

Piloting Copilot and Codex: Hot Temperature, Cold Prompts, or Black Magic?

Jean-Baptiste Döderlein

ENS Rennes

Rennes, France

jean-baptiste.doderlein@ens-rennes.fr

Djamel Eddine Khelladi

CNRS, Univ Rennes, IRISA, Inria

Rennes, France

djamel-eddine.khelladi@irisa.fr

Mathieu Acher

Univ Rennes, IUF, CNRS, Inria, IRISA

Rennes, France

mathieu.acher@irisa.fr

Benoit Combemale

Univ Rennes, CNRS, Inria, IRISA

Rennes, France

benoit.combemale@irisa.fr

Abstract—Language models are promising solutions for tackling increasing complex problems. In software engineering, they recently attracted attention in code assistants, with programs automatically written in a given programming language from a programming task description in natural language. They have the potential to save time and effort when writing code. However, these systems are currently poorly understood, preventing them from being used optimally. In this article, we investigate the various inputs of two configurations of a language model, and conduct a study to understand if variations of these input parameters (e.g. programming task description and the surrounding context, creativity of the language model, number of generated solutions) can have a significant impact on the quality of the generated programs. We design specific operators for varying input parameters and apply them over two code assistants (Copilot and Codex) and two benchmarks representing algorithmic problems (HumanEval and LeetCode). Our results showed that varying the input parameters can significantly improve the performance of language models, with, for example, up to 79.27% of success rate in one-shot compared to 22.44% for Codex in default settings and 31.1% for Copilot. Actioning this potential in practice is, however, highly challenging due to the complex interplay raised in our study – the optimal settings of the temperature, the prompt and the number of generated solutions differ from one problem to the other. Our study also yielded surprising and startling results (e.g. fully removing the prompt can be an effective strategy), suggesting some brittleness and room for improving language models. Overall, this work opens opportunities to envision (automated) strategies for enhancing performance of language model-based code assistants, but also questions their robustness.

I. INTRODUCTION

Language models are gaining momentum and capable of tackling more and more problems from linguistics, maths, commonsense reasoning, biology, physics, etc. BERT [1], GPT-2 [2], GPT-3 [3], PaLM [4], to name a few, are scaling to support a variety of tasks such as text generation, question-answering, text classification, arithmetic on numbers, and many others [5]–[9]. In software engineering, code assistants based on language models have been proposed and are now deployed at scale for supporting programmers, such as GitHub Copilot [10]. Based on *prompts*, composed of both the *descrip-*

tion of a programming task written in natural language and the surrounding *context* (e.g. existing code, function signatures, targeted language, cursor, authors, shebang), programs are automatically written in a given programming language (Python, Java, C++, etc.). The promise is to provide a comprehensive working solution (or a set of candidate programs) for a given programming task. Tools like Copilot or Codex hence have the potential to save time and effort when writing code.

However, the strengths and weaknesses of these systems are currently poorly understood, preventing them from being used optimally. On the one hand, there are impressive demonstrations, showing the ability to produce programs on non-trivial programming problems or tasks. But there also is the nagging assumption that these systems are simply reciting code that is already on the Internet (e.g. Github). Furthermore, early studies suggest that the quality of solutions appears to vary greatly in some problems and targeted programming languages [11]. These assistants seem in particular sensitive to the way the developer communicates and interacts.

Given a programming task, developers can pilot/drive code assistants in different directions to achieve their goal. They can vary the prompt, for example, formulate the programming task differently or change the context. They can also change other language models input parameters, such as augmenting the creativity of the assistant (through the *temperature* of language models), or change the number of expected solutions that are eventually proposed. With high flexibility, developers can communicate at a high level of abstraction, in a declarative way, focusing on the goal rather than the how. The counterpart is that the specification might be brittle and not properly or systematically understood by code assistants. There is also the question of what strategy to choose when developers try to find a solution: changing some terms in the programming task description? changing the signature of the function? augmenting or decreasing the temperature? etc. There are anecdotes here and there about “language model engineering” (e.g., prompt engineering), but this has not been systematically studied in the context of code assistants.

In this article, we hypothesize that variations of input parameters of language models (e.g. prompts and temperatures) on the same problem can have a significant impact on the quality of the generated programs. These variations can be leveraged to (1) assess and understand the sensitivity (or robustness) of code assistants (hence their potential and limitations); (2) envision (automated) strategies for improving performance.

To do so, we first design and develop a set of operators to automatically vary the input parameters. These operators can remove, augment, or simply rewrite an original programming task description, as well as varying the context and other input parameters, such as temperature and the number of expected solutions. The idea is to feed code assistants with different variations, observe the effects on generated programs, and eventually better understand the impact of the input parameters on the resulting performance of the language model. Performance is defined in this article as the ability or not to find at least one solution among the proposed ones that pass all the test cases.

We conducted a study that considers two code assistants (Copilot and Codex) and leverages two datasets (HumanEval and LeetCode) mostly representing algorithmic problems, as well as our set of operators. Our experiments span numerous programming tasks (446 problems) with different difficulties and six programming languages. We also vary the number k of code samples generated per task, from $k = 1$ (one shot) to $k = 100$. Similarly, we study the sensitivity of code assistants and the effectiveness of our variations in different settings and usage scenarios.

Our contributions can be summarized as follows.

- The design and development of a set of operators for automatically varying language models input parameters. The inspiration of our work both comes from software testing techniques (e.g. mutation testing, test amplification as variants of existing ones) and recent advances in language models for tuning prompts [12], [13] ;
- The design of a study over two code assistants and two benchmarks. Prior studies considered a limited number of problems, programming languages, and configurations of code assistants. We are also unaware of works that leverage prompt variations and temperatures' values in the context of code generation.
- The analysis of results that demonstrate that varying input parameters can significantly improve the performance of language models. However, there is a tight dependency when varying the temperature, the prompt and the number of generated solutions, making potentially hard for developers to properly control the parameters to obtain an optimal result.

II. BACKGROUND AND MOTIVATION

A. Language models and Code Suggestions

A language model (LM) is a probabilistic model over natural language. In practice, from a given prompt, a language model provides a set of results. In software engineering,

language models such as Codex are called from a prompt including a description of a programming task in natural language, as well as all the surrounding context. Such a context is composed of information such as the existing code (e.g. imports...), the offset of the cursor, the targeted language, the authors, the shebang...

Beyond the prompt, language models might be tuned regarding specific parameters. In particular, the *temperature* hyperparameter controls the creativity of the language model. The temperature value typically varies from 0 to 1. The temperature is used to adjust the distribution of the model's predicted next word: higher values lead to more diverse and unpredictable outputs, and lower values lead to more conservative, predictable outputs. Another parameter is the expected number k of generated solutions. The principle is to sample from the k most probable programs. When k equals to 1, only one program is generated and is hopefully a valid solution.

B. Prompts

When using Copilot and Codex to generate code, the user provides a context to the model. This could be a text in natural language or some pieces of existing code.

The prompt is the text/code that the model needs to complete. This includes the comment (e.g. the docstring of the function in Python) but also the function signature. The function signature consists of the function name, the number of arguments, their name, and also in type in the case of typed languages.

Prompt sensitivity: An example. When using language model-based assistant tools to generate code, there are several ways to express what should be completed. The most common is to use the comment of the function. But there are multiple ways to phrase the prompt. One can change the prompt while keeping the same meaning. Yet, sometimes, a small variation could drastically change the model performance.

In Figure 1 we use an example of a prompt from HumanEval [14] dataset. The function takes two integers and returns the biggest even number in the range of the two integers, -1 if no even number is found. With Copilot, the model fails to provide a correct answer (it returns the smallest even number instead). However, the model provides a correct answer when we add the sentence "Write a quick algorithm to solve this problem." at the end of the prompt. This sentence does not provide any additional information to the model about the problem or the algorithm to solve the problem, but it improves the model's output. Furthermore, we observe that if we further modify the prompt by removing the examples, the result is not correct.

These examples suggest that code generation is sensitive to prompt variation, and that modification of the prompt can cause the model to provide a correct or wrong answer within different contexts.

III. EXPERIMENTAL SET UP

This section describes our experimental setup to explore the effect of prompt variations and temperature parameter on the performance of language model-based code assistants.

```
def choose_num(x, y):
    """
    This function takes two positive
    numbers x and y and returns the
    biggest even integer number that
    is in the range [x, y] inclusive.
    If there's no such number, then
    the function should return -1.

    For example:
    choose_num(12, 15) = 14
    choose_num(13, 12) = -1
    """
    if x % 2 != 0:
        x += 1
    if y % 2 != 0:
        y -= 1
    if x > y:
        return -1
    if x % 2 == 0:
        x += 1
    while x <= y:
        if x % 2 == 0:
            return x
        x += 2
    return -1
```

(a) Original prompt

```
def choose_num(x, y):
    """
    This function takes two positive
    numbers x and y and returns the
    biggest even integer number that
    is in the range [x, y] inclusive.
    If there's no such number, then
    the function should return -1.

    For example:
    choose_num(12, 15) = 14
    choose_num(13, 12) = -1

    Write a quick algorithm to
    solve this problem.
    """
    if x % 2 == 0:
        x = x
    else:
        x = x + 1
    if y % 2 == 0:
        y = y
    else:
        y = y - 1
    if x > y:
        return -1
    else:
        return max(x, y)
```

(b) Modified prompt 1

```
def choose_num(x, y):
    """
    This function takes two positive
    numbers x and y and returns the
    biggest even integer number that
    is in the range [x, y] inclusive.
    If there's no such number, then
    the function should return -1.
    """
    if x % 2 == 1:
        x += 1
    if y % 2 == 0:
        y -= 1
    for i in range(x, y + 1, 2):
        if x <= i <= y:
            return i
    return -1
```

(c) Modified prompt 2

Fig. 1: Code generation of HumanEval problem `choose_num` with original prompt (a) and modified prompts (b and c). There is the prompt (blue background) and the code generated by Copilot (green background)

A. Two code assistants, two configurations of one language model

Several language models and code assistant exist for code suggestion. We consider two popular code assistants, Codex and Copilot. There are several reasons why we chose these two tools: they provide state-of-the-art performance; they are capable of targeting different programming languages; they are rather mature tools, already widely used, and come with a set of APIs. Another interesting property is that Codex and Copilot rely on the same language model. This apparent similarity in fact hides many differences that we wish to explore. *Copilot can be thought of as a thorough engineering of Codex, providing a chance for research to evaluate sensitivity in various configuration settings and acquire insights about how to configure (pilot) language models.*

1) *Copilot*: Copilot has been built on top of one of the Codex language model as a code assistant with fixed parameters (e.g. temperature) and an associated development tool that is available from Github as an IDE extension. Copilot is described as an "AI pair programmer" that offers code suggestions in real time [10]. It can produce code in different ways: It can write code from comments, write tests for code that is already written, or complete code that is being written like tools like Intellisens [15] does.

The focus here is on generating code from comments (and the function signature). In regular use, Copilot communicates in real time about all the changes made on the document and sends additional information about the context (document name, path, cursor position, language, etc.). Previous studies evaluating the performance [11] or security [16] of the code

produced by Copilot retrieved the results for each prompt, manually from VS Code. In order to increase the speed of the tests and to significantly increase the number of samples evaluated, we directly made calls to the backend of the Visual Studio Code module. The user is authenticated once manually from the Neovim extension, then the calls are made to Copilot executed using NodeJS with LSP. When used in the IDE, the Copilot extension does not simply make requests, but builds contexts during generation and decides according to the context if a request is needed [17]. However, as we use a primitive in the LSP to request a query, no context other than the name of the file and programming language are provided.

In the Copilot evaluation, we restricted ourselves to the default parameter (temperature, top_p). Although these parameters seem to be modifiable [16], the default values are not known, and the default parameters better reflect the codes proposed to the end user. Moreover, we did not use the possibility of the panel mode allowing generating several codes. Indeed, the codes retrieved by the backend sometimes correspond to the code of the whole file and sometimes to the simple completion of the code, thus preventing a good automation of the process. Overall, all Copilot codes are evaluated in one-shot.

2) *Codex*: Codex, more precisely code-davinci-002, is a language model developed by OpenAI and available in private beta at the time of writing. It is part of the same family as the model used by Copilot. Contrary to Copilot, it has an API that facilitates the automation of the evaluation of produced codes. The API offers many parameters like: temperature, top_p, number of code produced. For the evaluation, OpenAI advises

not to change the temperature and top_p at the same time, so we set top_p to 1 (default parameter) and then performed the tests for the temperatures 0.0, 0.2, 0.4, 0.6, 0.8, 1. Interestingly, given a prompt, Codex can generate more than one program and this feature is well-supported.

3) *Rationale*: Copilot and Codex have similarities, but also important differences. On the one hand, Copilot is treated as a black box applying modifications and an unknown choice of parameters and treatments. We do not know which model and exact parameters are used, though some technical insights have been reported in the grey literature [17]. On the other hand, Codex, is a raw language model that offers more freedom in the choice of parameters. It is thus an opportunity to explore the configuration space and the potential of a language model. This choice allows us to compare the results of a tool already *engineered* and configured (Copilot) against the results of the raw model (Codex) it uses.

B. Datasets

We selected two datasets, namely HumanEval and Leetcode.

1) *HumanEval*: HumanEval is a dataset originally proposed in [14], composed of 146 codes to complete written in Python. Each function is given a function name, its parameters and a docstring indicating the purpose of the function (see Fig 1). Moreover, each function has a test suite. This dataset is only composed of handwritten problems thus mitigating recitation, i.e. cloning the code of the training set. As this test set was designed and created to evaluate Codex itself, no code in this dataset is present in the training set of Codex and therefore Copilot.

2) *Leetcode*: LeetCode is an online platform that provides a collection of problems to help software engineers prepare for technical interviews. It offers a variety of problems in different areas and programming languages. Nguyen et al. originally considered 33 problems in 4 languages [11]. We considered a larger dataset : we compiled 300 problems from Leetcode, chosen among the most liked problems and equitably distributed by difficulty (100 Easy, 100 Medium, 100 Hard). Each problem is present in 6 languages (Python 3, Javascript, Java, C, C++, C#). Problems that could not be tested in any of the 6 languages, and problems requiring multiple functions were discarded. Each problem is given as a comment at the beginning of the file corresponding to a short description of the problem, and the signature of the function to be implemented. An additional comment is sometimes provided to indicate the implementation of the elements being passed in the signature (e.g., binary trees).

The tests used by Leetcode are not public, so the problems have been submitted to Leetcode through the GraphQL API. The API naturally exhibit rate limits, and it is hardly possible to check, e.g., 100 candidate programs for all problems. We thus decided to consider Leetcode in one-shot (only one program can be submitted), but in return we did explore the variations of temperature and prompt.

Unlike HumanEval, this dataset is subject to a high risk of recitation because many Github repositories contain solutions

to some of the problems and may be part of the training set [18]. There are not necessarily solutions to all the Leetcode problems and in all the programming languages. Even if a solution is available, sensitivity to prompts or temperature remains an interesting motivation.

3) *Rationale*: We have selected these two datasets for several reasons. The first, HumanEval, is widely used in the literature for the evaluation of language models generating code, has been designed to mitigate the recitation problem, and is composed of problems with a varied prompt format. One con is that HumanEval is only considering Python. The second dataset, Leetcode, presents higher risk of recitation but contains a greater number of problems, of a more complex nature, and in six distinct programming languages. The combination of these two datasets allows us to have a greater diversity of programs.

C. Variables and metrics

To generate one or more code suggestions from a language model LM , we feed it with a prompt P , a temperature T and a number of code to be generated K , such as $LM(P, T, K) \rightarrow \{code*\}$.

The prompt P is composed of the function signature, the description of the programming task (aka. documentation), and the context of the prompt. The context is composed of all information given at the time the language model is used. This includes the existing code (e.g. imports...), the offset of the cursor, the targeted language, the authors, the shebang...

Our experiment aims to measure the influence on the suggested code when varying the prompt and the temperature to the language models in contrast to when it was not. This was the independent variable we controlled, i.e. prompt variation and temperature variation. To measure their effects, we observed one dependent variable, namely the performance of the language models without any variation and with variations. We define the performance of a language model as follows:

$$LM_{performance} = \frac{problemSolved}{totalProblems}$$

problemSolved is the number of problems that a language model was able to generate at least one correct answer to from $\{code*\}$, i.e., a code suggestion compiling and passing the suite test of a given problem. We relied on the test suites that come with the different datasets.

We considered different scenarios:

- k equals to 1 (one-shot) where only one candidate program is considered. Copilot is necessarily in this case for both HumanEval and Leetcode. Although Codex can generate more than one program, we consider a one-shot scenario for Leetcode due to API restrictions for checking programs and as in [11]. The one-shot scenario is typical of developers' workflow that want a given solution and do not want to review alternative solutions.
- k equals to 10 (resp. 100) where 10 (resp. 100) candidate programs are considered. Only Codex can be used as such for the HumanEval dataset.

We used the pass@k metric, that, given k submitted solutions to a problem, considers a problem to be successful if one of the solutions passes all the tests [19]. Specifically, we computed pass@1, pass@10 and pass@100 using the unbiased estimator defined by Chen et al. [14] where k solutions are randomly picked from n samples:

$$\text{pass@k} := \mathbb{E}_{\text{Problems}} \left[1 - \frac{\binom{n-c}{k}}{\binom{n}{k}} \right] \quad (1)$$

For Leetcode, we only used pass@1 for Codex and Copilot ($k = 1$ and $n = 1$). For the codes generated with Codex on HumanEval, we generated 100 solutions for each problem (i.e., we fix $n = 100$) and then report on pass@1, pass@10, and pass@100.

D. Research Questions

We define the following research questions.

- RQ1 *What is the performance of Copilot and Codex over HumanEval and Leetcode?* We use the original prompts and the default temperature of Copilot and Codex. Hence, unlike the following research questions, we do not make vary the prompts or the temperature. Our goal is to establish a first trend and a baseline for the performance of the two tools that use the same language model. We also aim to gather insights about performance sensitivity over datasets (Leetcode vs HumanEval) and programming languages (e.g., Python vs C).
- RQ2 *What is the impact of prompt variation on Copilot and Codex performance?* Our goal is to assess the sensitivity of Copilot and Codex w.r.t. prompt modification. We make vary the prompts, leveraging different operators acting over the programming task description, and some information from the surrounding context (e.g. function signature). However, we rely on default temperature of Copilot and Codex.
- RQ3 *What is the impact of the variation of both temperature and prompts on Codex performance?* We aim to establish the impact of varying all input parameters, including temperature, prompt, and number k of generated solutions.
- RQ4 *What are the best prompt variations and temperatures for Codex to maximize its performance over a given set of problems?* We aim to identify the best parameters for Codex to maximize its performance for a given set of problems (on average).
- RQ5 *How much can we improve the performance of Codex by tuning the temperature and prompts per a specific problem?* We aim to identify the best parameters for Codex to maximize its performance for a given problem. Intuitively, the best parameters on average are not necessarily the best ones for a specific problem.

IV. PROMPT VARIATIONS APPROACH

To automate the variation of the prompts, we design various variation operators that belong to different categories, such as structural, semantics, and syntax changes. It should be noted

Categories	Modification
Documentation modification	Original
	No Documentation
	No Examples
	Chain of Thought prompt
	- "Algorithm :"
	- "Complexity"
	- "Let's thinks step by step :"
	Additionnal instruction
	- "Write a quick algorithm to solve this problem."
	Translation : French
Documentation modification	Keyword Removal : 20%,40%,60%,80%
	Isotopic Replacement : first verb of each sentence
Documentation modification	Function name masked
	Function name + arguments masked
Documentation modification	Shebang
	Authors
	- Guido von Rossum
	- Andrey Petrov
	- Jean-Baptiste Doderlein
Leetcode modification	Original
	No Documentation
	Function name masked

TABLE I: Variation operators on HumanEval and Leetcode

that the chosen mutation operators do not necessarily aim at mimicking a realistic developer modification. Some could like the inclusion of generic additional instruction, but others like the removal of keywords are more synthetic. In any case, our primary goal is to assess the sensitivity (or robustness) of Copilot/Codex to prompt variations.

A. Design of Variation Operators

1) *Documentation modification*: These modifications are applied to the description of the programming task provided in the prompt. Multiple changes can be applied :

- **Delete documentation**: Delete the description of the programming task in the prompt.
- **Delete examples**: Remove all examples from the documentation.
- **Additional instruction**: Add some information at the end of the documentation.
- **Chain of Thought prompt**: Add some word at the end of the documentation and don't close the end of the comment to allow the model to complete the comment before writing the code.
- **Translation**: Translate the description of the programming task in another language.
- **Keyword Removal**: Remove a certain percentage of the least important words from a programming task description. Words are ranked using the TF-IDF score

[20], which evaluates the importance of a word in relation to a text corpus.

- **Isotopic Replacement:** Replace some words using the isotopic replacement [21]. The words are selected in each sentence of the prompt with the model from [22], a list of possible replacements is generated by BERT Mask [23], and finally the modified sentence with the highest cosine similarity embedding [24] is chosen for the final prompt.

2) *Signature modification:* The prompt includes the function signature, i.e. its name and arguments. The tested modification is the hiding of the function name and arguments. A random string replaces the function name and then is replaced by the original function name for testing.

3) *Context modification:* The context is the part of the prompt that is not specific to the problem. Modifying the context is done by adding additional information at the beginning of the prompt that is not related to the problem itself.

B. Implementation for HumanEval

Table I shows the different operators we consider in our experiment under the three categories. We used the variation operators defined above and implemented some variations. We tested documentation modification:

- Additional instruction with "Write a quick algorithm to solve this problem."
- CoT prompt with "Algorithm :", "Complexity :" and "Let's think step by step" [25]
- Keyword Removal with 20%, 40%, 60% and 80%
- Isotopic Replacement with the first verb of each sentence with no example in documentation.

For signature modification, we have experimented by replacing first just the name of the function by a random string of 8 characters, then by replacing also the arguments.

Finally, for context modification we used:

- Shebang ("#!/user/bin/env python # -*- coding: utf-8 -*-") at the beginning of the prompt
- Add an author flag at the beginning of the prompt. The authors tested were Guido von Rossum (creator of Python), Andrey Petrov (lead author of Python's library urllib3) and Jean-Baptiste Doderlein (random name). This modification is inspired by [16].

C. Implementation for Leetcode

Only two prompts' variations have been considered on the Leetcode dataset. This choice was made due to the Leetcode API limits (see Section III-B2) for testing candidate programs generated at different temperatures and over 300+ problems in 6 programming languages. These two variations were selected based on the results found in the study of the variations of the HumanEval dataset. Specifically, we excluded variations that have neutral effect. We retained two prompt variations that question the sensitivity of Codex and Copilot over HumanEval – more details are given in Section V-B2. In addition to diversifying the set of problems, considering Leetcode allows one to determine whether results over HumanEval still hold for another dataset.

	Copilot pass@1	Codex pass@1
Original (HumanEval, Python3)	31.1	22.44
Original (Leetcode, Javascript)	37.3	32.3
Original (Leetcode, Java)	46.3	39.3
Original (Leetcode, C#)	44.3	33.7
Original (Leetcode, Python3)	33.7	30.3
Original (Leetcode, C)	18.7	18.3
Original (Leetcode, C++)	45.3	41.3

TABLE II: Pass@1 (original prompts; default temperature)

	Codex		
	pass@1	pass@10	pass@100
Original (HumanEval, Python3)	22.44	71.7	98.78

TABLE III: Pass@k (original prompts; default temperature)

V. EMPIRICAL EVALUATION RESULTS

A. RQ1: What is the performance of Copilot and Codex over HumanEval and Leetcode?

To answer this question, we use the original prompts and the default temperature of Copilot and Codex. Table II reports the pass@1 results for Codex and Copilot over HumanEval and Leetcode. Performance varies between 18.3% (Leetcode, C language) and 46.3% (Leetcode, Java). Numerous problems are resolved in one shot, but there is room for improvement: Developers cannot trust the generated program in most cases. Also, Codex appears to be capable of significantly improving performance when generating more programs (cf. Table III): from 22.44% at pass@1 to 71.7% (pass@10) and 98.78% (closed to perfect, pass@100) on HumanEval and Python3.

Table II also shows that, in default settings, Copilot is always superior to Codex, regardless of the dataset and programming language. Performance ranking according to the programming languages is highly stable among Copilot and Codex (Spearman correlation: 0.96 with pvalue=0.0004). In detail, C is the most difficult programming language, followed by Python while C++ is the most favorable language.

RQ1 The performance, though promising, can be improved (46.3% at best with Java) and varies across programming languages (only 18.3% for C) for both Copilot and Codex.

B. RQ2: What is the impact of prompt variation on Copilot and Codex performance?

For answering this question, we vary the original prompt using our operators while keeping the default temperature of Copilot and Codex.

	Copilot		Codex	
	pass@1	pass@1	pass@10	pass@100
Original	31.1	22.44	71.7	98.78
No Documentation	8.54 _↘	7.74 _↘	28.3 _↘	64.02 _↘
No Example	30.49	17.89 _↘	58.65 _↘	87.8 _↘
Algorithm	27.44	16.98 _↘	60.09 _↘	93.9 _↘
Complexity	16.46 _↘	22.85	70.69	96.34
Let's think step by step	15.85 _↘	13.49 _↘	54.66 _↘	89.63 _↘
Quick	21.95 _↘	17.38 _↘	66.7 _↘	96.95
French	26.22 _↘	16.63 _↘	58.62 _↘	90.85 _↘
Keyword Cut 20%	29.27	21.68	69.52 _↘	98.78
Keyword Cut 40%	29.27	20.83 _↘	66.07 _↘	98.17
Keyword Cut 60%	28.05	19.32 _↘	59.96 _↘	97.56
Keyword Cut 80%	22.56 _↘	17.5 _↘	54.96 _↘	93.29 _↘
Isotopic Replacement	26.83	16.24 _↘	55.92 _↘	87.8 _↘
Masked function name	30.49	19.76 _↘	67.84 _↘	98.17
Masked function signature	28.05	14.12 _↘	59.29 _↘	97.56
Shebang	17.07 _↘	23.05	69.15 _↘	95.73 _↘
Author Guido von Rossum	21.95 _↘	23.68 _↘	69.53 _↘	97.56
Author Andrey Petrov	20.12 _↘	24.63 _↘	70.07	95.73 _↘
Author Jean-Baptiste Doderlein	17.68 _↘	24.16 _↘	70.13 _↘	98.17

TABLE IV: pass@k results over HumanEval with prompt variations and default, fixed temperature. Bold values have $p < 0.05$ for independent T-test. _↘ is with the less alternative hypothesis and _↗ with the greater alternative hypothesis

1) *HumanEval*: In Table IV, we present the results obtained for Copilot at pass@1, and for Codex at pass@1, pass@10 and pass@100. Each result is compared to the performance of the original prompt with an independent T-test. In each case, less alternative hypothesis, which tests if the result is significantly worse, and greater alternative hypothesis, which tests if the result is significantly better, are made.

Quantitative observations. We observe that prompt changes have a negative impact on the results, most significantly. For Copilot, 10 of the 18 variations tested bring significantly lower results. For Codex, the results are also negative in general. Only 3 variations at pass@1 increase the scores: In this configuration, only adding the author at the beginning of the file with Codex in pass@1 provides better scores. The modification of the context of the file (e.g. Shebang and function signature) impacts strongly Copilot, mostly negatively. While the modification of the function signature does not seem to affect the performance of Copilot, the results for Codex pass@1 and pass10 are not as good with significant decrease.

Qualitative analysis. A purely quantitative analysis does not establish whether performance variations are as expected. Therefore, the nature of the operators of prompt variation, and their supposed impacts, deserve to be discussed in relation to quantitative observations. Here are a few remarkable insights:

- some variations were not supposed to significantly de-

	Language	No Documentation	Masked function name
Codex	Javascript	28.7 _{-3.6}	17.3 _{-15.0}
	Java	44.3 _{+5.0}	28.7 _{-10.6}
	C#	31.0 _{-2.7}	14.0 _{-19.7}
	Python3	41.0 _{+10.7}	16.3 ₋₁₄
	C	11.7 _{-6.6}	9.0 _{-9.3}
Copilot	C++	46.0 _{+4.7}	26.0 _{-15.3}
	Javascript	25.3 _{-12.0}	30.0 _{-7.3}
	Java	43.7 _{-2.6}	32.3 _{-14.0}
	C#	44.3	28.3 _{-16.0}
	Python3	34.3 _{+0.6}	19.0 _{-14.7}
	C	16.0 _{-2.7}	14.3 _{-4.4}
	C++	41.3 _{-4.0}	26.7 _{-18.6}

TABLE V: Copilot and Codex($t = 1$) performance on LeetCode with prompt variation, default temperature, and $k = 1$

crease/increase the performance of Codex/Copilot. For example, it is surprising to observe that the inclusion of Shebang or author name has so much impact (e.g. from 31.1% to 17.07% for Copilot pass@1). Cutting words in the prompt also is not impacting much Copilot.

- some prompt variations were expected to decrease the performance. It is the case of "No documentation" and results are in line with this intent.
- some prompt variations are more effective with Copilot or Codex. For example, "Complexity" has a significant negative impact with Copilot, but has a positive impact on Codex. A possible explanation is that Copilot really tries to leverage "Complexity" through code refactoring.

Overall, both Copilot and Codex are sensitive to prompt variations, sometimes in an unexpected way – inclusion of some contextual information, including of some keywords, or reformulation of the prompt.

2) *Leetcode*: We evaluated two prompt variations over Leetcode and thus different programming languages – see Table V. *No Documentation* is very dependent on the programming language. On Codex, there is a positive impact for Python, Java and C++, but a negative impact for C#, Javascript and C. Considering the nature of the operator, it is an unexpected result. Indeed, removing the problem description is supposed to alter the performance significantly (as in HumanEval). Yet, in Leetcode, the degradation is not necessarily significant, and even more surprising, "No documentation" can outperform performance with the original prompt (for Python). *Function name masked* leads to a decrease in performance for all languages, for both Copilot and Codex. Interestingly, the performance decrease of Copilot was not significant and closed to neutral in HumanEval. On Leetcode, masking the function name has a significant impact.

RQ₂ Both Copilot and Codex are sensitive to prompt variations, sometimes in an unexpected way – inclusion of some contextual information, inclusion of some keywords, or reformulation of the prompt can impact the performance significantly. However, the effectiveness of a prompt variation operator does not generalize and depends on the model chosen (Copilot, Codex), the number of generated solutions, or the dataset and programming language. For instance, fully removing a problem’s documentation significantly decreases performance on HumanEval (as expected), but can surprisingly improve performance on Leetcode.

C. RQ3: What is the impact of the variation of both temperature and prompts on Codex performance?

To answer this question, we vary the temperature of Codex over the original prompt and over different variations of the prompt. We recall that Copilot does not give access to modify the temperature, while the Codex API provides a parameter to control this parameter. Hence, in the following, we report the performance results of Codex only over HumanEval and LeetCode.

1) *Codex with varying temperature vs. Copilot, over the original prompt.*: Figure 2 and Figure 3 include the performance results of Codex for temperature variations over the original prompt. Hence, we can compare with the results of Table II, RQ1. For HumanEval, a temperature t of 0.2 (instead of 1.0 by default) for Codex reaches 38.8, a significant improvement over 22.44. Codex with $t = 0.2$ also outperforms Copilot at pass@1 (31.1). For Leetcode, a temperature of 0.0 or 0.2 is the best for Codex. This temperature significantly improves performance for all programming languages (e.g. for JavaScript, Codex $t = 0$ reaches 70.3 instead of 32.3 for $t = 1$). Codex with $t = 0.0$ or $t = 0.2$ also significantly outperforms Copilot for all languages at pass@1. Even non-optimal temperatures of Codex, different from the default one, outperform Copilot for Leetcode and HumanEval.

2) *HumanEval*: In Figure 2, we also report the pass@1, pass@10 and pass@100 scores for different variations of the prompt at different temperatures. A general observation is that there is a complex interplay between temperature, prompt, and number of codes generated. For instance, given a prompt variation, the best temperature for the various pass@k differs. If we consider pass@1, we observe two different cases: either the optimal temperature is 0 as in the variations *Complexity*, *No Documentation* and *Masked function name*, or the temperature is around 0.4 for the original prompt and the variations *No Example* and *Let’s think step by step*. For pass@10, the optimal temperature is 0.6, and for pass@100 around 0.6 and 0.8. Besides, we observe some particular cases like *Masked function name*, for which the best results for pass@10 and pass@100 are obtained with a temperature of 1.0 (the default temperature of Codex). That is, some prompt variations are effective only when the temperature is correctly set up with the optimal value.

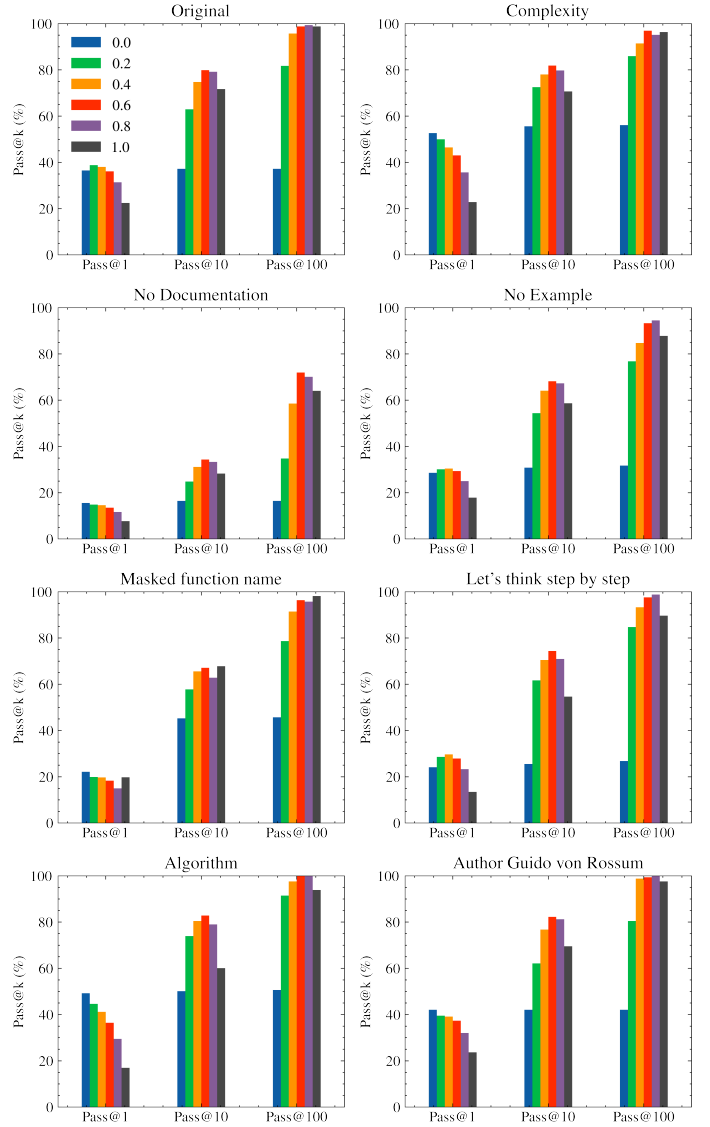


Fig. 2: Pass@k Evaluation of Codex on HumanEval dataset for some variation; $temp \in [0.0, 0.2, 0.4, 0.6, 0.8, 1]$

3) *Leetcode*: Figure 3 depicts pass@1 of Codex over Leetcode. For each programming language, we report the performance results over temperature variations and three prompts (original and two variations). A first observation is that the lower the temperature, the better the results for the original prompt. *Function name masked* at temperature $t = 0$ never exceeds 10% with an important difference with the original prompt, leading to catastrophic performance. This prompt variation and specific temperature value should thus be avoided for Leetcode. This contrasts with HumanEval, for which the lower the temperature, the more the result was optimal in pass@1. Other temperature values combined with *Function name masked* give more adequate results, but the performance is still weaker than with the original prompt. One would expect to have a similar result with *No Documentation*,

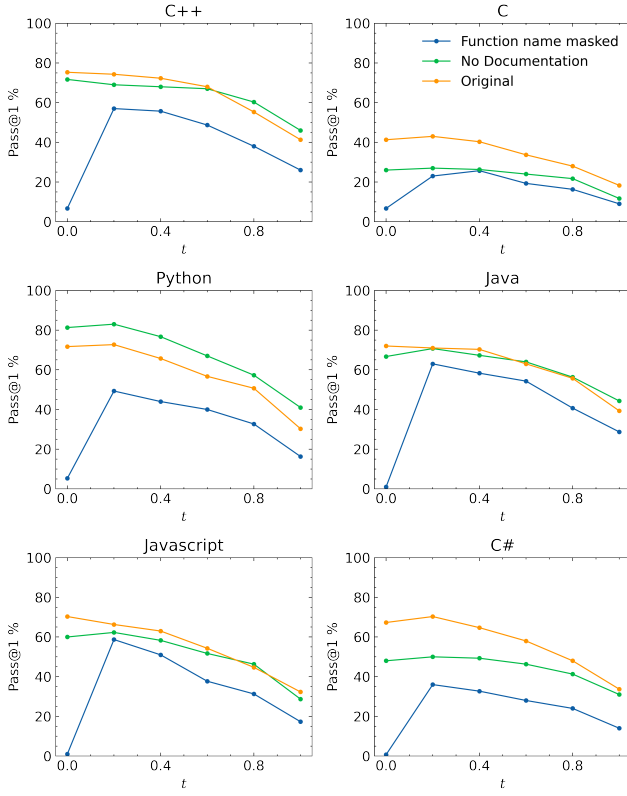


Fig. 3: Pass@1 Evaluation of Codex on Leetcode dataset; $temp \in [0.0, 0.2, 0.4, 0.6, 0.8, 1]$

which removes the description of the problem leaving only the function signature. However, this is not always the case. On the one hand, for Python, Javascript, Java, and C++, there is at least one temperature where we obtain similar or superior results with *No Documentation* than with the original prompt. This result is particularly visible in Python where we get improvements for all temperatures. On the other hand, for C and C#, *No Documentation* leads to lower performance for all temperatures. As in HumanEval, there is a complex interplay between prompt variation and temperature.

RQ₃ For both HumanEval and LeetCode, varying the temperature can significantly improve Codex performance, up to the point Codex with a configured temperature (not necessarily the best one) can strongly outperform Copilot. The optimal temperature depends on the chosen prompt variation, the number of generated codes, and to a lesser extent the targeted programming languages.

D. RQ4: What are the best prompt variations and temperatures for Codex to maximize its performance over a given set of problems?

For answering this research question, we identify what are the best combinations of temperature and prompt variations for Codex that maximize, on average, pass@k over HumanEval.

Model		Score		pass@100	
Variation	t	pass@1	pass@10	pass@100	
Best pass@100	Algorithm	0.6	36.44 ₊₁₄	82.84 _{+11.14}	100 _{+1.22}
		0.8	29.46 _{+9.63}	78.99 _{+9.5}	100 _{+1.22}
	Author Ap	0.6	38.15 _{+15.71}	80.53 _{+8.83}	100 _{+1.22}
	Author Gvr	0.8	32.07 _{+7.02}	81.20 _{+7.29}	100 _{+1.22}
		0.6	37.37 _{+14.93}	82.25 _{+10.55}	99.39 _{+0.61}
Best pass@10	Algorithm	0.6	36.44 ₊₁₄	82.84 _{+11.14}	100 _{+1.22}
	Author Gvr	0.6	37.37 _{+14.93}	82.25 _{+10.55}	99.39 _{+0.61}
	Complexity	0.6	43.02 _{+20.58}	81.85 _{+10.15}	96.95 _{-1.83}
	Shebang	0.6	38.24 _{+15.8}	81.41 _{+9.71}	99.39 _{0.61}
	Author Gvr	0.8	32.07 _{+9.63}	81.20 _{+9.50}	100 _{1.22}
Best pass@1	Complexity	0.0	52.67 _{+30.23}	55.60 _{-16.1}	56.10 _{-42.68}
		0.2	49.99 _{+27.55}	72.51 _{+0.81}	85.98 _{-12.8}
	Algorithm	0.0	49.22 _{+26.78}	50.10 _{-21.6}	50.61 _{-48.17}
	Complexity	0.4	46.50 _{+24.06}	78.03 _{6.33}	91.46 _{-7.32}
	Algorithm	0.2	44.62 _{+22.18}	73.95 _{2.25}	91.46 _{-7.32}

TABLE VI: Best prompt variations and temperatures for Codex on HumanEval at pass@1, pass@10 and pass@100

Table VI reports the five best configurations of Codex for pass@1, pass@10 and pass@100. Each configuration is composed of a prompt variation together with the temperature used. Every result reports the difference with the performance of the default configuration (i.e., the original prompt and temperature $t = 1$, see Table II, RQ1). At pass@100, the gains are low (+1.22) because the prompt without variation is already very high (98.78). However, we manage to reach the 100%, which means that among the 100 codes generated with these configurations and for each problem, one of the codes passes the test suite. We get at pass@1 a considerable performance improvement, from 22.44% to 52.67%. We observe that the best temperatures for pass@1 are low (0.0, 0.2) contrary to pass@10 or pass@100 for which the best temperatures are closer to 1.0 (0.6, 0.8). It is worth noticing that the best configuration for pass@1 is very bad for pass@10 (-16.1) and pass@100 (-42.68). Intuitively, the prompt variations and temperature used at pass@1 are too conservative at pass@10 and pass@100, limiting Codex to generate creative programs to find a solution.

RQ₄ A proper configuration of the temperature and prompt variation can significantly improve the results of Codex. A difficulty, though, is that the best configurations differ for a given pass@k. A general recommendation is to use low temperatures (0.0, 0.2) for pass@1, and higher temperatures (0.6 to 1.0) for pass@10 and @100.

E. RQ5: How much can we improve the performance of Codex by tuning the temperature and prompts per a specific problem?

For answering this question, we retrospectively look at each individual problem of HumanEval and report on the best performance that can be achieved when modifying the prompt

Temperature	pass@1	pass@10	pass@100
Original $t = 1.0$	22.44	71.70	98.78
0.0	74.99 _{+52.6}	79.06 _{+7.4}	79.27 _{-19.5}
0.2	65.23 _{+42.8}	90.43 _{+18.7}	99.39 _{+0.6}
0.4	56.83 _{+34.4}	92.5 _{+20.8}	100.0 _{+1.2}
0.6	49.93 _{+27.5}	92.49 _{+20.8}	100.0 _{+1.2}
0.8	41.37 _{+18.9}	90.45 _{+18.8}	100.0 _{+1.2}
1.0	30.47 _{+8.0}	83.01 _{+11.3}	100.0 _{+1.2}

TABLE VII: Pass@k results for each temperature of Codex, with the best variation for each problem

Variation	pass@1	pass@10	pass@100
Original $t = 1.0$	22.44	71.70	98.78
Original	50.15 _{+27.7}	84.81 _{+13.1}	100.0 _{+1.2}
No Documentation	20.23 _{-2.2}	40.08 _{-31.6}	89.63 _{-9.2}
No Example	41.82 _{+19.4}	73.94 _{+2.2}	98.78
Algorithm	59.13 _{+36.7}	87.29 _{+15.6}	100.0 _{+1.2}
Complexity	62.98 _{+40.5}	86.63 _{+14.9}	98.17 _{-0.6}
Let's think step by step	43.07 _{+20.6}	80.32 _{+8.6}	100.0 _{+1.2}
Quick	40.9 _{+18.5}	79.36 _{+7.7}	99.39 _{+0.6}
French	38.85 _{+16.4}	72.7 _{+1.0}	98.78
Keyword Cut 20%	47.27 _{+24.8}	84.14 _{+12.4}	100.0 _{+1.2}
Keyword Cut 40%	46.81 _{+24.4}	81.53 _{+9.8}	100.0 _{+1.2}
Keyword Cut 60%	44.21 _{+21.8}	77.01 _{+5.3}	98.78
Keyword Cut 80%	40.03 _{+17.6}	70.87 _{-0.8}	98.78
Isotopic Replacement	41.07 _{+18.6}	73.74 _{+2.0}	98.17 _{-0.6}
Masked function name	29.42 _{+7.0}	78.09 _{+6.4}	99.39 _{+0.6}
Masked function signature	47.84 _{+25.4}	81.42 _{+9.7}	100.0 _{+1.2}
Shebang	54.39 _{+32.0}	85.59 _{+13.9}	100.0 _{+1.2}
Author Guido von Rossum	53.96 _{+31.5}	87.12 _{+15.4}	100.0 _{+1.2}
Author Andrey Petrov	54.82 _{+32.4}	86.19 _{+14.5}	100.0 _{+1.2}
Author Jean-Baptiste Doderlein	52.93 _{+30.5}	84.76 _{+13.1}	100.0 _{+1.2}

TABLE VIII: Pass@k results for each variation, with the best temperature for each problem

and the temperature of Codex. Even if unrealistic, the results are interesting to evaluate the potential of a tuning strategy.

1) *Fixed Temperature* : First, we are interested in identifying the best temperature values. To do so, we fix a temperature value, select the best prompt variation, and report on pass@1, pass@10, and pass@100 for each problem. Table VII depicts the results. A first observation is that we can significantly improve the performance of the default configuration (up to 74.99% at pass@1 for $t = 0$). A tuning per problem also significantly outperforms the best *average* configurations (see RQ4, Table VI). Hence, it is worth combining temperature and prompt variation. However, the default temperature ($t = 1$) of Codex is by far the less effective at pass@1 and should be avoided in our context, as it is poorly effective regardless of the prompt variation. Also, the general recommendation is to use a temperature of 0.0 for pass@1, 0.4 for pass@10, and from 0.4 to 1.0 for pass@100.

	pass@1	pass@10	pass@100
Original $t = 1.0$	22.44	71.70	98.78
Oracle	79.27 _{+56.8}	95.59 _{+23.9}	100.0 _{+1.2}

TABLE IX: Pass@k results for best overall, with the best temperature and variation for each problem

2) *Fixed Prompt*: We are interested in identifying the best prompt variations. We fix the variation and take the best temperature ($t \in [0.0, 0.2, 0.4, 0.6, 0.8, 1.0]$) for each problem. Table VIII reports on the results. There are several prompt variations that can significantly outperform the default configuration at pass@1 and pass@10. The best variation is *Complexity* at pass@1, but even cutting words strategies are effective. *No documentation* on HumanEval has strong limitations at pass@1, pass@10, and pass@100, even with the best temperature. In general, results confirm the crucial role of the temperature for fully realizing the potential of prompt variation operators.

3) *Best overall*: Finally, we consider the case where we took the best temperature and the best variation for each problem. We obtain 79.27% at pass@1, 95.59% at pass@10 and 100% at pass@100 (see "Oracle" in Table IX). It is a great improvement over the default configuration of Codex, but also over the best average configurations (RQ4). It is also worth tuning temperature and prompt *together*. This result is unrealistic and unusable in practice, since there is no *a priori* strategy to determine the best combination of temperature and prompt for each problem. However, it gives an upper bound to the achievable results with the variation of these parameters. It calls to investigate in the future a *per-problem auto-tuning* capable of selecting the best temperature and/or prompt variations.

RQ₅ Tuning temperature and prompt variation per problem can provide strong performance improvements: up to 79.27% at pass@1 compared to 22.44% for the default configuration and outperforming best average configuration of RQ4 (52.67%).

VI. DISCUSSION

Recitation. One of the many issues of language model-based code assistants is the recitation problem. Indeed, it is believed that models generate code that comes directly from the training set. In the case of Copilot and Codex, this is problematic because of the licensing issues: Codex was trained from public repositories available on Github, and in the case of copyleft licenses, the code generated by Copilot could be under copyright. Github claims that recitation represents a minimal part of the results, less than 5% [18], but recent studies report up to 10% of recitation from language models in general [26].

Showing that a language model recites is challenging. On the one hand, the exact training set of Codex/Copilot is not precisely known. On the other hand, some codes are not recitation but the canonical way to solve a current problem. However,

there are several indications of our study that recitation might be involved. The performance of some prompt variations that are supposed to reduce the information of the problem on Leetcode get higher results. Removing the documentation focuses the attention of the model on the signature of the function (see Figure 3), and will produce results closer to the training set which certainly contains a solution to this problem.

Another evidence of possible recitation comes from the study of Nguyen et al. [11]. When replicating the results over Leetcode dataset (on a larger set of 300+ problems), we found that our performance of Copilot at pass@1 was inferior to what has been obtained in [11]. Specifically, performance of Copilot significantly differed for JavaScript (47.3 instead of our 37.3), Java (51.0 vs 46.3), Python (33.7 vs 49.0), C (18.7 vs 28.0), C# (50.3 vs of 44.3), and C++ (50.7 vs of 45.3). After careful investigation, we found that the only difference was an additional comment indicating the link to the Leetcode problem, included at the beginning of the original prompts. In Table X, we compare our version of problem formatting (*Copilot standard formatting*), a similar formatting of [11] on our dataset (*Copilot Nguyen et al. formatting*), and the results of their study (*Copilot Nguyen et al. study*). The results are dependent on the programming language. For Java and C, even with a modification of the formatting, we get worse results than in their study. This can be explained by the fact that these languages are compiled, and that the manual correction applied in their study corrects simple syntax mistakes (i.e., missing tokens, such as "(", ")", etc.). For Python, the original formatting was worse than their result, but with their formatting, we get better results than theirs. Finally, for JavaScript, our formatting was already getting better results, but their formatting on our dataset allows getting even better results. Overall, Copilot can leverage the presence of the link to Leetcode problem when generating programs. Stated differently, the links can trigger Copilot to recite existing solutions, thus explaining the unfair improvements. We avoid this phenomenon in our study through the systematic removal of links in Leetcode problems.

From an evaluation point of view, recitation can be a threat to validity. In particular, some benchmarks might be too simple, since it simply consists in reciting an existing solution. In our study, we have tried to mitigate this threat through the consideration of diverse problems and the removal of links in Leetcode. More datasets and benchmarks, for which language models have not been trained on, are more than welcome to assess in the future language models.

As a final note, even in the hypothesis of recitation, both Codex and Copilot remain highly sensitive to our variations. RQ1 results also show that the results of Leetcode are closed to HumanEval and far from being perfect (around 40%).

Fine-tuning code assistants. Prompt and temperature, though impactful, are not necessarily controlled by the same people. Temperature and other hyperparameters are often fixed and chosen by the entity that proposes the language model (e.g., OpenAI). From this regard, we have shown that on our datasets (algorithmic problems) the temperature of Copilot is worth tuning to improve the user experience. Our findings

Languages	Copilot standard formatting	Copilot Nguyen et al. formatting	Copilot Nguyen et al. original study
Javascript	37.3	47.3	27.0
Java	46.3	51.0	57.0
Python 3	33.7	49.0	42.0
C	18.7	28.0	39.0
C#	44.3	50.3	-
C++	45.3	50.7	-

TABLE X: Copilot performance comparison

therefore push organizations to enhance language model configuration.

On the other hand, the variation of the prompt – the way the query is formulated – is chosen by the end user of the model. Our results show that there is no systematic actionable strategy to reformulate, refine, or expand prompts. On the contrary, some prompt variations are effective for a limited set of problems, but not all. Owing to our findings, we cannot recommend a one-size-fits-all recipe when re-writing prompts.

In fact, there is a tradeoff to find between user effort and performance. A possibility, for instance, is to give the control of the temperature to the end user of the model (as in Codex). From this perspective, the general recommendations of RQ4 about the temperature can be followed. Though it can improve performance, tuning the temperature requires further effort and expertise for an uncertain result. Another possibility is to envision automated tools that can leverage both prompt variations and temperature to generate a certain number of programs. As shown in RQ5, it is an open problem to find effective heuristics to automatically tune *per-problem*. The result would be a set of candidate programs.

Another open challenge is then how to present to users, k generated programs (based on k prompt variations or k generations of the language model). The promise for users is to review proposed solutions and find a suited program, but it would require more cognitive effort. A promising direction is to filter out the k programs based on some criteria (well-formedness, ability to pass the test suite, complexity metric). We leave it as future work.

Reproducibility issues. Our study relies on many proprietary, closed-source services that (1) may challenge reproducibility of our experiments; (2) limit the scale of certain experiments or some investigations. First, we use Copilot a black box and a closed source running at a remote server, the general user (such as the authors of the article) cannot directly examine the language model and parameters used to generate outputs. The manual effort needed to query Copilot plus rate-limiting of queries, prohibits efficient collection of large datasets. This impacted and informed the research we conduct. In the future, Copilot may be retrained over new code repositories or with different parameters at a later date. As such, to reproduce this research, we stored all parameters' values for every provided prompt – data is available in the companion Web page. Second, we use Codex and similar

observations apply. Third, we rely on LeetCode to assess Codex and Copilot. There are several reasons: the desire to diversify problems, targeted programming languages, and revisit an early study on a similar topic [11]. We had to use an API with rate limits and some information is hidden about the checking of proposed programs. Furthermore, the test suite of some problems may evolve in the future.

Another related issue is the cost of our experiments. For instance, we had privileged and free access to a private API of Codex. The actual cost of creating numerous programs can run into the thousands of dollars. For example, 100 programs for each of HumanEval’s 146 problems and for each combination of temperature and prompt variations. Hence, the financial cost or limited access to computing resources can be a barrier for reproducing our experiments.

Despite all these concerns, we believe it is worth conducting such research over cutting-edge, impactful software services. We hope, however, that more open solutions at both the language model and benchmark levels will emerge to facilitate scientific inquiry.

Threats to validity. A first internal threat is the way we vary the temperature over Codex API. The documentation (last access: August 2022) suggests not to modify top p and temperature at the same time, so we chose to let top $p = 1$, the default value in Codex API. The evaluation of pass@ k with $k > 1$ was only performed on the HumanEval dataset with Codex. Indeed, the response time for each Leetcode test was important, not to mention the rate limits of the API. Hence, we have only evaluated pass@1 for this dataset. Lifting this technical limitation in the future could lead to more insights, but does not affect our results. In HumanEval, the maximum sampling size ($n=100$) differs from $n=200$ used in Chen et al. [27]. This choice results from the API limitations of OpenAI. Furthermore, we are reaching almost perfect performance at this scale. Threats to the generalization of our results are first the considered datasets. Though HumanEval and Leetcode have been partly considered in prior publications [11], [27], it is unclear how our findings would transfer to other benchmarks (e.g. less focusing on algorithmic problems). Another external threat is that the outputs of Copilot/Codex are subject to change, e.g. due to retraining over different corpus.

VII. RELATED WORK

Many machine learning models are used in software engineering, for tasks such as code completion, code summarization, code translation and code repair [28], [29]. Concerning code completion, many models have been developed in the last years like Alphacode, CodeParrot or Codex [14], [30]–[35]. To evaluate these different models several datasets have been proposed like HumanEval [14], APPS [36], Codenet [37], MBPP or MathQA-Python [35].

In [38] and [39], Codex results are reported on linear algebra, probability and statistics problems. Other studies are interested in Copilot: exploration of the security of the generated code [16], comparison of the performances of Copilot with mutation-based code generation techniques [40], studies

of the impact on productivity and the usefulness of Copilot for developers [41], [42]. In our study, we examined the validity of the programs generated by Copilot and Codex, but we did not assess the impact on productivity, security, or usefulness. Furthermore, these studies do not cover the interaction between prompt and temperature.

Nguyen et al. [11] performed an early empirical study on the performance and understandability of Copilot generated code on 34 problems from Leetcode. We exclusively focus on performance in our study. There are several differences in the experimental protocol used to obtain these results. First, our results were obtained automatically and no post-correction was applied to the generated codes as in [11]. Second, the size of the datasets used and the distribution of the difficulty of the problems highly differs. For Leetcode, we considered 300 problems on 6 languages against 33 problems on 4 languages in [11]. HumanEval is not considered in [11]. Third, we considered Codex in addition to Copilot, and we make vary both prompts, temperature, and pass@ k .

Ciniselli et al. [26] performed an empirical study on the T5 model to investigate whether the trained model tends to clone code from its training set when recommending code completions. The formation of the prompt is also an essential element in the use of language models. A recent paper [43] shows for example that by modifying the prompt, we can create several tools with a single model. The prompt is also used to optimize performance. This is the case of Shin et al. [12] who automatically search for tokens using a guided gradient descent. Jiang et al. [44] generates new prompts through reformulation to exploit the whole knowledge of language models. Li et al. [45] show that we can use prompts instead of fine-tuning to improve performances on some tasks. Chen et al. [27] use Codex to generate new tests for the HumanEval [14] problem.

Other works [46], [47] propose different methods of promptings – the chain of thought or meta prompting – that consist in encouraging the model to pose a reflection before answering the task. Lu et al. [48] show that the order of the given examples influences the result and is dependent on the model used (for text classification tasks and not for code generation).

VIII. CONCLUSION

We conducted a large empirical study of Copilot and Codex over 446 algorithmic problems and 6 different programming languages (leveraging HumanEval and Leetcode datasets). We showed that varying the temperature and the original prompt has the *potential* to significantly improve their performance: Up to 79.27% of success rate in one-shot, compared to 22.44% for Codex in default settings and 31.1% for Copilot. Actioning this potential in practice, however, would require to a priori configure the right temperate value and prompt variation for a given (set of) problems. It is highly challenging due to the complex interplay raised in our study – the optimal values differ from one problem to the other. Our results also showed surprising and unexpected results (e.g. fully removing the prompt can be an effective strategy), suggesting some

brittleness and room for improvement for language models. Hence, to the question: hot temperature, cold prompts, or black magic? Our answer is both: tuning temperature and varying prompts is worth considering for maintainers and end users of code assistants, but at this state there is some magic that definitely requires further understanding and research.

Reproducibility: The datasets and operators presented in this article are all available at <https://anonymous.4open.science/r/copilot-benchmark-F6AC>. The repository also contains the artifacts that were used to perform our experiments with Codex and Copilot.

REFERENCES

- [1] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," *arXiv preprint arXiv:1810.04805*, 2018.
- [2] A. Radford, J. Wu, R. Child, D. Luan, D. Amodei, I. Sutskever *et al.*, "Language models are unsupervised multitask learners," *OpenAI blog*, vol. 1, no. 8, p. 9, 2019.
- [3] T. Brown, B. Mann, N. Ryder, M. Subbiah, J. D. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell *et al.*, "Language models are few-shot learners," *Advances in neural information processing systems*, vol. 33, pp. 1877–1901, 2020.
- [4] A. Chowdhery, S. Narang, J. Devlin, M. Bosma, G. Mishra, A. Roberts, P. Barham, H. W. Chung, C. Sutton, S. Gehrmann *et al.*, "Palm: Scaling language modeling with pathways," *arXiv preprint arXiv:2204.02311*, 2022.
- [5] A. Srivastava, A. Rastogi, A. Rao, A. A. M. Shueb, A. Abid, A. Fisch, A. R. Brown, A. Santoro, A. Gupta, A. Garriga-Alonso *et al.*, "Beyond the imitation game: Quantifying and extrapolating the capabilities of language models," *arXiv preprint arXiv:2206.04615*, 2022.
- [6] N. Du, Y. Huang, A. M. Dai, S. Tong, D. Lepikhin, Y. Xu, M. Krikun, Y. Zhou, A. W. Yu, O. Firat, B. Zoph, L. Fedus, M. Bosma, Z. Zhou, T. Wang, Y. E. Wang, K. Webster, M. Pellat, K. Robinson, K. Meier-Hellstern, T. Duke, L. Dixon, K. Zhang, Q. V. Le, Y. Wu, Z. Chen, and C. Cui, "GLaM: Efficient scaling of language models with mixture-of-experts," 2021. [Online]. Available: <https://arxiv.org/abs/2112.06905>
- [7] A. M. Rush, S. Chopra, and J. Weston, "A neural attention model for abstractive sentence summarization," in *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*. Lisbon, Portugal: Association for Computational Linguistics, Sep. 2015, pp. 379–389. [Online]. Available: <https://aclanthology.org/D15-1044>
- [8] Z. Jiang, F. F. Xu, J. Araki, and G. Neubig, "How can we know what language models know?" *Transactions of the Association for Computational Linguistics*, vol. 8, pp. 423–438, 2020. [Online]. Available: https://doi.org/10.1162/tac1_a_00324
- [9] M. Geva, A. Gupta, and J. Berant, "Injecting numerical reasoning skills into language models," in *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. Online: Association for Computational Linguistics, Jul. 2020, pp. 946–958. [Online]. Available: <https://aclanthology.org/2020.acl-main.89>
- [10] GitHub copilot · your AI pair programmer. [Online]. Available: <https://copilot.github.com/>
- [11] N. Nguyen and S. Nadi, "An empirical evaluation of GitHub copilot's code suggestions," in *2022 IEEE/ACM 19th International Conference on Mining Software Repositories (MSR)*, 2022, pp. 1–5, ISSN: 2574-3864.
- [12] T. Shin, Y. Razeghi, R. L. Logan IV, E. Wallace, and S. Singh, "Auto-Prompt: Eliciting knowledge from language models with automatically generated prompts," *arXiv, Tech. Rep. arXiv:2010.15980*, 2022, type: article.
- [13] S. Gehman, S. Gururangan, M. Sap, Y. Choi, and N. A. Smith, "RealToxicityPrompts: Evaluating neural toxic degeneration in language models," in *Findings of the Association for Computational Linguistics: EMNLP 2020*. Online: Association for Computational Linguistics, Nov. 2020, pp. 3356–3369. [Online]. Available: <https://aclanthology.org/2020.findings-emnlp.301>
- [14] M. Chen, J. Tworek, H. Jun, Q. Yuan, H. P. d. O. Pinto, J. Kaplan, H. Edwards, Y. Burda, N. Joseph, G. Brockman, A. Ray, R. Puri, G. Krueger, M. Petrov, H. Khlaaf, G. Sastry, P. Mishkin, B. Chan, S. Gray, N. Ryder, M. Pavlov, A. Power, L. Kaiser, M. Bavarian, C. Winter, P. Tillet, F. P. Such, D. Cummings, M. Plappert, F. Chantzis, E. Barnes, A. Herbert-Voss, W. H. Guss, A. Nichol, A. Paino, N. Tezak, J. Tang, I. Babuschkin, S. Balaji, S. Jain, W. Saunders, C. Hesse, A. N. Carr, J. Leike, J. Achiam, V. Misra, E. Morikawa, A. Radford, M. Knight, M. Brundage, M. Murati, K. Mayer, P. Welinder, B. McGrew, D. Amodei, S. McCandlish, I. Sutskever, and W. Zaremba, "Evaluating large language models trained on code," *arXiv, Tech. Rep. arXiv:2107.03374*, 2021, type: article. [Online]. Available: <http://arxiv.org/abs/2107.03374>
- [15] IntelliSense in visual studio code. [Online]. Available: <https://code.visualstudio.com/docs/editor/intellisense>
- [16] H. Pearce, B. Ahmad, B. Tan, B. Dolan-Gavitt, and R. Karri, "Asleep at the keyboard? assessing the security of GitHub copilot's code

- contributions,” arXiv, Tech. Rep. arXiv:2108.09293, 2021, type: article. [Online]. Available: <http://arxiv.org/abs/2108.09293>
- [17] Copilot internals. [Online]. Available: <https://thakkarparth007.github.io/copilot-explorer/posts/copilot-internals.html>
 - [18] Research recitation. [Online]. Available: <https://ghdocs-prod.azurewebsites.net/en/github/copilot/research-recitation>
 - [19] S. Kulal, P. Pasupat, K. Chandra, M. Lee, O. Padon, A. Aiken, and P. S. Liang, “SPoC: Search-based pseudocode to code,” in *Advances in Neural Information Processing Systems*, vol. 32. Curran Associates, Inc., 2019. [Online]. Available: <https://proceedings.neurips.cc/paper/2019/hash/7298332f04ac004a0ca44cc69ecf6f6b-Abstract.html>
 - [20] A. Moon, T. A. Raju, and T. Cse, “A survey on document clustering with similarity measures,” 2013.
 - [21] Z. Sun, J. M. Zhang, Y. Xiong, M. Harman, M. Papadakis, and L. Zhang, “Improving machine translation systems via isotopic replacement,” in *Proceedings of the 44th International Conference on Software Engineering*. ACM, 2022, pp. 1181–1192. [Online]. Available: <https://dl.acm.org/doi/10.1145/3510003.3510206>
 - [22] S. Iyer, I. Konstantas, A. Cheung, and L. Zettlemoyer, “Mapping language to code in programmatic context,” arXiv, Tech. Rep. arXiv:1808.09588, 2018, type: article. [Online]. Available: <http://arxiv.org/abs/1808.09588>
 - [23] J. Devlin, M. Chang, K. Lee, and K. Toutanova, “BERT: pre-training of deep bidirectional transformers for language understanding,” *CoRR*, vol. abs/1810.04805, 2018. [Online]. Available: <http://arxiv.org/abs/1810.04805>
 - [24] N. Reimers and I. Gurevych, “Sentence-bert: Sentence embeddings using siamese bert-networks,” in *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 11 2019. [Online]. Available: <http://arxiv.org/abs/1908.10084>
 - [25] T. Kojima, S. S. Gu, M. Reid, Y. Matsuo, and Y. Iwasawa. (2022) Large language models are zero-shot reasoners.
 - [26] M. Ciniselli, L. Pascarella, and G. Bavota, “To what extent do deep learning-based code recommenders generate predictions by cloning code from the training set?” 2022. [Online]. Available: <https://arxiv.org/abs/2204.06894>
 - [27] B. Chen, F. Zhang, A. Nguyen, D. Zan, Z. Lin, J.-G. Lou, and W. Chen, “Codet: Code generation with generated tests,” 2022. [Online]. Available: <https://arxiv.org/abs/2207.10397>
 - [28] P. Bareiß, B. Souza, M. d’Amorim, and M. Pradel, “Code generation tools (almost) for free? a study of few-shot, pre-trained language models on code.” [Online]. Available: <http://arxiv.org/abs/2206.01335>
 - [29] W. U. Ahmad, S. Chakraborty, B. Ray, and K.-W. Chang, “Unified pre-training for program understanding and generation.” [Online]. Available: <http://arxiv.org/abs/2110.06333>
 - [30] Y. Li, D. Choi, J. Chung, N. Kushman, J. Schrittwieser, R. Leblond, T. Eccles, J. Keeling, F. Gimeno, A. D. Lago, T. Hubert, P. Choy, C. d. M. d’Autume, I. Babuschkin, X. Chen, P.-S. Huang, J. Welbl, S. Goyal, A. Cherepanov, J. Molloy, D. J. Mankowitz, E. S. Robson, P. Kohli, N. de Freitas, K. Kavukcuoglu, and O. Vinyals, “Competition-level code generation with AlphaCode.” [Online]. Available: <http://arxiv.org/abs/2203.07814>
 - [31] C. B. Clement, D. Drain, J. Timcheck, A. Svyatkovskiy, and N. Sundaresan, “PyMT5: multi-mode translation of natural language and python code with transformers.” [Online]. Available: <http://arxiv.org/abs/2010.03150>
 - [32] Z. Feng, D. Guo, D. Tang, N. Duan, X. Feng, M. Gong, L. Shou, B. Qin, T. Liu, D. Jiang, and M. Zhou, “CodeBERT: A pre-trained model for programming and natural languages.” [Online]. Available: <http://arxiv.org/abs/2002.08155>
 - [33] S. Black, S. Biderman, E. Hallahan, Q. Anthony, L. Gao, L. Golding, H. He, C. Leahy, K. McDonnell, J. Phang, M. Pieler, U. S. Prashanth, S. Purohit, L. Reynolds, J. Tow, B. Wang, and S. Weinbach, “GPT-NeoX-20B: An open-source autoregressive language model,” in *Proceedings of the ACL Workshop on Challenges & Perspectives in Creating Large Language Models*, 2022. [Online]. Available: <https://arxiv.org/abs/2204.06745>
 - [34] Natural language processing with transformers, revised edition [book]. ISBN: 9781098136796. [Online]. Available: <https://www.oreilly.com/library/view/natural-language-processing/9781098136789/>
 - [35] J. Austin, A. Odena, M. Nye, M. Bosma, H. Michalewski, D. Dohan, E. Jiang, C. Cai, M. Terry, Q. Le, and C. Sutton, “Program synthesis with large language models,” arXiv, Tech. Rep. arXiv:2108.07732, 2021, type: article. [Online]. Available: <http://arxiv.org/abs/2108.07732>
 - [36] D. Hendrycks, S. Basart, S. Kadavath, M. Mazeika, A. Arora, E. Guo, C. Burns, S. Puranik, H. He, D. Song, and J. Steinhardt, “Measuring coding challenge competence with APPS.” [Online]. Available: <http://arxiv.org/abs/2105.09938>
 - [37] R. Puri, D. S. Kung, G. Janssen, W. Zhang, G. Domeniconi, V. Zolotov, J. Dolby, J. Chen, M. Choudhury, L. Decker, V. Thost, L. Buratti, S. Pujar, S. Ramji, U. Finkler, S. Malaika, and F. Reiss, “CodeNet: A large-scale AI for code dataset for learning a diversity of coding tasks.” [Online]. Available: <http://arxiv.org/abs/2105.12655>
 - [38] I. Drori and N. Verma, “Solving linear algebra by program synthesis.” [Online]. Available: <http://arxiv.org/abs/2111.08171>
 - [39] L. Tang, E. Ke, N. Singh, N. Verma, and I. Drori, “Solving probability and statistics problems by program synthesis.” [Online]. Available: <http://arxiv.org/abs/2111.08267>
 - [40] D. Sobania, M. Briesch, and F. Rothlauf, “Choose your programming copilot: A comparison of the program synthesis performance of GitHub copilot and genetic programming,” arXiv, Tech. Rep. arXiv:2111.07875, 2021, type: article. [Online]. Available: <http://arxiv.org/abs/2111.07875>
 - [41] A. Ziegler, E. Kalliamvakou, S. Simister, G. Sittampalam, A. Li, A. Rice, D. Rifkin, and E. Aftandilian, “Productivity assessment of neural code completion.” [Online]. Available: <http://arxiv.org/abs/2205.06537>
 - [42] P. Vaithilingam, T. Zhang, and E. L. Glassman, “Expectation vs. experience: Evaluating the usability of code generation tools powered by large language models,” in *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems*, ser. CHI EA ’22. New York, NY, USA: Association for Computing Machinery, 2022. [Online]. Available: <https://doi.org/10.1145/3491101.3519665>
 - [43] Anonymous, “Large language models are human-level prompt engineers,” in *Submitted to The Eleventh International Conference on Learning Representations*, 2023, under review. [Online]. Available: <https://openreview.net/forum?id=92gvk82DE->
 - [44] Z. Jiang, F. F. Xu, J. Araki, and G. Neubig, “How can we know what language models know?” *Transactions of the Association for Computational Linguistics*, vol. 8, pp. 423–438, 2020. [Online]. Available: <https://aclanthology.org/2020.tacl-1.28>
 - [45] X. L. Li and P. Liang, “Prefix-tuning: Optimizing continuous prompts for generation,” 2021. [Online]. Available: <https://arxiv.org/abs/2101.00190>
 - [46] L. Reynolds and K. McDonnell, “Prompt programming for large language models: Beyond the few-shot paradigm,” 2021. [Online]. Available: <https://arxiv.org/abs/2102.07350>
 - [47] X. Wang, J. Wei, D. Schuurmans, Q. Le, E. Chi, S. Narang, A. Chowdhery, and D. Zhou, “Self-consistency improves chain of thought reasoning in language models,” 2022. [Online]. Available: <https://arxiv.org/abs/2203.11171>
 - [48] Y. Lu, M. Bartolo, A. Moore, S. Riedel, and P. Stenetorp, “Fantastically ordered prompts and where to find them: Overcoming few-shot prompt order sensitivity,” 2021. [Online]. Available: <https://arxiv.org/abs/2104.08786>