, as presented by the colors of "`<dfg>`" tokens (indicating different DFG nodes). Note that such cases are widespread. Figure 5 further shows the attention ratio of each attention head of GraphCodeBERT for program tokens. We find that most attention heads pay most of their attention (around 90% averagely) to program tokens, indicating that the attention for DFG is rather limited, i.e., the DFG information is inadequately leveraged for enhancing pre-trained models. Therefore, we call for future research to better leverage the power of integrating more information for pre-training.

Finding 7: Current strategies for improving the robustness of pre-trained models, e.g., considering advanced learning strategies or additional code semantics, have limited effectiveness. We call for future research on more robust pre-trained models.

We then compare the performance variance across different attack approaches. Interestingly, we find that the Random approach can achieve the optimal attack performance in 6 of 8 studied models for defect detection, while for the other models, it also enables rather strong performance, e.g., 6.47 v.s. 4.98 on GraphCodeBERT. For code summarization, the Hard-Label approach outperforms the Random approach on several subjects, e.g., the *BLEU*-4 results of CodeBERT and GraphCodeBERT on code summarization (2.30 and 1.31 of the Random approach v.s. 1.69 and 0.58 of the Hard-Label approach). We observe that the average query number, i.e., the number of searching the optimal perturbance, of the Hard-Label approach largely exceeds the Random approach (i.e., 925.51 and 814.53 v.s. 130.46 and 156.51 in terms of defect detection and code summarization). Thus, we hypothesize that the superiority of the Hard-Label approach over the Random approach is caused by generating and evaluating more perturbations. Accordingly, we attempt to improve the Random approach by adopting a larger n in Algorithm 1 which allows more perturbations for each site. In this way, the Random approach outperforms all the other attack approaches in 14 of 16 subjects as in "Random+" of Table 7.

Table 7: Attack approach study

Performance under adversarial attack	Defect Detection		Code Summarization	
	WIR-Random	Random+	WIR-Random	Random+
CodeBERT	21.30	**13.94**	2.15	**1.24**
GraphCodeBERT	5.95	**2.16**	1.10	**0.41**
ContraCode	3.61	2.27	3.45	**1.69**
CodeGPT	34.35	**33.38**	3.31	**2.87**
PLBART	12.42	**7.21**	1.29	**0.96**
CodeTrans	18.51	**13.53**	4.36	**2.83**
CoTexT	19.55	**15.28**	5.24	**3.88**
CodeT5	25.80	**16.21**	4.99	4.59
Avg num queries	129.18	583.11	154.09	762.27

Finding 8: A simple random attack approach can already be rather powerful for attacking NL-PL pre-trained models.

We further analyze the difference of the performance impact between the search and transformation method. For the transformation method, the NLP attack approaches tend to preserve the semantics at the natural language level by adopting synonyms for substitution, i.e., selecting the semantically similar words with extra embedding model. On the other hand, program semantics can be preserved even when the variable names are changed. Therefore, unnecessary restrictions can decrease the transformation method effectiveness. Subsequently, to analyze the impact of the search method, we build WIR-Random approach that combines the Word Importance Rank (WIR) search method and Random transformation method. Then, by comparing the WIR-Random result in Table 7 and the Random result in Table 5, we find that the WIR search method enables limited advantage over the Random search method. From such result we can infer that transformation methods incur a greater impact on attack performance than search methods. While in the NLP domain, the search methods may incur more performance significant impact as discussed in [77], because there are more attackable sites in natural statements than programs.

Finding 9: Transformation methods tend to impact more on attack performance than search methods for NL-PL pre-trained models.

4 IMPLICATIONS AND DISCUSSIONS

Our study reveals the following important practical guidelines for future research on pre-trained models.

Pre-training for code is promising. Our study results show that the pre-trained code models can outperform the non-pre-trained SOTA techniques upon almost all the evaluation tasks. Therefore, we strongly recommend applying pre-trained models for various program understanding and generation tasks.

More rigorous evaluations are needed. Considering the stochastic nature of neural networks and the small performance deviations between different models on some tasks (Finding 1), we recommend researchers to replicate experiments when validating their techniques to prevent over-claiming their advantages.

Multi-objective v.s. single-objective pre-training Our study demonstrates that it can be rather challenging for researchers to propose general-purpose pre-trained models for dominating both program understanding and generation tasks. Specifically, it is hard because the models targeting multi-objective optimization tasks can potentially compromise their efficacy compared with the ones targeting single-objective optimization task.

Model robustness shall be further explored. Our experimental results show that the existing pre-trained models encounter significantly decreased performance even under random attacks. Moreover, so far, simply incorporating program semantics fails to enhance their robustness. Therefore, we recommend researchers to put more efforts to enhance robustness of pre-trained models.

5 THREATS TO VALIDITY

Threats to Internal Validity. The threats to internal validity mainly lie in the potential bugs in our implementation. To reduce such threats, we directly obtain the original source code from the GitHub repositories of the studied techniques. Also, we adopt the same hyperparameters as their original papers. The authors also carefully reviewed the experimental scripts to ensure the correctness. Meanwhile, while re-pretraining a model can be essentially helpful for our study, most of the studied models do not provide their pre-training code and dataset which prevent us from realizing such options. To reduce such threat, we design three research questions for evaluating their provided pre-trained models from multiple dimensions for assessing their characteristics.

Threats to External Validity. The threats to external validity mainly lie in the benchmark and techniques adopted in this study. To reduce such threats, we not only use the CodeXGLUE benchmark studied in many original pre-trained model papers, but also include more datasets to construct an extended benchmark. Meanwhile, through an exhaustive literature review, we believe that the pre-trained models adopted in this study are sufficiently representative and influential in this domain, and we also assure that the non-pre-trained models adopted in this study are the SOTA techniques for their respective tasks.

Threats to Construct Validity. The threats to construct validity mainly lies in the adopted metrics in our evaluations. To reduce such threats, following the prior CodeXGLUE work, we adopt multiple widely-used metrics to evaluate the performance of the studied approaches, i.e., $Accuracy$, $F1$, $Precision$, $Recall$, MAP, MRR, $BLEU$-4, and $CodeBLEU$. Meanwhile, for some tasks, we apply more than one metrics to evaluate their performance. To further reduce the threats, we also perform case studies to validate our hypothesis.

6 RELATED WORK

Pre-trained language models have been shown to be effective in NLP [15, 33, 39, 55]. BERT [15] is one of the most representative works of its kind, a multilayer transformer-based encoder, which achieves SOTA results on several natural language understanding (NLU) tasks. By investigating the BERT, Liu et al. [39] find that BERT was significantly undertrained, and a fine-grained selection of hyperparameters can dramatically improve the performance of BERT. However, noticing that BERT-based pre-trained language models are not suitable for natural language generation (NLG) tasks, the decoder structure was introduced (e.g, BART [33], T5 [56]) to cope with both NLG and NLU tasks. With the remarkable success of pre-trained models in NLP, multi-modal pre-trained models have also been proposed. Such models can learn implicit alignments between different modal inputs and thus can be used for cross-domain tasks, e.g., ViLBERT [42] for language and image, VideoBERT [64] for language and video, and SpeechT5 [7] for language and speech.

In recent years, researchers have explored various techniques in the intersection of software engineering and machine learning [5, 8, 23, 36, 41, 70, 72, 78, 81, 82]. Program understanding and generation bring together various program-related tasks, such as defect detection, clone detection, code search, code summarization, code generation, etc. Such tasks can be well transformed into machine learning problems. For instance, Alon et al. [5] applied neural network techniques for generating distributed representations of code. Bui et al. [8] proposed InferCode to learn program representations by predicting subtrees sampled from program ASTs. Hoang et al. [23] proposed CC2Vec to learn a representation of commits by commit messages and commit code changes. Meanwhile, pre-trained language models have also been applied to various program understanding and generation tasks. In addition to our studied models, Kanade et al. [31] apply BERT model to learn the contextual embedding of source code. Liu et al. [38] pre-trained a BERT model for code completion. Lachaux et al. [60] pre-trained a transformer on source code from open source projects for code translation, and such a model can achieve high accuracy under code translation task between C++, Java, Python functions. Futhermore, Chen et al. [12] proposed an enormous program language GPT-3 model with up to 12 billion parameters and introduced its commercial application GitHub Copilot. In this paper, we conduct the first comprehensive study on multiple SOTA pre-trained models upon universal benchmarks with in-depth analysis to advance future research. Note that CodeXGLUE [43] with its leaderboard mainly presents a benchmark and evaluates baselines with limited analytical results and hardly evaluates all studied models simultaneously on universal benchmarks.

7 CONCLUSIONS

In this study, we have extensively investigated the effectiveness and limitations of NL-PL pre-trained models for program understanding and generation tasks. We first discover the performance fluctuation of different pre-trained models over different tasks and datasets, which indicates that it can be challenging to propose an almighty pre-trained model across task types and it is essential for reliable experiments to demonstrate the superiority of proposing new models. Furthermore, we also validate the superiority of pre-trained models over conventional/previous SOTA methods on different downstream tasks. Finally, we perform the first study for NL-PL pre-trained model robustness via adversarial attacks and find that the existing pre-trained models are rather vulnerable, e.g., they can be easily attacked by a simple random attack approach, and current strategies for improving the robustness of pre-trained code models have limited effectiveness. Therefore, researchers should make more efforts on proposing integration schemes of additional information with pre-training.

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