# A Novel Approach for Automated Program Repair using Round-Trip Translation with Large Language Models

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Research shows that grammatical mistakes in a sentence can be corrected by translating it to another language and back using neural machine translation with language models. We investigate whether this correction capability of Large Language Models (LLMs) extends to Automated Program Repair (APR). Current generative models for APR are pre-trained on source code and fine-tuned for repair. This paper proposes bypassing the fine-tuning step and using Round-Trip Translation (RTT): translation of code from one programming language to another programming or natural language, and back. We hypothesize that RTT with LLMs restores the most commonly seen patterns in code during pre-training, i.e., performs a *regression toward the mean*, which removes bugs as they are a form of noise w.r.t. the more frequent, *natural*, bug-free code in the training data. To test this hypothesis, we employ eight recent LLMs pre-trained on code, including the latest GPT versions, and four common program repair benchmarks in Java. We find that RTT with English as an intermediate language repaired 101 of 164 bugs with GPT-4 on the HumanEval-Java dataset. Moreover, 46 of these are unique bugs that are not repaired by other LLMs fine-tuned for APR. Our findings highlight the viability of round-trip translation with LLMs as a technique for automated program repair and its potential for research in software engineering.

CCS Concepts: • Software and its engineering  $\rightarrow$  Correctness; Automatic programming; Software testing and debugging.

Additional Key Words and Phrases: automated program repair, large language models, machine translation

## **1 INTRODUCTION**

As software becomes ubiquitous and more people engage in software engineering (SE) tasks, the need to ensure its reliability and integrity increases. Automated program repair (APR) aims to fix errors in source code with minimal human involvement, thus reducing code maintenance needs and releasing resources for creative code writing. With the advent of language models trained on source code, learning-based methods that use generative and translation models to fix bugs have started to compete with traditional heuristic and constraint-based approaches for APR [22, 28].

Despite all progress, it remains a challenge for both learning-based and other repair methods to correctly address all bugs in APR benchmarks. A particular challenging class of bugs are those that require the model to understand complex contexts and logic. To overcome this situation, alternative techniques for APR must be investigated.

The starting point for this paper is the observation that grammatical errors in natural language can be fixed by translating sentences to another intermediate language and then back, a process known as *round-trip translation* (RTT) [14]. Inspired by how RTT can correct errors in natural language, we set out to investigate to what extent it can fix bugs in code in a similar fashion.

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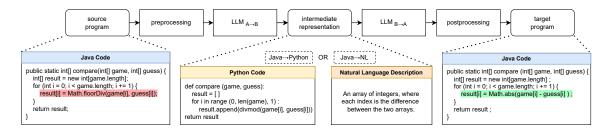


Fig. 1. High-level overview of the RTT process with concrete examples taken from our empirical evaluation. The red highlight on the left indicates the buggy line, the green highlight on the right is the repaired line.

We propose a novel RTT pipeline for APR using state-of-the-art large language models (LLMs) for code translation, summarization, and generation. The pipeline uses either a programming language (PL) or a natural language (NL) as intermediate representation. Moreover, the LLMs are used in zero-shot fashion: Unlike other neural APR methods, RTT does not fine-tune models on the bug repair task, but applies them *off-the-shelf* as provided by the model authors.

Our hypothesis is that RTT is capable of fixing bugs as a result of the *regression toward the mean* performed by generative language models. Studies show that frequent code patterns in large code corpora are bug-free [35]. Thus, as a result of training LLMs on these corpora, RTT will regress toward the same mean of bug-free code.

To empirically investigate this hypothesis, we conduct the first comprehensive study on RTT with LLMs for APR. Our experiments use eight LLMs, including the latest GPT versions, and four APR benchmarks. The models vary in size from 140M to ca.1.7T parameters and in objectives from code and docstring infilling to code summarization, translation and generation. The benchmarks contain code with different context size and bug complexity, ranging from student assignments to real-world projects.

**Contributions.** The main contributions of this work are: (*i*) we propose a novel approach for automated program repair using round-trip translation with large language models; (*ii*) we thoroughly test RTT with eight language models, four APR benchmarks with various context sizes and bug types, and 10 different seeds for open-source models; (*iii*) we investigate the performance of RTT with two intermediate representations: another PL and English language; (*iv*) we explore the trade-off between LLM size and repair performance; (*v*) we show that RTT repairs 101 of 164 bugs in the HumanEval-Java benchmark and repairs 46 bugs that were not fixed by other methods, even those fine-tuned on APR tasks; (*vi*) we release the code for RTT and results obtained to ensure replication and verification of our work.<sup>1</sup>

## 2 BACKGROUND AND RELATED WORK

#### 2.1 Neural Machine Translation

Traditional methods for translating text from one language into another are increasingly replaced by Neural Machine Translation (NMT), where neural networks are used to predict a sequence of translated words [40, 51]. Sequence-to-sequence models enable NMT to automatically learn complex mappings between different languages, efficiently capturing context and offering more accurate translations compared to their predecessors.

To generate translated sentences, NMT methods use the whole source sentence and the initial part, or *prefix*, of the target sentence. Assuming  $x = \{x_1, ..., x_n\}$  is the source sentence split into *n* tokens,  $y = \{y_1, ..., y_m\}$  is the target sentence and  $y_{<i} = \{y_1, ..., y_{i-1} | i \le m\}$  is the beginning of the target sequence generated up to token i - 1, we can

<sup>&</sup>lt;sup>1</sup> Replication package on Zenodo: https://doi.org/10.5281/zenodo.10500593.

formulate the generation as a conditional probability P(y|x):

$$P(y|x) = \prod_{i=1}^{m} P(y_i|x, y_{< i}).$$
(1)

## 2.2 Software Naturalness

*Software naturalness* is the observation that source code exhibits patterns and follows conventions that are statistically similar to other forms of human expression [4, 15]. This means that NLP techniques such as NMT can be applied to source code. Neural Program Translation (NPT) applies NMT to understand the underlying logic and semantics of the source code and generates functionally equivalent programs in the target language [37].

## 2.3 Language Models for Automated Program Repair

Ray et al. [35] observed bugs to be deviations that manifest as unnatural *noise* which increases entropy in otherwise predictable and repetitive natural code. This observation has been used to address various tasks, such as APR [43], vulnerability identification [6], and patch ranking [20, 21].

Interpreting APR as a translation from buggy to fixed sequences further stimulated the use of language models [8, 18]. Early models used RNN and LSTM architectures that cannot handle long-range dependencies and scale poorly [53]. Transformers [44] addressed these challenges and are now the prevalent choice. Transformers for APR and other SE tasks have evolved by incorporating new representations [13], new loss functions [16], and increasing their size [48]. This enables them to understand more complex syntactical structures [29, 52], and make human-competitive repairs [10]. These techniques differ from the RTT approach proposed in this paper in that they are fine-tuned on, or prompted to perform, the APR task, whereas the proposed RTT approach uses LLMs without any fine-tuning or prompting for APR. Furthermore, recent work has leveraged the use of zero-shot LLMs to successfully perform *cloze-style* APR on numerous benchmarks [17, 48, 49]. These studies masked buggy lines in a function and used off-the-shelf LLMs to predict the masked lines given surrounding code tokens as context.

#### 2.4 Round-Trip Translation

RTT involves translating a text from its original language to an intermediate language and then translating it back to the original language. Our use of RTT was inspired by the practical observation that, for our secondary languages, we would check or correct errors using RTT through publicly available NMT tools. The value of this practice was confirmed in a study by Hermet and Désilets [14]. Other uses of RTT in NMT include improving translation results [27], and testing the accuracy of a translation model [54]. In the context of APR research, RTT has previously been used for data augmentation [2, 38].

## **3 REPAIR THROUGH ROUND-TRIP TRANSLATION**

We propose a novel method for APR that is based on round-trip translation using state-of-the-art LLMs. A high-level overview of the approach is presented in Figure 1, together with concrete examples that are taken from our experiments. The method uses two LLMs to translate code from one programming language to another programming or natural language, and back to the first programming language.

#### 3.1 Motivation to Use Round-Trip Translation for Program Repair

We hypothesize that RTT is capable of repairing bugs as a result of the *regression toward the mean* or homogenization performed by generative language models. The reasoning is as follows: The LLMs employed in RTT are trained on vast real-world code corpora. Such models can treat code as natural language due to the naturalness hypothesis [15]. They generate or summarize code by iteratively selecting the sequence of the most probable tokens, or the most probable sub-sequences of tokens using beam search [41]. The probability is estimated by the language model based on its weights, and adapted during the model training to return the most frequently occurring tokens in similar contexts. Ray et al. [35] have shown that frequent code patterns in large real-word code corpora are bug-free. Thus, as a result of training LLMs on these corpora, they have a tendency to generate code that is also bug-free. This process in which LLMs return the most probable tokens during generation can be viewed as regression toward the mean, where noisy samples are replaced by samples closer to the mean. Therefore, each translation step in RTT homogenizes the source fragment toward a less noisy variant that is closer to the expected most probable code, a patch candidate. In the context of code, bugs have been shown to act as a form of noise that is less natural than the mean [35], so they should be reduced or eliminated over the course of round-trip translation.

## 3.2 Formulation of Round-Trip Translation

Formally, our approach can be described as follows. Let  $x = \{x_1, ..., x_n\}$  be a buggy code snippet split into *n* tokens and  $\tilde{x} = \{\tilde{x}_1, ..., \tilde{x}_m\}$  its round-trip translated version with *m* tokens, i.e., a candidate patch. We use LLMs as neural machine translation models:  $LLM_{A\to B}(\cdot)$  from language *A* to *B*, where  $A \neq B$ , and  $LLM_{B\to A}(\cdot)$ . The round-trip translation of a code snippet *x* is a two-legged translation. The first leg, *forward translation*, produces a sequence in language *B*, and the second one, *backward translation*, generates code in language *A* from the sequence in language *B*. The whole process can be expressed as:

$$\tilde{x} = LLM_{B \to A}(LLM_{A \to B}(x)). \tag{2}$$

The total probability of the candidate patch generated by RTT, can be expressed with an intermediate representation r of x as follows:

$$P(\tilde{x}) = P(\tilde{x}|r) \cdot P(r).$$
(3)

Probabilities P(r) and  $P(\tilde{x}|r)$  can be approximated with available LLMs according to Eq. 1 as follows:

$$P(r) \approx \prod_{i=1}^{k} P_{LLM_{A \to B}}(r_i | x, r_{j < i}), \tag{4}$$

$$P(\tilde{x}|r) \approx \prod_{i=1}^{m} P_{LLM_{B\to A}}(\tilde{x}_i|r, \tilde{x}_{j
(5)$$

Therefore, we use two legs of translation to approximate the candidate patch  $\tilde{x}$  in Eq. 3. In this work, we use different intermediate languages with the goal of encouraging a diverse range of representations, namely natural language (English) and programming languages.

We also formalize the notion used to investigate if RTT can indeed repair bugs. We denote a benchmark with *N* buggy code snippets as  $\{x^i\}_{i=1}^N$ , and let  $Plausible(x) \rightarrow \{0, 1\}$  be a function that returns 1 if code snippet *x* passes all test cases [53]. Then, to evaluate if RTT can indeed repair bugs, we check if a collection of snippets after round-trip translation has a higher overall plausibility than the original collection, expressed by the following equation:

$$\sum_{i=1}^{N} Plausible(\tilde{x}^{i}) > \sum_{i=1}^{N} Plausible(x^{i}).$$
(6)

The practical implementation and evaluation of RTT is discussed in more detail in Section 4.3.

## 4 EXPERIMENT DESIGN

Our evaluation of RTT is guided by three research questions: **RQ1:** How well does RTT perform with a programming language as intermediate representation? **RQ2:** How well does RTT perform with a natural language (in particular, English) as an intermediate? **RQ3:** What qualitative trends can be observed in the patches generated by RTT?

To address these research questions, we use eight LLMs and four APR benchmarks discussed in detail below. The selection of these models and benchmarks was guided by ensuring a diverse and thorough evaluation of RTT for APR.

### 4.1 Models

We use eight distinct transformer-based language models for our evaluation. Their sizes, architectures, and characteristics of training datasets are shown in Table 1. We select the models based on two main requirements: (*i*) they are trained on large code corpora and perform well on code-related tasks; (*ii*) they can perform both legs of a round-trip translation, through an NL or another PL. None of the model variants we use were originally trained or fine-tuned for code repair, and we use them *as-provided*, without additional fine-tuning or training. Although the models' original goal was not code repair, we consider the *outputs* of the backward (second) translation leg as *candidate patches* in our experiments. Observe that one can choose to use different models in each leg of the translation, removing the need for our second requirement. However, in the context of this paper, we focus on using the same model in each leg.

**PLBART** is an LLM for code-related tasks pre-trained on Java, Python, and natural languages [1]. It is released in two sizes, *base* and *large*, and 53 versions fine-tuned on different PLs and tasks. Of those, we use the *base* models fine-tuned on code-to-code translation between Java and C# and the *base* models fine-tuned on code summarization (Java  $\rightarrow$  NL) and code generation (NL  $\rightarrow$  Java).

Model	Size	Architecture	Data Source
PLBART	base (140M)	BART (encoder-decoder)	StackOverflow BigQuery
CodeT5	base (220M)	T5 (encoder-decoder)	CodeSearchNet BigQuery
TransCoder	~440M	T5 (encoder-decoder)	Google BigQuery
SantaCoder	1.1B	GPT-2 (decoder)	The Stack (v1.1)
InCoder	1.3B 6.7B	MoE (decoder)	StackOverflow GitHub/GitLab
StarCoderBase	e 15.5B	GPT-2 (decoder)	The Stack (v1.2)
GPT-3.5	175B	GPT-3 (decoder)	Public Data
GPT-4	(estim.) ~1.7T	GPT-4 (decoder)	Public Data

Table 1. Overview of language models used for RTT.

**CodeT5** extends T5 capabilities [34] to code-related tasks [45]. The model comes in three sizes (*small, base, large*) and versions fine-tuned on multiple tasks and programming languages. We use the *base* size models fine-tuned on the same types of tasks as PLBART.

**TransCoder** is an LLM designed for translation between C++, Python, and Java [37]. The model was trained using a denoising auto-encoding objective where source sequences in one PL contain noise, and the goal is to generate target sequences in another PL without noise. This makes it a promising candidate for an RTT pipeline where we aim to reduce noise or bugs in two steps, from the original buggy example to the translated intermediate representation and the final candidate patch.

**SantaCoder** is a model primarily for Java, JavaScript, and Python code generation via infilling [3]. The model was designed to address ethical concerns about the use of LLMs for code. Despite its smaller size, it performs comparably to larger models on code generation and infilling. We use SantaCoder for RTT with NL because the model learned to operate with docstrings during pre-training.

**InCoder** is an LLM able to perform code generation and editing via infilling across 28 languages [11]. The model achieves high performance on code generation and infilling due to the use of bidirectional context and the casual masking objective used during pre-training. The model is released in two sizes trained on the same amount of data. We use InCoder in a similar fashion to SantaCoder.

**StarCoder** is a generative LLM trained with infilling objective on more than 80 programming languages, Jupyter Notebooks, and Git communications [23]. Two versions are released: StarCoderBase and StarCoder (fine-tuned for Python), of which we use StarCoderBase in the infilling mode for experiments with NL as intermediate.

**GPT-3.5** [5] and **GPT-4** [30] are the two latest iterations of the Generative Pre-Training Transformer series, the black-box models released via the OpenAI API.<sup>2</sup> They are not specifically designed for code-related tasks, but perform well due to their diverse training dataset. Because RTT with PLs as intermediate shows worse results than with NL as intermediate, we chose to use the GPT models only with NL as intermediate to limit the costs.

## 4.2 Benchmarks

We have chosen four diverse APR benchmarks, following Jiang et al. [17]. This choice enables direct comparison between the RTT approach and results of previous work on the NMT-style APR, in which buggy code is directly translated to patches. All the benchmarks are in Java and contain buggy and fixed code, as well as tests to check the test pass rate of the candidate patches generated by RTT. Note that we use the concepts *problem*, *bug*, and *code example* interchangeably, because we use buggy code examples with single-hunk bugs only.

**Defects4J v1.2** is a collection of 395 (4 depreciated) reproducible bugs from open-source Java projects [19]. We followed Jiang et al. [17] and selected the 130 single-hunk bugs. The bugs have a wide range of complexity and are related to multiple domains.

**Defects4J v2.0** is the latest stable version of Defects4J. This version provides an even more comprehensive and diverse collection of defects to test APR techniques. It includes 438 additional bugs from nine open-source Java projects from which we selected the 89 single-hunk ones.

**QuixBugs** contains 40 common student-level algorithmic programs, such as *bitcount*, and spans 17 types of single-hunk bugs [24].

 $<sup>^2</sup>$  See https://platform.openai.com/docs/guides/gpt. Specifically, we use the  $gpt\mathchar`-3.5\mathchar`-4$  models.

HumanEval-Java [17] is a synthetic program repair dataset of 164 programs and unit tests translated to Java from the original version of HumanEval [7] in Python. The injected single-hunk bugs range from simple incorrect operator usages to more complex logical bugs. One advantage of HumanEval-Java is that it was not available during the training of the models used in this study, which eliminates the data leakage risk.

## 4.3 Implementation of Round-Trip Translation

The RTT pipeline comprises four main steps: preprocessing of input buggy code, generation of translations, postprocessing of RTT-generated outputs, and their validation. We refer to *input* source code as *buggy code*, *buggy examples* or simply *bugs*, while *outputs* of the RTT pipeline correspond to *candidate patches* in APR terminology. The first three steps are shown in Figure 1. We add the fourth evaluation step in the current section. The result is a versatile and parallelizable pipeline able to generate and validate RTT patches with diverse models and test against different benchmarks. Our pipeline extends the framework of Jiang et al. [17].

**Step 1: Preprocessing and Prompting.** We follow the common practice and extract solely the buggy function as is also done by Jiang et al. [17]. To conform with language models requirements, we add prefixes, suffixes, masks and/or general style changes, such as removing newline characters, before tokenization. We insert a Javadoc header that serves as a prompt for the infilling models (SantaCoder, StarCoderBase, InCoder). Section 4.5 contains the exact prompts used for the models.

**Step 2: Round-trip Translation.** In the round-trip translation step, we generate two translations for each buggy example using the same type of LLM for both RTT legs: from preprocessed buggy code to an intermediate language and from the intermediate language back to the original language. We generate 5 different translations per leg in the round-trip translation using LLMs with non-zero temperature to ensure the diversity of the intermediate representations and final candidate patches. Therefore, for each buggy example in a benchmark, we obtain 5 translations in the intermediate language and 25 final candidate patches, i.e., 5 from each intermediate translation. Temperature and other model-specific hyperparameters are described in Section 4.4.

**Step 3: Postprocessing.** We also perform minor postprocessing of the RTT-generated candidate patches to ensure that function signatures are as expected by the test suites. Therefore, we extract code if both code and text are generated and remove extra tokens. This process also increases the readability of patches. Section 4.6 contains more details on postprocessing with an NL and PLs as intermediate translations.

**Step 4: Evaluation of RTT Results.** The final step evaluates the postprocessed RTT results against the test suites provided by the benchmarks. We calculate additional metrics for each candidate patch to evaluate the performance of the models and measure the effectiveness of RTT for APR.

#### 4.4 Hyperparameters for Language Models

We use the recommendation of the authors of the models when choosing the hyperparameters, unless specified otherwise in the current section. All the final hyperparameter values are reported in Table 2. In detail, we set the number of beams to 10 and the temperature to 1 for PLBART,<sup>3</sup> CodeT5,<sup>4</sup> and TransCoder.<sup>5</sup> For SantaCoder,<sup>6</sup> StarCoder,<sup>7</sup> and InCoder,<sup>8,9</sup>

<sup>&</sup>lt;sup>3</sup> https://github.com/wasiahmad/PLBART

<sup>&</sup>lt;sup>4</sup> https://github.com/salesforce/CodeT5

<sup>&</sup>lt;sup>5</sup> https://github.com/facebookresearch/TransCoder

<sup>&</sup>lt;sup>6</sup> https://huggingface.co/bigcode/santacoder

<sup>&</sup>lt;sup>7</sup> https://huggingface.co/bigcode/starcoderbase

<sup>&</sup>lt;sup>8</sup> https://huggingface.co/facebook/incoder-1B

<sup>&</sup>lt;sup>9</sup> https://huggingface.co/facebook/incoder-6B

we follow the hyperparameter setup reported in their public demos with a number of beams of 1 and Top-P nucleus sampling of 0.95. To account for the increased number of generated outputs (5 on each translation step), we modify the recommended temperature to 0.3 for the first leg (code-to-text) and 0.4 for the second leg (text-to-code).

For the GPT models, we follow the advice where code-generating tasks, dealing with structured code, should have a lower temperature than natural language. We decide to use top-p close to 1 to increase diversity but follow OpenAI guidelines to not drastically modify temperature and top-p simultaneously. Moreover, we experimented with different other hyperparameters. For example, we tried different tags in the Javadoc header and values of *repetition\_penalty*, *length\_penalty*, *no\_repeat\_ngram\_size*. Albeit we did not perform a systematic study, the results from other prompts and the use of these hyperparameters did not show any promising improvement in our use case. Therefore, we have used the parameters as reported in Table 2 and the prompts described in Section 4.5.

Model	Number of beams	Temperature first leg	Temperature second leg	Тор-р
PLBART	10	1	1	-
CodeT5	10	1	1	-
TransCoder	10	1	1	-
SantaCoder	1	0.3	0.4	0.95
InCoder	1	0.3	0.4	0.95
StarCoderBase	1	0.3	0.4	0.95
GPT-3.5	1	0.3	0.2	0.95
GPT-4	1	0.3	0.2	0.95

Table 2. Hyperparameters used in RTT.

#### 4.5 Prompt Choice

The prompts for the instruction and cloze-style models differ due to the presence of the system message in the GPT models and the special infilling tokens for the cloze-style models.

*4.5.1 GPT models.* We do not use conversation memory in-built in GPT-3.5 and 4 and run only one forward and one backward translation step. The **system message** is as follows:

You are an expert programmer in all programming languages.

The **user prompt** for  $PL \rightarrow NL$  summarization (forward translation) has been chosen in the following way:

Create a Javadoc for the Java function delimited by triple backquotes. Do not return generate the method again, return only the Javadoc. Java function: ```{buggy code}```.

For  $NL \rightarrow PL$  code generation (backward translation), the **user prompt** is as follows:

Given the signature of a Java function and its Javadoc delimited by triple backquotes, generate the body of the function. Do not generate any additional methods nor repeat the Javadoc nor give any explanations. Return only the completed function without any comments.```{NL description as a comment and function signature}```.

4.5.2 *Open-source Models.* For the rest of the models, we follow the default settings with the exception of the following modifications. We ban the word *TODO* when generating code with StarCoder and SantaCoder, since a considerable amount of generated candidate patches were left blank after the use of the word. In addition, the tag *@description* is inserted in the Javadoc header to prompt the models to generate natural language summaries after the description tag.

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```
The resulting prompt for the PL \rightarrow NL step (forward translation) has the following form:
/* @description <INFILL>
*/
{buggy code}.
```

We prepend the NL summary with the header  $\langle |file \ ext = .java| \rangle$  when using InCoder for the code generation (second leg) to improve the overall results of the model by giving context. The prompt for NL  $\rightarrow$  PL code generation (backward translation) is, therefore:

```
<| file ext=.java |>
/* @description {NL description}
*/
{function signature}.
```

The prompts are chosen code or NL summary generation are straightforward. Investigation into other prompting strategies may positively affect the results.

# 4.6 Ensuring Testability of Candidate Patches

When generating a candidate patch with RTT, we take two approaches according to the intermediate language used, PL or NL. When using a PL, we overwrite the scope and name of the generated candidate patch with the appropriate ones from the buggy code. This ensures that the candidate patch is tested regardless of small errors such as an upper-cased name.

When using NL, we provide the function signature known from the original buggy example alongside the NL description generated in the first RTT leg (forward translation step). We choose this procedure, because we observe that the models do not generate such detailed descriptions in NL that can direct the NL $\rightarrow$  PL models to recreate the name and types of input arguments and return values consistently.

Finally, we set up the RTT pipeline so that we skip a buggy example if its original code or the generated translation does not fit in the context window of the model and mark such cases in the final results. However, out of the four benchmarks and eight models from our evaluation setup, it happens only for the *Jsoup 15* bug and the StarCoderBase model that we are forced to skip a buggy example due to a lack of computing resources.

# 4.7 Evaluation Metrics

We compute a total of seven common APR metrics for each candidate patch generated by the RTT pipeline to evaluate the performance of RTT with different models and assess the effectiveness of RTT for APR [53]. We report the following metrics to *Weights & Biases*,<sup>10</sup> an online tool to analyze the models and their results:

- *Compilability*  $\in$  {0, 1}: ability of the candidate patch to be compiled successfully.
- *Plausibility*  $\in$  {0,1}: ability of the candidate patch to pass all test cases of the corresponding benchmark.
- *Test pass rate*  $\in$  [0, 100]: percentage of tests passed by the candidate patch.
- *Exact Match*  $\in$  {0, 1}: binary metric to check if the candidate patch exactly matches the target solution.
- *BiLingual Evaluation Understudy (BLEU)* ∈ [0, 1] [31]: evaluates by comparing the n-grams against target solution.

<sup>10</sup> https://wandb.ai

	Defects4J	Defects4J	QuixBugs	Human
Model	v1.2	v2.0		Eval-Java
	(130 bugs)	(89 bugs)	(40 bugs)	(164 bugs)
PLBART (C#)	$1.0 \pm 0.0$	$0.0 \pm 0.0$	$0.0 \pm 0.0$	$0.0 \pm 0.0$
CodeT5 (C#)	$2.0\pm0.0$	$1.3\pm0.4$	$0.0\pm0.0$	$1.0\pm0.0$
TransCoder (C++)	$1.8\pm0.4$	$3.0\pm0.0$	$0.0\pm0.0$	$7.0\pm0.0$
TransCoder (Python)	$\textbf{3.0} \pm \textbf{0.0}$	$2.0\pm0.0$	$0.1 \pm 0.3$	$\textbf{8.0} \pm \textbf{0.0}$

Table 3. Average number of plausible patches ± standard deviation over 10 runs, generated with a PL as intermediate. The best results are highlighted in **bold**.

- *CodeBLEU* ∈ [0, 1] [36]: extension of BLEU designed for source code. It includes abstract syntax trees and code semantics in the calculation of the score.
- *CrystalBLEU* ∈ [0, 1] [9]: extension of BLEU designed for source code. It takes into account common n-grams due to syntactic verbosity and coding conventions in the calculation of the score.

## 4.8 Addressing Model Stochasticity

To account for randomness in LLMs with non-zero temperatures, we run each experiment that uses open source models with 10 different seeds and refer to these as *10 runs*. This helps mitigate the impact of randomness and presents a more accurate representation of RTT capabilities. We perform only one run for each of the experiments with GPT-3.5 and GPT-4, because these models do not allow setting a seed.<sup>11</sup>

# 4.9 Hardware

We run the patch generation on 3 NVIDIA V100 GPUs or 2 NVIDIA A100 GPUs, depending on model needs. We run the test suites for patch validation on a 32-Core AMD EPYC 7601 CPU with 2TB RAM.

## 5 RESULTS AND DISCUSSION

# 5.1 Round-Trip Translation through PL

We first investigate the capabilities of LLMs to fix bugs via RTT using another programming language as the intermediate. For this purpose, we use the LLMs which are able to translate Java code into another PL: PLBART (Java  $\leftrightarrow$  C#), CodeT5 (Java  $\leftrightarrow$  C#), and TransCoder (Java  $\leftrightarrow$  C++, Java  $\leftrightarrow$  Python). Table 3 summarises the bug fixing performance of RTT along with the intermediate language used in RTT. We set plausibility to 1 if at least one of the 25 generated candidate patches passes all the tests for a given buggy code sample, sum up plausibility over buggy code examples in a dataset, and then take an average over 10 runs with different seeds. We refer to the number of buggy samples with plausible patches for a dataset as *plausibility rate*. For RTT through PL, we observe that the average plausibility rate is low, with at most eight bugs repaired on average for the HumanEval-Java dataset with 164 buggy code examples and at most three code examples repaired on average for the remaining three datasets. PLBART only fixes a single bug across the four datasets with RTT. CodeT5 provides at most two plausible patches for any of the datasets.

The best performance with RTT through PL is achieved by TransCoder with Python as intermediate PL on three out of four datasets. Moreover, TransCoder is the only model that provided a plausible patch for QuixBugs. We observe that

 $<sup>^{11}</sup>$  This has the added benefit of limiting overall experiment costs, especially for GPT-4. The approximate cost for the single run using GPT-3.5 was  $\sim$ 10USD, while for GPT-4 it was  $\sim$ 140USD.

larger models fix more buggy examples than smaller ones, which is aligned with the general tendency of larger models to perform better on downstream tasks [46].

The models tend to repeat the candidate patches for a given buggy example over the 10 runs regardless of the non-zero temperature and different random seeds. This trend, in addition to the low plausibility rates and standard deviation obtained, can indicate a potential rigidity in the conceptual mapping between languages, which may limit the model to literal translation, preventing efficient use of context to filter out noise, or bugs. In other words, code-to-code NMT models with similar target and source languages keep the same tokens and logical bugs. This is supported by the fact that TransCoder with Python as intermediate performs the best on three out of four datasets. Python and Java are less alike than C# or C++ and Java, which motivates bigger changes when translating.

**RTT through PL.** The use of PL as an intermediate language in our approach, while yielding a very low number of plausible patches, has shed light on a few key points: *(a)* the intermediate translation should differ enough from the buggy code; *(b)* larger models produce better RTT results on APR through PL.

#### 5.2 Round-Trip Translation through NL

We continue our experiments with RTT that uses a natural language (English) as intermediate representation. We report the number of buggy code examples with plausible patches in Table 4. We include average and standard deviation of the plausibility rate over 10 runs with different seeds, as well as the exact values observed in the union of all runs (Any Run) and their intersection (Every Run). Note that the models in Table 4 are ordered by size.

A clear correlation is observed between the model size and the average plausibility rate (Pearson's r = 0.78). The only outlier is SantaCoder, which also performs comparably to larger models on other tasks in related work [3]. The growth of the average plausibility rate from SantaCoder (1.1B) to StarCoderBase (15.5B) is less pronounced. This result can be affected by a larger proportion of Java code within SantaCoder training data compared to StarCoderBase training set. In addition, the majority of models with more than 1B parameters fix at least one bug with RTT through NL that is not repaired by RTT through NL with other models. Note that for a fixed model, bug repair performance differs based

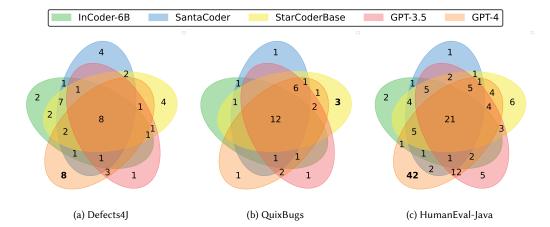


Fig. 2. Number of unique bugs fixed in various datasets by RTT through NL with a fixed language model.

		Defects4J	Defects4J	QuixBugs	Human
	Model	v1.2	v2.0		Eval-Java
		(130 bugs)	(89 bugs)	(40 bugs)	(164 bugs)
Ð	PLBART	$2.0\pm0.0$	$4.3\pm0.5$	$3.0 \pm 0.0$	$4.0\pm0.0$
	CodeT5	$2.0\pm0.0$	$2.0\pm0.0$	$1.0\pm0.0$	$5.0\pm0.0$
Avg ± STD	SantaCoder	$9.0\pm1.4$	$6.9 \pm 2.2$	$16.1\pm0.9$	$37.0 \pm 1.7$
ğ	InCoder (1.3B)	$4.6\pm0.7$	$4.7 \pm 1.2$	$5.8 \pm 1.2$	$20.4 \pm 1.8$
Ā	InCoder (6.7B)	$7.0\pm0.8$	$6.7\pm1.1$	$10.5 \pm 1.0$	$31.7 \pm 1.3$
	StarCoderBase	10.5 ± 1.5	$7.2 \pm 1.2$	$21.6\pm0.9$	$42.8\pm7.9$
u	PLBART	2	5	3	4
	CodeT5	2	2	1	5
	SantaCoder	14	13	23	50
Any Run	InCoder (1.3B)	6	10	8	34
hy	InCoder (6.7B)	16	10	16	43
A	StarCoderBase	19	10	26	61
	GPT-3.5	14	3	25	60
	GPT-4	17	7	27	101
Every Run	PLBART	2	4	3	4
	CodeT5	2	2	1	5
	SantaCoder	3	4	8	26
rery	InCoder (1.3B)	4	2	2	12
Еv	InCoder (6.7B)	2	1	7	20
	StarCoderBase	6	3	18	18

Table 4. Number of plausible patches over 10 runs, with NL as intermediate. GPT-3.5 and GPT-4 are run once, and reported in the last two rows of "Any Run". The best results in each group are shown in **bold**.

on the dataset. Thus, the proportion of the buggy input examples with plausible patches is lower for more complex datasets (Defects4J variants) and larger for simpler tasks (in QuixBugs and HumanEval-Java).

The low standard deviation of the plausibility rate indicates that most models tend to repair a similar number of bugs in every run. However, the number of fixed bugs on *Any Run* is two to three times higher on average than the number of repaired bugs in *Every Run*. For example, StarCoderBase fixes 19 Defects4J v1.2 buggy input examples in the aggregation of 10 runs and only 6 same bugs in every run. This confirms RTT is capable of repairing diverse bugs.

The aggregated metrics over 10 runs bring additional perspectives, such as a comparison of unique bugs fixed by RTT and those in related work. Although the number of repaired bugs tends to vary between the models, Figure 2 indicates that in our approach, most models tend to solve at least one unique problem. Therefore, the kind of problems solved by RTT are not only size-dependant, but also model-dependant. Table 5 compares the results of our RTT approach with those obtained in previous work using the exact same models, but either fine-tuned for APR [17], or using APR specific prompting on GPT-3.5 [39]. The majority of models used in RTT repair at least one buggy example not repaired by the same models fine-tuned for NMT-type of APR methods.

We compare the top-performing model in RTT, GPT-4, against the 10 LLMs studied in the work of Jiang et al. [17], fine-tuned and non-finetuned for the APR task, in Figure 3. Not only is GPT-4 able to generate more plausible patches than any of the tested models in [17], but 30 out of the 101 bugs are only fixed by RTT through NL and not repaired by

any of the tested models without RTT. This comparison highlights that RTT generates plausible patches for the bugs that common APR approaches have not fixed and emphasizes the added value of RTT in the APR landscape.

Studies show that generating more candidate patches can result in higher repair performance on the datasets used in our evaluation [48, 50]. The authors generate 200 patches per model, compared to 25 patches in our case, which may be the reason why they fix all bugs in QuixBugs with GPT-3.5 [50] or get 26 and 29 plausible patches with InCoder 1.3B and 6.7B, respectively [48]. However, we could not find enough details or replication packages for those studies and do not include them in Table 5. The latter work also shows that plausible patches have, on average, lower entropy than non-plausible ones. In our experiments, we obtain an almost uniform distribution of the number of plausible patches depending on their position, i.e., how far on the list of 25 candidate patches the plausible ones occur. This suggests that results can be improved by generating more candidate patches with RTT, at higher resource usage.

	Defects4J	Defects4J	QuixBugs	Human
Model	v1.2	v2.0		Eval-Java
	(130 bugs)	(89 bugs)	(40 bugs)	(164 bugs)
PLBART	33 / 2 / 0	24 / 5 / 3	15 / 3 / 1	36 / 4 / 0
CodeT5	33 / 2 / 1	25 / 2 / 1	17 / 1 / 1	54 / 5 / 0
InCoder (1.3B)	43 / 6 / 3	38 / 10 / 2	20 / 8 / 4	64 / 34 / 14
InCoder (6.7B)	56 / 16 / 5	38 / 10 / 3	24 / 16 / 4	70 / 43 / 16
GPT-3.5	-	-	19 / 25 / 12	-

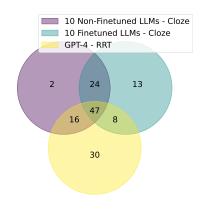
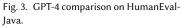


Table 5. Number of unique problems with plausible patches, shown as P / O / N, with P in previous work, O in our work using RTT through NL (*Any Run*), and N only in our work, not in previous.



**RTT through NL.** We observe that (*a*) the leading models for bug fixing with RTT are SantaCoder, StarCoderBase, GPT-3.5 and GPT-4, thus confirming the trend that larger models obtain better results; (*b*) although standard deviation of plausibility rate is low, the number of bugs repaired in the union of runs is 2-3 times higher on average than the rate for every run; (*c*) RTT through NL is able to repair bugs not repaired by the same models fine-tuned on the APR task.

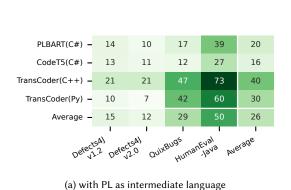
## 5.3 Qualitative Analysis of Generated Candidate Patches

Through a close inspection of candidate patches generated, we are able to gain more insights into the quality of RTT-generated patches. We investigate compilability, test pass rates, CodeBLEU and other characteristics of patch candidates.

*5.3.1 Compilability.* We explore the average ratio of compilable patches out of all candidate patches generated over 10 runs and present the results in Figures 4a and 4b for RTT through PL and NL, correspondingly. In general, RTT through PL generates less compilable patches than RTT through NL. TransCoder helps RTT through PL generate a high number of compilable patches, which we associate with its rigorous denoising pre-training objective.

For RTT through NL, the trend of obtaining better compilability ratios with larger models holds. The previously discussed pattern, where SantaCoder obtains better results than InCoder and slightly worse than StarCoderBase, holds,

#### Ruiz et al.



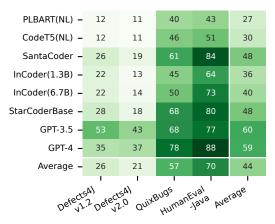




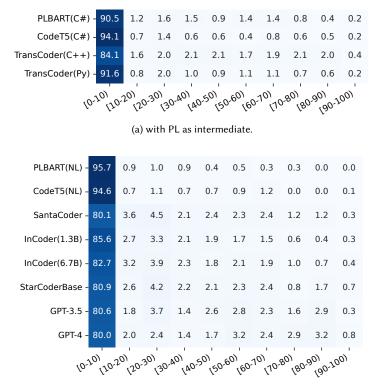
Fig. 4. Percentage of compilable candidate patches generated in 10 runs, where applicable, and at 25 attempts for each buggy example.

too. It is worth mentioning that GPT-3.5 yields high compilability rate for the Defects4J datasets, which can be appointed to possible data leakage during training. Overall, compilability on the datasets with challenging contexts (Defects4J's) is lower than on simpler tasks. Although compilability rates vary across the models and datasets, the majority (80-96%) of candidate patches generated by RTT have low test pass rate (0-10%).

The trends observed for plausibility rates are also present for the ratio of compilable candidate patches. Similarly to plausibility rates, compilability percentage is higher for experiments with NL than for RTT through PL. On average, the percentage of compilable patches out of all generated candidate patches ranges from 7.3% to 72.7% per dataset for RTT through PL and from 11.1% to 88.2% for RTT through NL. Moreover, RTT generates a higher proportion of compilable candidate patches on average for datasets with simpler tasks (QuixBugs, HumanEval-Java) than for datasets with more complex contexts and bugs (Defects4J variants). SantaCoder and StarCoderBase are the leading models in terms of the average compilability for the RTT through NL, in addition to the GPT variants. However, the best average results are obtained with TransCoder (Java  $\leftrightarrow$  C++) in the RTT through PL, unlike for plausibility rate which was the best for TransCoder (Java  $\leftrightarrow$  Python).

*5.3.2 Test Pass Rates.* To further explore the properties of RTT-generated candidate patches, we analyze the test pass rate of the non-plausible patches. We aim to explore what proportion of non-plausible patches miss smaller and larger ratios of benchmark tests and are close to plausible solutions.

The test pass rate results are presented in Figures 5a and 5b for RTT through PL and NL, respectively. We take a union of all non-plausible candidate patches over four benchmarks and all runs for each model and report the percentage of candidate patches in these unions that fall into test pass rate ranges from 0-10%, 10-20% and so on, including the beginning and excluding the end of the intervals. The vast majority of such a union of RTT-generated candidate patches pass 0 to 10% of test cases both for PL and NL as intermediate. This result indicates that non-plausible patches require more fixing updates to repair the bugs in the chosen benchmarks. One avenue for future work is to experiment with more iterations in the RTT and update the model prompts or descriptions with bug summaries or results of not passing test cases, similarly to Liventsev et al. [25].



(b) with NL as intermediate.

Fig. 5. Percentage of candidate patches in the different test passed rate ranges. We explore what ratio of candidate patches generated by a specific models for any of the datasets pass from A% (incl.) to B% (excl.) tests and report percentage over all generated candidate patches. For example, 96% of candidate patches generated with PLBART with NL as intermediate pass between 0% (incl.) and 10% (excl.) of tests.

5.3.3 *Characteristics of RTT-generated candidate patches.* To reiterate, we generate 5 intermediate translations in the first RTT leg, for example, in English language, and 5 final translations from each of the intermediates. We denote the first 5 intermediate translations as A, B, C, D, and E. We enumerate backward translations obtained from each of the five forward translations as A1–A5, B1–B5, ..., E1–E5. The ratio of compilable patches out of a union over all runs and datasets of all generated patches with a fixed model is presented in Figure 6 for RTT through PL.

With RTT through PL, the number of compilable patches is decreasing from the first to the last candidate patch generated from a fixed intermediate translation. In other words, RTT-generated candidate patches at positions A1, B1, ..., E1 compile more frequently than candidate patches at positions A5, B5, ..., E5. The percentage of compilable patches out of all generated patches at positions between A1 and A5, B1 and B5, ..., E1 and E5 decreases for PLBART (C#), CodeT5 (C#), and TransCoder (C++) but does not follow any trend for TransCoder (Python). The number of plausible patches obtained with RTT through PL is below eight on average, as mentioned previously. Thus, the trend between plausibility and the position Ax,..., Ex is not observable from such low average plausibility rates.

For RTT through NL, we do not observe any trend in terms of how frequently first (A1, B1, ..., E1) or later (Ax, ..., Ex, x > 1) patches are plausible or compilable. This result is in line with TransCoder (Python) in the RTT through

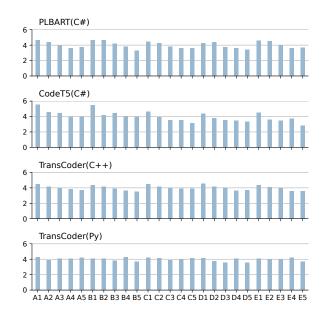


Fig. 6. Percentage of compilable candidate patches in the 25 positions with PL as intermediate. The percentage is calculated over all patches in four benchmark datasets generated with RTT using a fixed model

PL. Remarkably, RTT through NL and RTT through PL with TransCoder (Python) have higher plausibility rates than RTT with other models and through other PLs, as shown previously. This observation points back at the discussion of rigidity of code-to-code translation models in the RTT setting: They keep same variable names, other tokens and logical bugs in place. By contrast, NL models and code-to-code models with a PL that differs enough from the original PL show better results in RTT for bug fixing. They abstract and change the input buggy code enough to obtain a different representation that can in the next step lead to a bug fix. The uniform estimated distribution of compilable and plausible patches over the position at which they are generated also supports the argument that sampling more candidate patches from LLMs in the RTT pipeline can improve the bug fixing scores.

Other common APR metrics. Exact Match, BLEU, and CodeBLEU are frequently used to check whether candidate patches resemble the ground truth in benchmarks [26]. Since RTT is aimed at finding functionally correct patches, not stylistically equivalent ones, we have found these metrics non-descriptive for RTT. Especially when using NL as intermediate, RTT can freely deviate from the original buggy code's style, evidenced by the average BLEU and CodeBLEU scores  $\pm$  std over the patches that pass all tests being less than 40.1  $\pm$  0.09 and 63.7  $\pm$  6.7, respectively.

*5.3.4 CodeBLEU.* We calculate average CodeBLEU values for buggy examples and candidate patches generated by RTT with each fixed model over all runs and datasets and show the frequency of observed values in Figure 7. The metric values are scaled to [0; 100], with highest values being the best. The majority of buggy examples have high CodeBLEU scores, which indicates that target bug fixes are very similar to original buggy code. High CodeBLEU for the majority of buggy examples is also explained by the type of bugs: We only consider single-hunk bugs.

The majority of candidate patches obtained with RTT through PL have CodeBLEU between 40 and 60, with the outlier value of ca. 26 frequently observed among candidate patches for Defects4J variants. The most frequently observed average CodeBLEU values for RTT through NL are between 20 and 50, with a similar outlier value ca. 26 and an

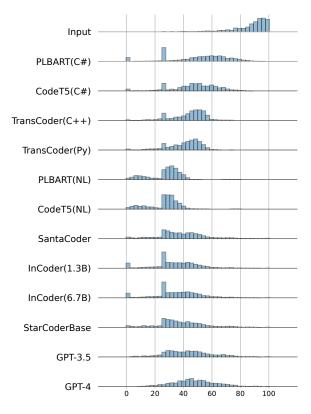


Fig. 7. Histogram on the CodeBLEU scores of candidate patches generated with RTT through PL or NL (NL is default, if not mentioned). The distribution is calculated over all patches generated for four APR benchmarks.

additional outlier of zero CodeBLEU noticeable for a number of candidate patches for Defects4J versions. The frequency of higher CodeBLEU values increases with larger model sizes. CodeBLEU values are considerably lower than 100 for the vast majority of RTT-generated candidate patches. However, one can observe the trend of regressing towards the mean type of candidate patches with similar CodeBLEU calculated between targets and RTT-generated patches.

Limitations of RTT for APR. Studies show that the original style of writing can be diluted by generative language models [12, 33]. Furthermore, LLMs have been known to generate code containing security flaws [32, 42]. These flaws may compromise the integrity of the application therefore it is recommended that developers thoroughly audit and review any generated code. Our experiments show that bugs in code can be corrected via RTT, but we also see that the original styling of the code is not always retained. Such a restyle leads to challenges with code maintainability, which can reduce the willingness of developers to adopt the approach. This issue will be less of a challenge in projects that enforce a uniform coding style through automated tools. Moreover, the impact will be lower if RTT is applied in smaller contexts, for example, in highly modular projects with localized bugs where restyling will have limited impact on maintainability.

**Properties of RTT patches.** (*a*) The average compilability rate of RTT-generated candidate patches is higher than their average plausibility rate. (*b*) RTT can change the code considerably, reducing usefulness of metrics for

ground-truth matching, such as BLEU and CodeBLEU. (c) Because RTT can dilute the coding style, it is best used in circumstances where rephrasing does not impact maintainability.

## 6 THREATS TO VALIDITY

This section discusses four types of threats to validity for this study, structured cf. Wohlin et al. [47, Sec. 6.7 & 6.8]. **Internal Validity:** To support the validity of our results, we applied RTT with two intermediate representations to four benchmarks and tested eight models. As the benchmarks are publicly available, there is a risk that they were used during training, also referred to as *data leakage*. This threat can be mitigated by using models that remove the benchmarks from their training data. Here, we use HumanEval-Java, which was constructed after the training of any of the models used in this work. For the other three datasets, we find an exact match in only 0.03% of the generated candidate patches, which reinforces the validity of the data and results.

#### **Construct Validity:**

To evaluate the RTT performance, we apply widely used APR metrics, including compilability and plausibility rates. For metrics that depend on test suites, low-quality or easy-to-pass tests could positively bias the evaluation. We mitigate this risk by employing four widely used APR benchmarks with different bug types.

# External Validity:

Threats to the external validity concern the generalizability of our approach. We have validated the approach on a representative sample of APR benchmarks, but have not extended the results to language pairs that were not covered. Moreover, we applied the approach using only eight transformer-based models. Extending the evaluation requires more computational resources and language models that comply with the RTT requirements in Section 4.1.

**Conclusion Validity:** For our experiments, we used off-the-shelf language models that are publicly available and can be used without retraining. The four benchmarks are also publicly available and widely used in APR research. To support open science and enable replication and verification of our work, a replication package is made available via Zenodo.<sup>1</sup>

## 7 CONCLUSION

In this work, we explore the potential of round-trip translation with LLMs for automated program repair. Our experiments confirm that RTT can fix various bugs, including a good amount that are not fixable through other APR approaches. Our analysis of the results has highlighted the complex relation between RTT and naturalness of code. While RTT leverages the regression to the mean to remove bugs, this process may also dilute the original code's author style and remove comments. We confirm the viability of RTT as a novel approach to APR, but also caution to consider potential pitfalls and limitations. Although RTT does not outperform the NMT and cloze-style APR, we show that RTT, without any additional fine-tuning costs, is able to repair unique bugs which were not fixed by the same models fine-tuned for NMT and cloze-type of APR.

**Future Work:** This study opens up several avenues for future research, such as constrained forms of RTT where changes can only be made in certain masked areas of the code, as well as reification of comments from the source code with the fixed code, to ease adoption and ensure future maintainability. Our replication package can be used as a base to expand the study to new models, intermediate languages, and datasets. Gaining a deeper understanding of characteristics and limitations of unique patches, such as model rigidity or optimal number of candidate patches to generate, can help to develop more sophisticated translation and repair techniques.

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