Automatic Program Repair with OpenAI’s Codex
Evaluating QuixBugs

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Abstract—OpenAI’s Codex, a GPT-3 like model trained on
a large code corpus, has made headlines in and outside of
academia. Given a short user-provided description, it is capable of
synthesizing code snippets that are syntactically and semantically
valid in most cases. In this work, we want to investigate whether
Codex is able to localize and fix bugs, a task of central interest
in the field of automated program repair. Our initial evaluation
uses the multi-language QuixBugs benchmark (40 bugs in both
Python and Java). We find that, despite not being trained for
APR, Codex is surprisingly effective, and competitive with recent
state of the art techniques. Our results also show that Codex is
slightly more successful at repairing Python than Java.

I. INTRODUCTION
Finding and fixing bugs costs billions yearly [1] and takes
up a considerable proportion of developer time [2]. The field
of Automatic program repair (APR) attempts to develop tools
that can automatically find and fix bugs in software. Many
existing APR tools follow a test-driven approach: bugs need
to be exposed by a failing test case. A variety of different APR
approaches have been proposed in the recent years; i) using
genetic-programming (e.g., GenProg [3] or ARJA [4]), ii) using
repair patterns (such as PAR [5], ELIXIR [6] or TBar [7]),
iii) code retrieval-based approaches (e.g., ssFix [8] or LSRe-
pair [9]), iv) or using deep learning (e.g., SequenceR [10],
HOPPITY [11], CoCoNuT [12] or CURE [13]).

While there has been some promising work using deep
neural networks for program repair, several avenues of re-
search are yet to explore in this area. In particular, Kaplan,
McCandlish, Henighan, et al. observed that Transformer-based
language models are subject to several scaling laws, including
that the performance of a language model has a power law
relationship with model size, dataset size, and amount of
computing power invested in training the language model, as
long as none of these factors is a bottleneck. Other laws show
that model performance during training is strongly correlated
with out of distribution performance, and that larger models
require less optimization steps and data points than smaller
models to achieve the same performance. Taken together, these
laws provide evidence for training very large language models.

One such model is GPT-3, an auto-regressive Transformer
language model with 175 billion parameters, which has set a
new state of the art in many human language understanding
tasks [15]. Unlike previous models (such as BERT [16])

that are pre-trained on unlabelled text and fine-tuned on a
target task, GPT-3’s size allows it to achieve this performance
without fine-tuning on the target task, solely through its pre-
training as a language model (which consists in “guessing the
next word” on a large amount of text). Adapting GPT-3 to a
particular task is done in a few-shot setting by feeding a task
description and a handful to a few dozens examples of the
task to the model at inference time, and asking the model
to complete the text. In some cases, just feeding the task
description without examples (zero-shot setting) shows very
good performance. Thus, instead of gathering new data and
fine-tuning the model on it, the user’s task shifts to defining
a prompt that triggers the desired behaviour in the language
model.

Recently, OpenAI released Codex [17], a GPT-3 like model
targeted towards code tasks. Codex is at the core of CodePilot,
GitHub’s AI coding assistant that provides code completion
in Visual Studio Code. In OpenAI demos, Codex is able to
synthesize whole functions from a short description. Codex is
mostly used in a zero-shot setting: the input is comprised of a
short task description and a final prompt. Codex then generates
code that “naturally” “completes” the prompt.

In this paper we investigate whether Codex can be applied
to the challenging task of Automatic Program Repair. Rather
than generating code from scratch, we ask: 1) whether Codex
shows promise in repairing buggy code, a task that it was
not trained on, and 2) which types of prompts yield the best
performance (we experiment with 5 different configurations).
Since, unlike the majority of APR tools, Codex supports multi-
ple programming languages, we evaluate performance on two
programming languages. This multi-lingual requirement leads
us to choose the QuixBugs [18] program repair benchmark
to conduct this initial investigation in Codex’s performance
for APR. QuixBugs contains buggy Python and Java implementa-
tions of 40 classical computer science algorithms, such
as counting bits in an integer, calculating the Levenshtein
distance or finding the shortest path in a graph (see Table III
for the full list of algorithms).

We further discuss most common model mistakes and
compare repair performance between Python and Java and
between Codex and previous neural repair approaches. We
find that, especially considering it was not trained on the task,
Codex is surprisingly competitive with three recent APR tools
(CURE [13] and DeepDebug [19] released in 2021, CoCoNut

1[1]the authors are not affiliated with OpenAI

2https://copilot.github.com/
def gcd(a, b):
    if b == 0:
        return a
    else:
        return gcd(a % b, b)

... return gcd(a % b, b)

Input:
  a: A nonnegative int
  b: A nonnegative int

Greatest Common Divisor

Precondition:
  isinstance(a, int) and
  isinstance(b, int)

Output:
  The greatest int that
  divides evenly into a and b

Example:

>>> gcd(35, 21)

Fig. 1. Buggy versions of the algorithm calculating the greatest common divisor between two integers in Python and Java. The recursive call should read gcd(b, a % b).

Code only: We simply input the buggy function (without the docstring in Python) in the template.

Code with hint: To simulate a more precise bug localization, in this configuration we add hint comments. Specifically, we put the comment ### fix the bug in the following function <buggy function and/or docstring here>

Code with docstring (Python): We input the buggy code along with the original docstring, which describes the correct behavior of the function. Note that some docstrings contain examples. For Java, docstrings are not available.

Docstring only (Python): This corresponds to the default usage of Codex, in which it synthesizes a full algorithm implementation, and thus acts as a baseline.

Correct code (Python): To see if Codex would break already correct code, in this configuration we input the bug-free ground-truth program, instead of the buggy one; ideally, Codex would repeat the code unchanged. We slightly alter the input format changing the first line to ### fix a possible bug in the following function, indicating that the input might be bug-free.

Input-output examples: For seven Python bugs that no configuration involving code (i.e., excluding the docstring-only configuration) could correctly fix, we additionally tried including input-output examples derived from the corresponding test
cases as an additional specification. The input-output examples are given in a docstring-like comment and follow the general format; for instance, the docstring in Figure 1 contains an example. We include all test cases associated to a program, except those exceeding a certain size (120 characters).

C. Codex Parameters

| Parameter   | Value       |
|-------------|-------------|
| Engine      | davinci-codex |
| Temperature | 0           |
| Max Tokens  | 1024        |
| Top-p       | 1.0         |
| Frequency Penalty | 0.0 |
| Presence Penalty | 0.0 |
| Stop        | ‘###’, ‘///’ |

We set Codex’ parameters as shown in Table I. We did not yet systematically investigate the effect of these parameters on repair success, as our evaluation involves a significant manual step. The temperature and top-p parameters control the randomness of the model: a higher temperature or a lower top-p yield more diverse output. The Codex documentation recommends to set temperature to zero or a low value and not to vary both, temperature and top-p. We set the temperature to zero and top-p to one, which lowers diversity but ought to give high robustness. The frequency and presence penalties prevent the model from outputing the same tokens repeatedly. Since large portions of the input (everything except the buggy line) should in fact be repeated, we do not use such a penalty.

D. Evaluation

For each configuration and language we manually evaluated the output of Codex, using the following procedure:
- When Codex output multiple functions we only considered the first and discarded the remaining output.
- If the output exactly matched the correct ground-truth patch, we considered it correct.
- We inspected the code to determine whether the output was semantically equivalent to the ground truth.
- When in doubt, we ran the associated test cases.
- If any test failed, the output was considered incorrect.

We observed output that passed all test cases but was semantically incorrect only for the kheapsort bug, where QuixBugs’ test cases do not check an edge case: the tests simply check for sortedness of the program output; however, it should only be sorted up to the $k^{th}$ largest element.

Acceptable variations. Since Codex is generating code as a language model, and is not explicitly trained for program repair, we were more lenient in a few cases. In particular, it is natural for a source code language model to try to avoid defining multiple functions or methods with the same name. Thus, if the output of Codex was a function or method with a slightly different name, but otherwise correct, this was not considered an error; we assume that post-processing could ensure such a rename is done automatically. On the other hand, in several cases, Codex simply repeated the input program (bug included); this was, of course, deemed incorrect output.

For various graph related problems (e.g., breath-first-search or detect-cycle) Codex assumed that the attribute pointing to the next node should be named next, while tests assumed it to be named successor. We considered this as semantically correct, as this is a reasonable assumption and the proper name was not specified in the input.

IV. RESULTS

A. Overall Performance

Table II compares Codex’s performance with recent previous work. We report results from the literature from three recent neural APR approaches: CoCoNut [12] uses the Neural Machine Translation (NMT) paradigm of program repair, with an ensemble of CNNs, and supports multiple languages. DeepDebug [19] is a large pre-trained Transformer that also uses the NMT paradigm (Python only): the model is fine-tuned on artificially generated bug-introducing commits, and also stack traces and program context. CURE builds on CoCoNut, adding a pre-trained language model (on Java Code) and filters suggestions based on additional context from static analysis [13]. Note that the assessment for correctness was done manually and evaluation criteria might slightly differ between these works.

Codex correctly fixed considerably more Python than Java bugs (up to 23 Python bugs, only 14 Java bugs), indicating that it can handle Python much better than Java; OpenAI does state that Codex is more capable in Python than other languages. Moreover, it is intriguing to see that Codex, without explicit training on the task, outperforms CoCoNut and DeepDebug on Python, and outperforms CoCoNut in Java. While CURE does outperform Codex in Java, Codex outperforms the only other multi-lingual APR tool (CoCoNut).

Codex is surprisingly competitive with recent work, and its performance is considerably better for Python than Java.

B. Performance of different prompts

Table III provides detailed results for each bug and configuration. For many bugs, the choice of prompt matters significantly. In fact, only 6 bugs are fixed in all scenarios and all languages. On the other hand, the prompts do complement each other: only 8 bugs are not fixed by any of the prompts.

Hints are not effective: Providing a hint comment for precise fault localization was overall not effective in our experiments. For both Python and Java, some bugs were fixed only with hints, but for others adding the hint was harmful. Overall, for Java the total number of fixed bugs was the same, while it decreased from 21 to 19 in Python. However, hints led Codex to correctly repair two bugs that could not be successfully repaired otherwise (shunting-yard and minimum-spanning-tree).
Synthesis from docstrings: Table [III] shows that only providing the Python docstrings, Codex is able to synthesize a correct solution for 45% of the problems in QuixBugs. Providing buggy code as a starting point and asking to model to fix it led to five more (+28%) correct program implementations.

Additional input-output examples: For the seven bugs that no other configuration could solve, a single one (subsequences) was successfully repaired when adding input-output examples from test cases.

Correct code: When requested to fix a possible bug in correct code, Codex broke six of the total 40 programs. In two cases, Codex slightly altered the input program, preserving correctness, however.

Prompts have a major effect on Codex’ bug fixing ability

V. LIMITATIONS AND FUTURE WORK

Codex is a very large language model, that has shown impressive ability in completing source code. In this work, we have evaluated—and found surprisingly competitive—the performance of Codex as an APR tool, with no further training on the task. While this initial evaluation of Codex as an APR tool is promising, it has various limitations.

More annotators: The correctness of the code output was assessed by a single annotator. Not only is manual evaluation subjective, it is also prone to mistakes. We hope that we will be able to provide a more reliable evaluation in the future, involving at least two annotators.

Additional benchmarks and languages: Currently our evaluation is limited to a single benchmark and two programming languages. Extending this study to benchmarks that involve more complex codebases (e.g., Defects4J [21]) or additional programming languages (e.g., BugsJS [22], a JavaScript benchmark) would provide additional interesting insights into Codex’ repair capabilities.

Data leakage: Codex was trained on very large amounts of code; only OpenAI staff can know with certainty which repositories were included. We cannot rule out that the correct ground-truth programs were in Codex’ training set. This issue is very difficult to address. There are however mitigating factors: First, if present, these versions would constitute a tiny portion of the training data (54 million repositories). Second, if the correct program versions were in the training set, so would, very likely, also be the incorrect versions, without labels of which version is correct or incorrect. Moreover, a preliminary study of Codex for GitHub Copilot, found that while the model can indeed repeat data from the training set, this was rare (less than 0.1% of the cases), concerned code that was cloned many times, and happened mostly when the context was nearly empty [23]. Finally, Codex was never specifically trained for the task of repairing or localizing bugs.

More Automation: For this study, we had to perform several manual steps to validate the correctness of the proposals. This includes removing extraneous output from Codex, and making sure the function/method name was the one expected by the tests. Automating these tasks would make the process significantly smoother.
Testing multiple outputs: Given the lack of automation, we tried a single completion from Codex for each problem and prompt. With more automation, we would be able to try multiple outputs from Codex (by increasing the temperature). Evaluating more than one output significantly increased the performance of Codex for program synthesis (from 29 up to 70% [17]), so this could help APR as well.

Fine-Tuning: While the most common use case for Codex is to use it directly after pre-training, a fine-tuning API is available for GPT-3. If such an API is made available for Codex, this would be worthwhile exploring to improve performance.

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