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# Between Lines of Code: Unraveling the Distinct Patterns of Machine and Human Programmers

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**Abstract**—Large language models have catalyzed an unprecedented wave in code generation. While achieving significant advances, they blur the distinctions between machine- and human-authored source code, causing integrity and authenticity issues of software artifacts. Previous methods such as DetectGPT have proven effective in discerning machine-generated texts, but they do not identify and harness the unique patterns of machine-generated code. Thus, its applicability falters when applied to code. In this paper, we carefully study the specific patterns that characterize machine and human-authored code. Through a rigorous analysis of code attributes such as lexical diversity, conciseness, and naturalness, we expose unique patterns inherent to each source. We particularly notice that the syntactic segmentation of code is a critical factor in identifying its provenance. Based on our findings, we propose a novel machine-generated code detection method called DetectCodeGPT, which improves DetectGPT by capturing the distinct stylized patterns of code. Diverging from conventional techniques that depend on external LLMs for perturbations, DetectCodeGPT perturbs the code corpus by strategically inserting spaces and newlines, ensuring both efficacy and efficiency. Experiment results show that our approach significantly outperforms state-of-the-art techniques in detecting machine-generated code.

**Index Terms**—Machine-generated code detection, large language models, code generation, empirical analysis

## 1 INTRODUCTION

THE advent of large language models (LLMs) such as Codex [1] and ChatGPT [2] has revolutionized software engineering by automating program generation, once the exclusive domain of human intellect. LLMs trained on code [3], [4], [5], [6], sophisticated yet accessible, have democratized the act of coding, allowing individuals without formal expertise to effectively engage with software creation [7], [8]. Their ability to generate syntactically correct and functionally robust code challenges traditional dynamics and introduces a new era of efficiency and innovation in software creation, maintenance, and evolution.

While capable of generating human-like programs, LLMs bring ambiguity of whether a software artifact is created by a human or machine, causing integrity and authenticity issues in software development. This indistinction can lead to various challenges, such as the misattribution of code ownership for bug/fault triage and potential vulnerabilities in machine-generated code that may go unnoticed due to overreliance on its perceived robustness. Furthermore, the ease of generating code could lead to inflated assessments of project workloads, skewing economic valuations and potentially compromising the reliability of software. This blending of human and machine efforts not only raises questions about the trustworthiness of the software but also threatens the integrity of coding as a discipline, wherein the

true authorship and the effort invested in creating software artifacts become obscured. Addressing these concerns is pivotal in maintaining a transparent and secure software development lifecycle.

Recently, there has been a growing research trend in detecting machine-generated texts [9], [10]. Perturbation-based methods like DetectGPT [11], have achieved state-of-the-art results in identifying machine-generated text. DetectGPT employs likelihood score discrepancies between the original text and its perturbed variants to enhance detection accuracy. And the perturbation process is performed by a pretrained language model (e.g., T5 [12]) to mask portions of the original text and then reconstruct it. While natural language text can accommodate a degree of variation without losing coherence, code must adhere to rigid syntactic constraints. Perturbation strategies designed for text often lead to code syntax errors, thereby diminishing the efficacy of these methods when applied to machine-generated code [13].

In this paper, we conduct a comparative analysis of the patterns between machine- and human-authored code from three aspects, including lexical diversity, conciseness, and naturalness. Through our exploration, we uncovered that compared to human, machine tends to write more concise and natural code with a narrower spectrum of tokens, towards regularization to programming principles, and the disparity is more pronounced in stylistic tokens such as whitespace tokens.

Capitalizing on our findings, we propose a novel method called DetectCodeGPT for detecting machine-authored code. Our DetectCodeGPT improves DetectGPT by capturing the distinct styles of code. Diverging from conventional techniques that depend on external pretrained model (e.g. CodeT5 [14]) to perform Masked Language Modeling (MLM) for perturbations, our DetectCodeGPT ingeniously perturbs the code by strategically inserting spaces and newlines.

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Eschewing the need for an LLM for perturbations, our method provides much higher efficiency. Since the proposed perturbation strategy well captures the stylistic distinctions between machine- and human-authored code, our DetectCodeGPT also ensures higher efficacy.

To rigorously evaluate the effectiveness of DetectCodeGPT, we conducted extensive experiments using two varied datasets across six code language models, ranging from 1.3 to 7 billion parameters, and operating at two different decoding conditions. The results demonstrate that, unlike in the text domain where training a supervised model is relatively straightforward [9], [15], detecting machine-authored code presents a unique challenge. Nevertheless, DetectCodeGPT markedly outperforms contemporary state-of-the-art methods in the machine-generated code detection task, delivering a stable and significant improvement.

Our contributions can be summarized as follows:

- To our knowledge, we are the first to conduct a comprehensive and thorough analysis of the differences between machine- and human-authored code. Our study sheds light on essential insights that further advance the utility of LLMs in coding.
- We propose a novel machine-authored code detection method called DetectCodeGPT leveraging the distinct stylistic patterns of code.
- We extensively evaluate the DetectCodeGPT across a variety of settings and show the effectiveness of our approach.

## 2 BACKGROUND

### 2.1 Large Language Models for Code

GPT language models [16], [17] based on Transformer [18] decoder has achieved remarkable success in natural language processing tasks [19]. In the field of code generation, Codex [1] and AlphaCode [20] are pioneering works to train large language models on code. These models are usually trained with the MLE objective to maximize the likelihood of the next token given the previous tokens [16]. Mathematically, this is captured as:

$$\theta^* = \arg \max_{\theta} \sum_i \log p_{\theta}(x_i) \quad (1)$$

where  $x_i$  denotes each instance in the training dataset and  $p_{\theta}(x_i)$  represents the model’s probability distribution parameterized by  $\theta$ . And the training data often contain millions of code in different programming languages collected from open source repositories like GitHub [21], [22], [23].

Later advances to improve LLMs on code include designing new pretraining tasks like fill-in-the-middle [14], [24], [4], [5] and also instruction fine-tuning [25], [6]. And recent large language models pretrained on a mixture of code and natural language like ChatGPT [26], GPT4 [27] and LLaMA [28] has also shown promising results on code generation tasks benefiting from the enormous amount of data and model parameters.

### 2.2 Perturbation-Based Detection of Machine-Generated Text

In the realm of machine-generated text detection, perturbation based method like DetectGPT [11] stands as the state-of-the-art technology [9]. In this section, we take DetectGPT as

an example to illustrate the idea of perturbation-based detection methods. DetectGPT distinguishes between machine and human-generated text by analyzing the patterns in their probability scores [11]. The core idea is that when a text  $x$  generated from a machine is subtly changed to  $\tilde{x}$  through a perturbation process  $q(\cdot|x)$  (e.g., MLM with T5 [29]), there is a sharper decline in its log probability scores  $\log p_{\theta}(x)$  than that in human-generated text. This is because a machine-generated text is usually more predictable and tightly bound to the patterns it was trained on, leading to a distinct negative curvature in log probability when the text is perturbed. By contrast, human-written texts are characterized by a rich diversity that reflects a blend of experiences and cognitive processes. As a result, it doesn’t follow such predictable patterns, and its log probability scores  $\log p_{\theta}(x)$  do not plummet as dramatically when similarly perturbed. Based on such discrepancy, we can define a *likelihood discrepancy score* for each input code to measure the drop of log probability after perturbation.

$$\mathbf{d}(x, p_{\theta}, q) \triangleq \log p_{\theta}(x) - \mathbb{E}_{\tilde{x} \sim q(\cdot|x)} \log p_{\theta}(\tilde{x}) \quad (2)$$

By inspecting these scores, we can detect the source of  $x$ . A significant drop indicates machine authorship and a smaller change suggests a human creator. This method effectively captures the more nuanced and variable nature of human-generated text compared to the more formulaic and patterned output of language models.

## 3 EMPIRICAL ANALYSIS

In this section, we conduct a comparative analysis of the distinct features of machine- and human-authored code.

### 3.1 Study Design

To gain insights into distinctions between human and machine programmers, we consider three primary aspects that are relevant to coding styles, namely diversity, conciseness, and naturalness [30], [31], [32], [33], [34], which can be measured by specific metrics.

#### 3.1.1 Lexical Diversity

Lexical diversity indicates the richness and variety of vocabulary present in a corpus. In the context of programming, this refers to the diversity in variable names, functions, classes, and reserved words. Analyzing lexical diversity offers a deeper understanding of the creativity, expressiveness, and potential complexity of code segments. There are four important empirical metrics in both natural and programming languages revealing the lexical diversity: token frequency, syntax element distribution, Zipf’s law [35] and Heaps’ law [36].

**Token Frequency** stands for the occurrence of distinct tokens in the code corpus. The attribute indicates the core vocabulary utilized by human and machine programmers, shedding light on their coding preferences and tendencies.

**Syntax Element Distribution** refers to the proportion of syntax elements (e.g., keywords, identifiers) in the code corpus. Understanding the distribution of syntax elements in code is akin to dissecting the anatomy of a language. It gives us a lens to view the nuances of coding style, the emphasis

Table 1: Studied categories of Python code tokens

Category	Tree-sitter Types
keyword	def, return, else, if, for, while, ...
identifier	identifier, type_identifier
literal	string_content, integer, true, false, ...
operator	<, >, =, ==, +, ...
syntactic symbol	:, ), ], [, (, ,, ", ', {, }, .
comment	comment
whitespace	space, \n

on structure, and the intricacies that distinguish human- and machine-authored code.

To delve into the syntax element distribution, we analyze code with tree-sitter<sup>1</sup> and classify tokens into distinct categories, as detailed in Table 1. We then compute the proportion of each category in the code corpus.

**Zipf’s and Heaps’ Laws** were initially identified in natural languages [35], [36], and later verified in the scope of programming languages [30], [31]. Zipf’s law states that the frequency value  $f$  of a token is inversely proportional to its frequency rank  $r$ :  $f \propto \frac{1}{r^\alpha}$ , where  $\alpha$  is close to 1 [35]. In programming languages, it states that a few variable names or functions are very commonly used across different scripts, while many others are rarely employed. Heaps’ Law characterizes the expansion of a vocabulary  $V$  as a corpus  $D$  increases in size:  $V \propto D^\beta$ , where  $\beta \in (0, 1)$  captures the rate of vocabulary growth relative to the size of the corpus.

We investigate how closely machine-authored code aligns with Zipf’s and Heaps’ laws compared to human-authored code, which could reflect the models’ ability to mimic human lexical usage.

### 3.1.2 Conciseness

Conciseness stands as a cornerstone attribute when characterizing code [37], [33], [34]. The intricate balance of code conciseness directly influences readability, maintainability, and even computational efficiency. We investigate two metrics that characterize code conciseness, namely, the number of tokens and the number of lines.

**Number of tokens** gives us an indication of verbosity and complexity, showing the detailed composition of the code [37].

**Number of lines** helps us understand organizational choices, as spreading code across more lines can reflect a focus on readability and structure [34].

### 3.1.3 Naturalness

The concept of code naturalness suggests that programming languages share a similar degree of regularity and predictability with natural languages [32]. This idea has been operationalized by employing language models to assess the probability of a specific token’s occurrence within a given context. Under this framework, we inspect how “natural” machine-generated code is compared to human-written code.

**Token Likelihood and Rank** are two metrics that measure the naturalness of each token in the studied code corpus. The token likelihood stands for the probability  $p$  of a token  $x$  under the model  $p_\theta$ , denoted as  $p_\theta(x)$ . The rank of a token  $x$  is the position of  $x$  in the sorted list of all tokens based on their likelihoods, denoted as  $r_\theta(x)$ . Both metrics

evaluate how likely a token is preferred by the model [38], [39], [40]. We calculate log scores on each token and then take the average to represent the whole code snippet as advised in [39]. To pinpoint the code elements that most significantly affect the score discrepancies, we also present the mean scores on different syntax element categories in Table 1 for comparison.

## 3.2 Experimental Setup

We choose the state-of-the-art CodeLlama model [6] to generate code. Limited by our computational resources, we use the version with 7B parameters. As for the decoding strategies, we adopt the top- $p$  sampling method [41] with  $p=0.95$  following [1]. The temperature  $T$  is an important parameter controlling the diversity of the generated code [41]. Since current LLMs on code are usually evaluated across different decoding temperatures [5], [42], [1], [6], we generate code with  $T = 0.2$  and  $T = 1.0$  to capture the model’s behavior under different settings. The maximum length of the generated code is set to 512 tokens. All experiments are conducted on 2 NVIDIA RTX 4090 GPUs with 24GB memory.

## 3.3 Dataset Preparation

To compare with human-authored code, we extracted 10,000 Python functions randomly from the CodeSearchNet corpus [21], a compilation of open-source GitHub projects that provides a wide-ranging and varied codebase. We used function signatures and their accompanying comments as prompts for the model as in [1], and we collected the corresponding bodies of these functions to represent human-written code.

While acknowledging that current models, including CodeLlama and even ChatGPT [43], may not yet craft code of unparalleled quality for intricate tasks such as those in CodeSearchNet [7], [43], the choice of this dataset is deliberate and insightful. Pitting the model against various real-world project code rather than simple programming problems, akin to those in the HumanEval [1] or MBPP [44] dataset, offers a more representative assessment. It allows us to analyze the differences between human and machine’s code when faced with broader, practical applications.

## 3.4 Results and Analysis

We present the results and analysis regarding each code attribute introduced in Section 3.1.

### 3.4.1 Token Frequency

Table 2 lists the top 50 tokens from human- and machine-authored code when  $T=0.2$ . Due to space limit, we omit the results when  $T=1.0$ , which has a similar result. From the results, we have several noteworthy observations:

**Common Tokens:** Human- and machine-authored code shares a commonality in their usage of certain tokens, including punctuation marks such as “.”, “(”, “)”, and structural keywords such as “if”, “return”, and “else”. This is because LLMs acquire foundational coding syntax after being trained on extensive human-written code corpora.

1. <https://github.com/tree-sitter/tree-sitter>

Table 2: Top 50 tokens from human- and machine-authored code from CodeLlama

Rank	Human-Authored Tokens	Machine-Authored Tokens
1-10	. ( ) = ' , : self " [	. - , ( ) self : " ' if
11-20	] if return in for not None 0 1 ==	= return not [ def raise isinstance ] == path
21-30	else + is name { } path data raise -	name 0 __class__ __name__ None os { / } %
31-40	try * os len format get and True value isinstance	else TypeError str ' __init__ is ; // the
41-50	args key % np i x kwargs except False or	in 1 ; value kwargs #include + __str__ for ValueError

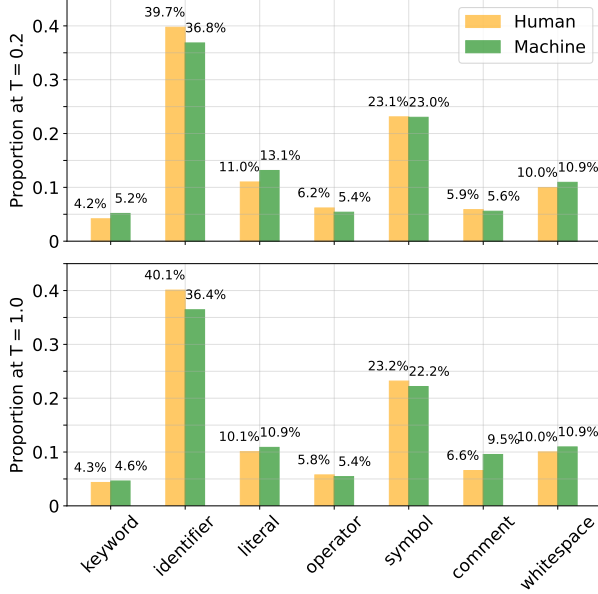


Figure 1: Syntax element distribution of the studied code corpus

**Error Handling:** Tokens associated with error handling like “raise” and “TypeError”, are more prevalent in machine-authored code. This difference implies that machine programmers emphasize robustness and exception handling more explicitly.

**Programming Paradigms:** Tokens indicating object-oriented programming like “self” and “\_\_init\_\_” are prominent in both human- and machine-authored code, which illustrates the model’s training alignment with this paradigm. However, machine-authored code appears to favor more boilerplate tokens like “\_\_class\_\_” and also “\_\_name\_\_”, which could stem from its training on diverse object-oriented codebase.

**Finding 1:** Machine-authored code focuses more on exception handling and object-oriented principles than human, suggesting an emphasis on error prevention and adherence to common programming templates.

### 3.4.2 Syntax Element Distribution

The analysis of syntax element distributions, as visualized in Figure 1, reveals intriguing insights into the coding conventions and stylistic nuances between human- and machine-authored code. The “keyword”, “operator”, “syntactic symbols”, and “whitespace” proportions remain largely consistent between human and machine-authored code, across both temperatures. This consistency suggests that the foundational syntactical elements manifest similarly in both datasets.

Delving deeper into the more nuanced discrepancies, a few categories emerge that underscore the differential preferences or tendencies of human and machine writers (statistical significance  $p < 0.01$ ):

**Identifier:** The identifiers constitute a significantly lower proportion among machine-authored code across both temperatures, indicating that machines favor reusing established identifiers over creating new ones, possibly a reflection of its programming paradigm influenced by its training data.

**Literal:** Machine-authored code consistently shows a marginally higher inclination towards literals. Across both temperatures, the machine exhibits an increase in the literal proportion as opposed to the human-written code. This indicates a potential proclivity of machine-authored code to process raw data more frequently. This could be attributed to the machine’s broader exposure to varied tasks involving data manipulations.

**Comment:** Machine-authored code has much more comments when  $T=1.0$ . This observation hints machine’s increased emphasis on code documentation and explanation with higher temperatures, when it becomes less deterministic and more exploratory.

**Finding 2:** Machine-authored code tends to favor existing variables and data manipulation over new identifiers, and tends to have more comments to maintain clarity when the generation temperature grows.

### 3.4.3 Zipf’s and Heaps’ Laws

Figure 2 offers a comprehensive understanding of coding tendencies of both human and machine programmers. Starting with Zipf’s law, Figure 2a and 2b both delineate similar trends for human and machine programmers, corroborating the law’s applicability. And we can observe machine’s heightened proclivity towards tokens ranked between 10 and 100, especially at  $T=0.2$ . Turning our attention to Heaps’ law, the near-linear trends in Figure 2c-2d reaffirm the law’s validity. Also, there’s a noticeable shallowness in the slope for machine’s code at  $T=0.2$  revealing machine’s decreased lexical diversity.

The obvious differences at  $T=0.2$  can be ascribed to *human creativity and variability*. The varied approaches and methodologies humans employ can lead to a diversified token usage within this range. Another plausible interpretation can be its *risk aversion*. A machine, especially at lower temperatures, might be reverting to familiar patterns ensuring correctness in code generation. Additionally, certain patterns within the training data might have been overemphasized due to *model overfitting*, leading the machine to a skewed preference.

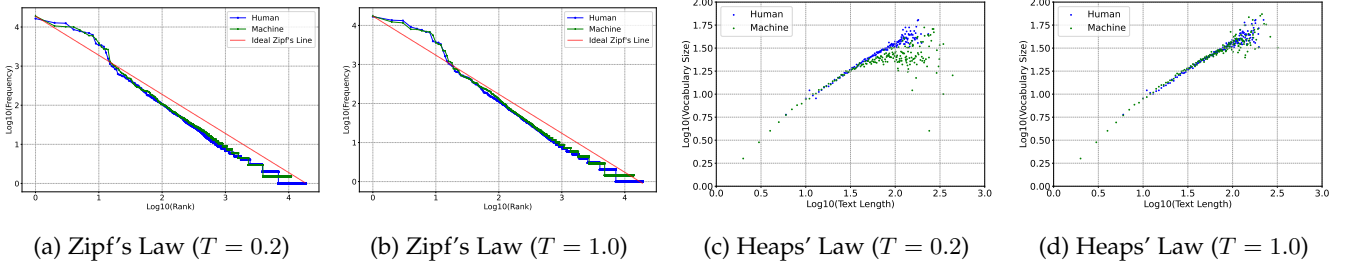


Figure 2: Comparison of Zipf's and Heaps' laws on machine- and human-authored code

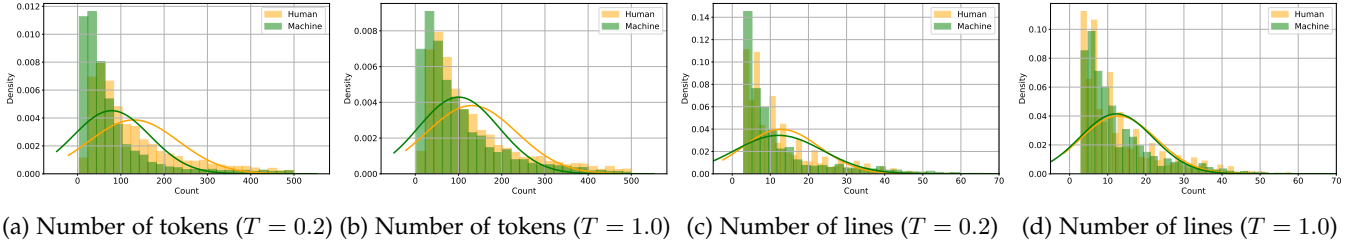


Figure 3: Distribution of code length for machine- and human-authored code

**Finding 3:** Machines demonstrate a preference for a limited spectrum of frequently-used tokens, whereas human code exhibits a richer diversity in token selection.

### 3.4.4 Number of Tokens and Lines

Figure 3 presents the distribution of code length under different settings. For the temperature setting of 0.2, machine-authored code exhibits more conciseness, both in token and line numbers. As the temperature increases to  $T = 1.0$ , we witness a convergence of distributions. The gap narrows, yet the machine's preference for relatively concise code persists. This reveals that higher temperatures induce more exploratory generative behavior in the model, leading to diverse coding styles.

One could hypothesize several reasons for these observed patterns. The propensity for conciseness at lower temperatures may reflect LLM's training data, where probably concise solutions were more prevalent or deemed more "correct". On the flip side, human developers, often juggling multiple considerations like future code extensions, comments for peer developers, or even personal coding style, might craft lengthier solutions. Furthermore, the narrowing of disparities at higher temperatures can be attributed to the model's increased willingness to explore varied coding styles. At higher temperatures, the LLM possibly mimics a broader spectrum of human coding patterns, capturing the essence of diverse coding habits and styles found in its training corpus.

**Finding 4:** Machines tend to write more concise code as instructed by their training objective, while human programmers tend to write longer code, reflective of their personal styles.

### 3.4.5 Token Likelihood and Rank

Figure 4 shows that there is a great discrepancy of naturalness between machine- and human-authored code. Compared to

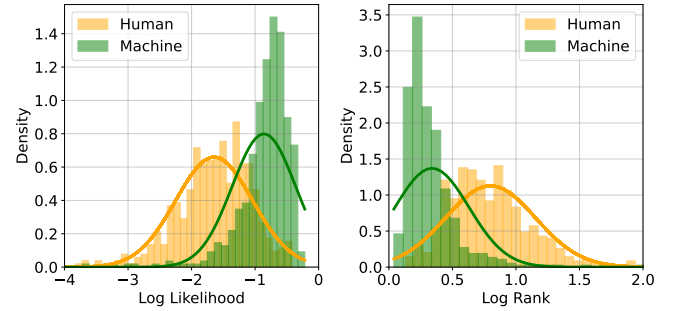


Figure 4: Distribution of naturalness scores for machine- and human-authored code

Table 3: The naturalness of different categories of syntax elements. Statistical significance  $p < 0.001$ .

Category	Log Likelihood			Log Rank		
	Machine	Human	$\Delta$	Machine	Human	$\Delta$
keyword	-1.701	-2.128	0.428	0.837	1.053	0.217
identifier	-0.459	-0.874	0.415	0.163	0.378	0.215
literal	-0.506	-1.364	0.858	0.152	0.630	0.479
operator	-0.938	-1.835	0.897	0.367	0.872	0.504
symbol	-0.868	-1.639	0.771	0.321	0.781	0.460
comment	-1.503	-3.028	1.525	0.608	1.610	1.002
whitespace	-1.131	-2.740	<b>1.609</b>	0.429	1.441	<b>1.012</b>
ALL	-1.658	-0.827	0.831	0.319	0.811	0.492

human-authored code, the log likelihood scores of machine-authored code are mostly higher and the log rank scores are mostly lower, indicating that machine's code is more "natural" than human-written code. Such observation in source code is consistent with the findings in natural language [39], [38], [11], [40].

Table 3 summarises the comparison results in terms of each token category at  $T = 0.2$ . An intriguing finding is that whitespace tokens stand out with the highest deviation of naturalness, surpassing even the combined use of all tokens. This highlights a distinctive aspect of coding styles: machines, trained on extensive datasets, typically generate code with

regular, predictable whitespace patterns. Humans, however, influenced by individual styles and practices, exhibit a wider variety in their use of whitespaces. The distinct patterns in machine-generated whitespaces, therefore, point to an inherent variation in coding style between machine and human.

**Finding 5:** Machine-authored code exhibits higher “naturalness” than human-authored code, and the disparity is more pronounced in tokens such as comments, and whitespaces, which are more reflective of individual coding styles.

## 4 DETECTING MACHINE GENERATED CODE

The empirical results suggest that machine tends to write more concise and natural code with a narrower spectrum of tokens, towards regularization to programming principles, and the disparity is more pronounced in stylistic tokens such as whitespaces. This sparks a new idea for detecting machine-generated code: instead of perturbing arbitrary tokens, we focus on perturbing those stylistic tokens that best characterize the machine’s preference. Based on this idea, we introduce DetectCodeGPT, a novel zero-shot method for detecting machine-generated code. Our approach adapts the perturbation-based detection framework DetectGPT [11] to the code domain.

### 4.1 Problem Formulation

We formulate machine-generated code detection as a classification task that predicts whether a given code snippet  $x$  is produced by a source model  $p_\theta$ . For this purpose, we transform  $x$  to an equivalent form  $\tilde{x}$  through a perturbation process  $q(\cdot|x)$ . We anticipate a sharper decline in its naturalness score if  $x$  is written by an LLM. The key problems here are how to define the naturalness score and how to design the perturbation process. We introduce the naturalness score and the perturbation strategy  $q(\cdot|x)$  in our approach in the following sections.

### 4.2 Measuring Naturalness

Previous methods usually use the log likelihood of tokens to measure the naturalness of machine-authored content [32], [40]. However, the log rank of tokens shows better performance comparing the naturalness of machine- and human-authored text [11], [39], because it offers a smoother and robust representation of token preference.

Unlike DetectGPT which directly calculates the log likelihood of tokens, we adopt the Normalized Perturbed Log Rank (NPR) score [45] to capture the naturalness. The NPR score is formally defined as:

$$\text{NPR}(x, p_\theta, q) \triangleq \frac{\mathbb{E}_{\tilde{x} \sim q(\cdot|x)} \log r_\theta(\tilde{x})}{\log r_\theta(x)}, \quad (3)$$

where  $\log r_\theta(x)$  is the logarithm of the rank order of text  $x$  sorted by likelihood under model  $p_\theta$ . In practice,  $\text{NPR}(x, p_\theta, q)$  has been demonstrated to be more accurate for differentiating text origins, outperforming the log likelihood discrepancy  $\mathbf{d}(x, p_\theta, q)$  [45].

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### Algorithm 1: DetectCodeGPT: Machine-Generated Code Detection with Stylized Code Perturbation

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**Data:** code  $x$ , source model  $\mathcal{M}$ , number of perturbations  $k$ , decision threshold  $\epsilon$ , parameters  $\alpha, \beta, \lambda_{\text{spaces}}$ , and  $\lambda_{\text{newlines}}$

// Detection using NPR score on Perturbed Samples

```

1 for  $i \leftarrow 1$  to  $k$  do
  // Random decision for type of
  // perturbation
2   $p \sim \mathcal{U}(0, 1)$ ;
3  if  $p \leq 0.5$  then
    // Spaces Insertion
4    Let  $C$  represent the set of all possible locations to
    // insert spaces in  $x$ ;
5    Select  $C_s \subseteq C$  such that  $|C_s| = \alpha \times |C|$ ;
6    for each location  $c \in C_s$  do
7       $n_{\text{spaces}}(c) \sim \mathcal{P}(\lambda_{\text{spaces}})$ ;
8      Insert  $n_{\text{spaces}}(c)$  spaces at location  $c$  in  $x$ ;
9    end
10  else
    // Newlines Insertion
11    Split the perturbed code  $x$  into a set  $L$  of lines;
12    Select  $L_n \subseteq L$  such that  $|L_n| = \beta \times |L|$ ;
13    for each line  $l \in L_n$  do
14       $n_{\text{newlines}}(l) \sim \mathcal{P}(\lambda_{\text{newlines}})$ ;
15      Insert  $n_{\text{newlines}}(l)$  newlines after line  $l$  in  $x$ ;
16    end
17  end
18  Store the perturbed code as  $\tilde{x}_i$ ;
19 end
20 Calculate expectation:  $\tilde{\mu} \leftarrow \frac{1}{k} \sum_i \text{NPR}(\tilde{x}_i, p_\theta, q)$ ;
21 Estimate NPR for original code:
    $\text{NPR}_x \leftarrow \text{NPR}(x, p_\theta, q) - \tilde{\mu}$ ;
22 if  $\text{NPR}_x > \epsilon$  then
23   return true; // Probably machine-authored
24 else
25   return false; // Probably human-authored
26 end
```

---

### 4.3 Perturbation Strategy

Our empirical study indicates that the whitespace tokens serve as an important indicator of machine’s regularization and human’s diversity, which points to an inherent variation in coding style. Therefore, we propose an efficient and effective perturbation strategy with the following two types of perturbations below. Detailed explanations on the effectiveness of these perturbations are given in Section 6.1.

#### 4.3.1 Space Insertion

Let  $C$  represent the set of all possible locations to insert spaces in a code segment. We randomly select a subset  $C_s \subseteq C$  such that  $|C_s| = \alpha \times |C|$ , where  $\alpha \in [0, 1]$  is a fraction representing the code locations. For each location  $c \in C_s$ , we introduce a variable number of spaces,  $n_{\text{spaces}}(c)$ , which is drawn from a Poisson distribution  $\mathcal{P}(\lambda_{\text{spaces}})$ . Mathematically, this can be represented as:

$$n_{\text{spaces}}(c) \sim \mathcal{P}(\lambda_{\text{spaces}}). \quad (4)$$

#### 4.3.2 Newline Insertion

We split the codes into lines and obtain a set  $L$  of lines. A subset  $L_n \subseteq L$  is then chosen randomly, where  $|L_n| = \beta \times |L|$ , with  $\beta \in [0, 1]$  denoting the proportion of the line locations.

For each line  $l \in L_n$ , we introduce a variable number of newlines,  $n_{\text{newlines}}(l)$ , sampled from a Poisson distribution  $\mathcal{P}(\lambda_{\text{newlines}})$ . Formally, this is expressed as:

$$n_{\text{newlines}}(l) \sim \mathcal{P}(\lambda_{\text{newlines}}). \quad (5)$$

We randomly choose one type of perturbation to the code snippet  $x$  to generate a set of perturbed samples  $\tilde{x}_i$  for  $i \in [1, k]$ , where  $k$  is the number of perturbations. Through this step, we instill randomness at a granular stylistic level, thereby amplifying the perturbation’s efficacy. Our perturbation strategy introduces several distinct advantages over the conventional methods [11], [45] using MLM to perturb the code, which will be discussed in Section 6.2.

Algorithm 1 summarizes the entire workflow of DetectCodeGPT. Our algorithm harnesses stylized code perturbation to differentiate between human- and machine-authored code. At the core of our approach is the strategic insertion of spaces (Lines 4-9) and newlines (Lines 11-16) in code, a process that simulates the inherent randomness in human coding styles. The algorithm operates by generating perturbed versions of the code and then evaluating their NPR scores (Lines 20-21) with respect to the source model  $\mathcal{M}$ .

The threshold parameter  $\epsilon$  in Line 22, pivotal for making the detection decision, offers flexibility in catering to different application scenarios. By adjusting  $\epsilon$ , users can balance between false positives and false negatives, tailoring the detection sensitivity according to the specific needs of the deployment context.

## 5 EVALUATION

We conduct experiments to evaluate the effectiveness of DetectCodeGPT, aiming to answer the following research questions.

- **RQ1:** How effectively does our method distinguish between machine-generated and human-written code?
- **RQ2:** To what extent do individual components influence the overall performance of our method?
- **RQ3:** What is the impact of varying the number of perturbations on the detection performance?
- **RQ4:** How resilient is our method to cross-model code source detection?

### 5.1 Datasets

Apart from *CodeSearchNet* [21] described in Section 3.3, we select Python code from *The Stack* [22] as another evaluation dataset. Similar to *CodeSearchNet*, *The Stack* provides codes from a variety of open-source projects representative of real-world scenarios. We use a parsed and filtered version [46] of this dataset and also concatenate the function definitions with their corresponding comments as prompts as in [1]. For each combination of dataset and model, we construct 500 human and machine code pairs for evaluation. The maximum length of both human- and machine-authored code is trimmed to 128 tokens.

### 5.2 Evaluation Metric

Following prior works [11], [45], our primary metric for performance evaluation is the Area Under the Receiver Operating Characteristic curve (AUROC), which can be interpreted as the probability that a piece of machine-generated code is assigned a higher score than a piece of human-written code. Formally, given a set of true positive rates (TPR) and false positive rates (FPR) across different thresholds, the AUROC can be represented as:

$$\text{AUROC} = \int_0^1 \text{TPR}(t) dt, \quad (6)$$

where  $t$  denotes varying threshold values. It provides a comprehensive view of performance across all possible thresholds, making it threshold-independent. This makes the metric both interpretable and insightful, offering a clearer picture of the model’s discriminating capabilities.

### 5.3 Baselines and Models

Our evaluation is benchmarked against a diverse range of zero-shot machine-generated text detection techniques, all of which leverage the predicted token-wise conditional distributions of the source model for detection. A supervised baseline is also included to demonstrate the effectiveness of our method.

- **Log  $p(x)$**  [40]: Utilizes the source model’s average token-wise log probability to gauge code naturalness. Machine-generated code tends to have a higher score.
- **Entropy** [39]: Interprets high average entropy in the model’s predictive distribution as indicative of machine generation.
- **(Log-) Rank** [39], [38]: The average observed rank or log rank of each token in the LLM prediction, with machine-generated passages typically showing smaller average values.
- **DetectGPT** [11]: Leverages the log probability of the original code and its perturbed variants to compute the perturbation discrepancy gap.
- **DetectLLM** [45]: Introduces two methods, one blends log likelihood with log rank to compute **LRR**, and the other improves DetectGPT by incorporating the **NPR** score.
- **GPTSniffer** [47]: a supervised baseline that trains CodeBERT [48] to predict the authorship of a given code snippet. Following OpenAI’s RoBERTa-based [49] GPT detector<sup>2</sup>, we train the model on a combination of 1000 samples generated by each model at each setting.

As for models to generate machine’s code, in consideration of GPU memory limitations, we judiciously selected a range of advanced LLMs with varying parameter counts, from 1 billion to 7 billion. We selected InCoder [24], Phi-1 [50], StarCoder [51], WizardCoder [25], CodeGen2 [4] and CodeLlama [6] from Huggingface<sup>3</sup>. This diverse array of models, each trained on distinct datasets and boasting different capacities, offers a comprehensive spectrum for evaluating our method.

2. <https://github.com/openai/gpt-2-output-dataset/tree/master/detector>

3. <https://huggingface.co/models>



Table 4: Performance (AUROC) of various detection methods. Statistical significance  $p < 0.001$ .

Dataset	Code LLM	Detection Methods								
		$\log p(x)$	Entropy	Rank	Log Rank	DetectGPT	LRR	NPR	GPTSniffer	DetectCodeGPT
CodeSearchNet ( $T = 0.2$ )	Incoder (1.3B)	0.9810	0.1102	0.8701	0.9892	0.4735	0.9693	0.8143	0.9426	<b>0.9896</b>
	Phi-1 (1.3B)	0.7881	0.4114	0.6409	0.7513	0.7210	0.4020	0.7566	0.3855	<b>0.8287</b>
	StarCoder (3B)	0.9105	0.2942	0.7585	0.9340	0.6949	0.9245	0.9015	0.7712	<b>0.9438</b>
	WizardCoder (3B)	0.9079	0.2930	0.7556	0.9120	0.6450	0.7975	0.8677	0.7433	<b>0.9345</b>
	CodeGen2 (3.7B)	0.7028	0.4411	0.7328	0.7199	0.6051	0.7997	0.6177	0.5327	<b>0.8802</b>
	CodeLlama (7B)	0.8850	0.3174	0.7265	0.9016	0.8212	0.8332	0.5890	0.7496	<b>0.9095</b>
CodeSearchNet ( $T = 1.0$ )	Incoder (1.3B)	0.7724	0.4167	0.7797	0.7876	0.6258	0.7427	0.6801	0.6761	<b>0.7882</b>
	Phi-1 (1.3B)	0.6118	0.4588	0.5709	0.6299	0.7492	0.4528	0.7912	0.4158	<b>0.8365</b>
	StarCoder (3B)	0.6574	0.4844	0.6987	0.6822	0.6505	<b>0.7050</b>	0.6751	0.6299	0.6918
	WizardCoder (3B)	0.8319	0.3363	0.7273	0.8338	0.5972	0.6965	0.7516	0.7068	<b>0.8392</b>
	CodeGen2 (3.7B)	0.4484	0.6263	0.6584	0.4632	0.4797	0.5530	0.5208	0.4024	<b>0.6798</b>
	CodeLlama (7B)	0.6463	0.4855	0.6759	0.6656	0.6423	0.6768	0.6515	0.6442	<b>0.7239</b>
The Stack ( $T = 0.2$ )	Incoder (1.3B)	0.9693	0.1516	0.8747	0.9712	0.6061	0.9638	0.8571	0.9291	<b>0.9727</b>
	Phi-1 (1.3B)	0.8050	0.4318	0.6766	0.7622	0.7295	0.4022	0.8106	0.4640	<b>0.8578</b>
	StarCoder (3B)	0.9098	0.3077	0.7843	<b>0.9329</b>	0.6824	0.9135	0.9233	0.7715	0.9274
	WizardCoder (3B)	0.9026	0.3196	0.7963	0.9010	0.6385	0.7742	0.8574	0.7794	<b>0.9243</b>
	CodeGen2 (3.7B)	0.7171	0.4051	0.7930	0.7301	0.5288	0.7604	0.5670	0.4520	<b>0.8513</b>
	CodeLlama (7B)	0.8576	0.3565	0.7366	0.8793	0.8087	0.8358	0.5436	0.7619	<b>0.8852</b>
The Stack ( $T = 1.0$ )	Incoder (1.3B)	0.7310	0.4591	0.7673	0.7555	0.6124	0.7446	0.6787	0.6846	<b>0.7833</b>
	Phi-1 (1.3B)	0.7841	0.4205	0.6666	0.7475	0.6718	0.4106	0.7755	0.4984	<b>0.8376</b>
	StarCoder (3B)	0.6333	0.5025	0.7010	0.6609	0.5896	<b>0.7080</b>	0.6638	0.7243	0.6890
	WizardCoder (3B)	0.8293	0.3459	0.7484	0.8223	0.6377	0.6436	0.7929	0.7766	<b>0.8384</b>
	CodeGen2 (3.7B)	0.4816	0.6046	0.5631	0.4956	0.4337	0.5740	0.5178	0.4265	<b>0.6660</b>
	CodeLlama (7B)	0.5929	0.5260	0.6451	0.6091	0.6116	0.6365	0.6226	0.7494	<b>0.6595</b>
Average	-	0.7649	0.3961	0.7228	0.7724	0.6357	0.7050	0.7178	0.6507	<b>0.8308</b>

## 5.4 Experimental Setup

For code generation with different models, we adopted the top- $p$  sampling strategy [41] with  $p=0.95$  following [1]. We explored two temperature settings,  $T=0.2$  and  $T=1.0$ , as discussed in Section 3.2. The maximum length constraint for generated codes was set at 128 tokens. With respect to the perturbation-specific hyperparameters, a grid search on a held-out set from the *CodeSearchNet* dataset, using the SantaCoder model [3], revealed optimal values. Consequently, we set  $\alpha$  and  $\beta$  to 0.5, while  $\lambda_{\text{spaces}} = 3$  and  $\lambda_{\text{newlines}} = 2$ . For all experiments, we maintained a consistent configuration of generating 50 perturbations. For the DetectGPT and DetectLLM, which involve an LLM in restoring perturbed code, we utilized the CodeT5+ (770M) model [52]. And as for the supervised baseline GPTSniffer, we trained the CodeBERT model for 5 epochs with a batch size of 16 and a learning rate of  $2e-5$  with AdamW optimizer. All experiments are conducted on 2 NVIDIA RTX 4090 GPUs with 24GB memory.

## 5.5 Detection Performance (RQ1)

Table 4 delineates the results of various methods. According to the results, DetectCodeGPT consistently outperforms baseline methods. Compared to the strongest baseline Log Rank, our method achieves an average relative improvement of 7.6% in AUROC. In an impressive 21 of 24 combinations of dataset and model, our method provides the most accurate performance, which underscores its robustness across a variety of generative models, ranging from the 1.3 billion parameter InCoder to the 7 billion parameter CodeLlama.

We also repeated the experiments 10 times and employed a paired t-test to assess the statistical significance of the

performance differences between the methods, setting the significance level at 0.05. Results show that the performance superiority of our method was statistically significant, with p-values less than 0.001. The high AUROC scores achieved across these diverse settings confirm the method’s superior capability to generalize and reliably differentiate between machine-generated and human-written code.

We can observe that the challenge of detection notably increases at a temperature setting of  $T=1.0$  than  $T=0.2$ . This is possibly due to the higher randomness at this temperature, where models are likely to generate outputs with greater diversity in styles. Despite these increased difficulties, the proposed method maintains its leading position in detection accuracy.

It is also worth mentioning that our method, leveraging a zero-shot framework, frequently surpasses the accuracy of the supervised GPTSniffer. The unstable performance of the supervised model reveals that it’s hard to detect machine-generated codes relying on the training data. The ability of our zero-shot approach to adapt and retain high performance under different levels of generative temperature variations is indicative of its sophisticated detection capability, making it a valuable tool for maintaining the integrity of codebases against the infiltration of machine-generated code in practical applications.

To further illustrate the effectiveness of our approach, we present some representative examples of machine-generated code detection by DetectCodeGPT and two most competitive baselines in Figure 5. We set the mean score of all the code snippets as the decision threshold  $\epsilon$  for each method.

Examples 1 is a machine-generated code snippet. DetectCodeGPT can correctly detect it, while the baselines fail. In this example, the first and last “if” statements are separated

```
import os
import re

if not os.path.isdir(path):
    raise ValueError('%s is not a directory' % path)

if not isinstance(include, (list, tuple)):
    include = [include]
if not isinstance(exclude, (list, tuple)):
    exclude = [exclude]

if not show_all:
    exclude.append(r'\.pyc$')
...
```

Truth: 🤖  
Log  $p(x)$ : 🤖  
Log Rank: 🤖  
DetectCodeGPT: 🤖

(a) Example 1

```
args_names = []
args_names.extend(function_spec.args)
if function_spec.varargs is not None:
    args_names.append(function_spec.args)

args_check = {}

for arg_name in arg_specs.keys():
    if arg_name not in args_names:
        args_check[arg_name] = self.check(
            arg_specs[arg_name], arg_name
        )

return args_check
```

Truth: 🤖  
Log  $p(x)$ : 🤖  
Log Rank: 🤖  
DetectCodeGPT: 🤖

(b) Example 2

```
save_test = random() > 0.8
audio = load_audio(fn)
num_chunks = len(audio) // chunk_size
listener.clear()

for i, chunk in enumerate(chunk(audio, chunk_size)):
    print('\r' + str(i * 100 / num_chunks) + '%')
    buffer = update(buffer[len(chunk):], chunk)
    conf = listener.update(chunk)
```

Truth: 🤖  
Log  $p(x)$ : 🤖  
Log Rank: 🤖  
DetectCodeGPT: 🤖

(c) Example 3

```
# If num is 0.
if (n == "0"):
    return 0

# Count sum of digits under mod 9
answer = 0
for i in range(0, len(n)):
    answer = (answer + int(n[i])) % 9

# If digit sum is multiple of 9, answer
# 9, else remainder with 9.
if (answer == 0):
    return 9
else:
    return answer % 9
```

Truth: 🤖  
Log  $p(x)$ : 🤖  
Log Rank: 🤖  
DetectCodeGPT: 🤖

(d) Example 4

Figure 5: Examples of machine- and human-authored code snippets with corresponding predictions.

from the rest of the code with newlines, and the two “if” statements in the middle are modularized together since they have similar functionalities. Such modularization and separation of code blocks are captured by DetectCodeGPT thanks to the stylized perturbation. Example 2 and 3 are human-written codes that are misclassified by other baselines, but DetectCodeGPT correctly identifies them. In Example 2, we can observe that the code blocks are sometimes separated with newlines (e.g., lines 5-7), but sometimes not (as seen with the rest of the code). In Example 3, although the code blocks are well separated with newlines, the human author omitted the spaces between operators “//” and “/”, but add spaces between “\*” and “+”. Such freely and randomly stylized code reveals the inherent randomness in human coding habits. It’s hard for the baselines that only rely on token-wise conditional distributions to capture such randomness in coding styles. In contrast, DetectCodeGPT effectively leverages the style information to distinguish between machine-generated and human-written code again. These examples demonstrate the effectiveness of our method in detecting machine-generated code via stylized code perturbation.

However, there are also some cases where DetectCodeGPT fails to detect machine-generated code. Example 4 is a human-written code misclassified as machine-generated by all the approaches. We can observe that this code snippet is well-structured with newlines and spaces, and the comments are well-aligned with the code. Its resemblance to machine-generated code is striking, posing a significant challenge for distinction. This example highlights the difficulty of detecting machine-generated code among well-structured human-written codes with standard coding styles.

## 5.6 Ablation Study (RQ2)

In our ablation study, we compared the effectiveness of different perturbation strategies for detecting machine-

Table 5: Performance of different perturbation strategies

Perturb. Type	MLM	Newline	Space	Newline&Space
$T = 0.2$	0.5436	0.8703	0.8639	<b>0.8852</b>
$T = 1.0$	0.6226	0.6453	0.6504	<b>0.6660</b>

generated code using the CodeLlama (7B) model on *The Stack* dataset. The results summarized in Table 5 illuminates the comparative advantage of our stylistic perturbation approach. We observe that both newline and space perturbations independently offer substantial improvements over the traditional MLM-based (CodeT5+) perturbation technique as in DetectGPT and DetectLLM [11], [45] for natural language. Also, the combination of newline and space perturbations further enhances the detection performance, with the highest AUROC score of 0.8852 at  $T = 0.2$  and 0.6660 at  $T = 1.0$ . The consistent outperformance of our combined perturbation strategy across both temperature settings affirms its potential as a robust solution for detecting machine-authored code.

## 5.7 Impact of Perturbation Count (RQ3)

To gauge the impact of perturbation count on the efficacy of our method, we conducted experiments with varying numbers of perturbations.

Table 6: Impact of varying the number of perturbations

#Perturbations	10	20	50	100	200
$T = 0.2$	0.6537	0.8825	0.8852	<b>0.8855</b>	0.8846
$T = 1.0$	0.5558	0.6584	0.6660	0.6660	<b>0.6662</b>

Results in Table 6 reveal a rapid ascent in the AUROC score as the number of perturbations increases from 10 to 20, underscoring the efficiency of our perturbation approach. Notably, an increase to 20 perturbations already yields robust detection performance, with further increments leading to

diminishing improvements. This suggests that our method requires a relatively small number of perturbations to effectively discern between human- and machine-authored code. This implies that our method is not only effective but also resource-efficient.

## 5.8 Performance of Cross-Model Detection (RQ4)

	InCoder	Phi-1	StarCoder	WizardCoder	CodeGen2	CodeLlama
InCoder	0.97	0.83	0.90	0.88	0.90	0.86
Phi-1	0.72	0.86	0.77	0.79	0.76	0.68
StarCoder	0.84	0.82	0.93	0.92	0.89	0.87
WizardCoder	0.82	0.86	0.91	0.92	0.87	0.85
CodeGen2	0.59	0.83	0.65	0.69	0.85	0.68
CodeLlama	0.81	0.80	0.87	0.87	0.86	0.89
Source Model	Detection Model					

Figure 6: Cross-model detection performance

In previous sections, we primarily assessed the efficacy of DetectCodeGPT within a white-box framework, where the detection model can be the same as the source model. Nonetheless, in real-world applications, it is often infeasible to access to the original code generation model for detection. To simulate such conditions, we engaged in cross-model detection experiments, wherein distinct models were utilized to compute the naturalness scores for detecting code generated by others. These evaluations were carried out using *The Stack* dataset at a temperature of 0.2.

The results presented in Figure 6 highlight DetectCodeGPT’s adaptability in cross-model detection. While the algorithm excels in the white-box setting, its performance endures with only a slight reduction when subjected to cross-model application. For instance, StarCoder, when detecting code generated by WizardCoder and CodeLlama, yields AUROC scores of 0.92 and 0.87, respectively, compared to an AUROC of 0.93 when detecting its own output. And we can also notice a performance decrease when detecting CodeGen2’s output. This is possibly due to the fact that CodeGen2 is trained on a more diverse dataset containing more natural language text [4]. However, Phi-1 demonstrates a relative proficiency with a score of 0.83 to detect CodeGen2’s output, which implies an ensemble of diverse detection models may enhance the system’s robustness, as suggested in [53].

These results indicate that DetectCodeGPT is a model-free method that is robust against model discrepancies, making it a viable solution for real-world applications where the source model could be unknown or inaccessible.

## 6 DISCUSSION

### 6.1 Why is DetectCodeGPT Effective?

We attribute the effectiveness of our DetectCodeGPT to the following two factors:

#### 6.1.1 Preservation of Code Correctness

While the perturbation method in DetectGPT masks continuous spans of text and requires another LLM to recover, such recovery often leads to structurally compromised code. The unique syntax and constraints inherent to programming languages mean that even minor misinterpretations (e.g., misuse of an identifier) can render the code non-functional. The originally masked spans could be the only correct solution to recover the code and the recovered version from LLM bring minor mistakes easily. Such code-cracking perturbations will possibly lead to both a decrease in naturalness scores for human’s and machine’s codes, violating the assumption that the perturbation will have minimal impact on the code’s naturalness score if it is human-written in Section 2.2. In contrast, inserting newlines and spaces does not affect the correctness of the code in most cases. So our perturbation strategy ensures that the underlying structure and correctness of the code remain intact, thereby ensuring the effectiveness of our method.

#### 6.1.2 Emulation of Human Randomness

As discussed in Section 3.4.5, human inherently exhibit less naturalness and more randomness in their use of stylistic tokens such as spaces and newlines than machines. For example, a human programmer may freely insert whitespace, especially newlines, in the code as they deem fit, whereas a machine programmer usually tries to stylize the code in a more standardized and modularized manner. Our proposed perturbation strategy mimics human’s free usage of spaces and newlines, thereby making the perturbation more “random” as is desired according to Section 3.

## 6.2 Strength of DetectCodeGPT

DetectCodeGPT presents a perturbation strategy that is not only efficient but also maintains the structural integrity of the code while closely mirroring human coding styles. We summarize the strengths of DetectCodeGPT as follows:

#### 6.2.1 Enhanced Efficiency

Since it’s necessary to perturb each text for multiple times to ensure the effectiveness of detection [11], [45], as verified in Section 5.7, perturbing code using masked language modeling with other pretrained models will lead to huge computational cost. On the contrary, our method will save much more time and bring more efficiency. This translates to a significant conservation of computational resources, thus expediting the detection process and enhancing scalability. Mathematically, if  $T_{\text{DetectGPT}}$  and  $T_{\text{Ours}}$  denote the computational times of DetectGPT and our method respectively, we know that  $T_{\text{Ours}} \ll T_{\text{DetectGPT}}$ .

#### 6.2.2 Superior Zero-Shot Performance

DetectCodeGPT distinguishes itself with a zero-shot learning capability, enabling it to detect machine-generated code without the necessity for training on extensive datasets. This model-agnostic advantage means that it can be generalized across various code LLMs and can still remain robust even when applied to unseen models, as demonstrated and verified in Section 5.8. In comparison to the supervised methods, which may suffer from data drift or the need for

constant updates, our approach is not only more adaptable but also delivers better performance across various data sources. This makes DetectCodeGPT an agile and reliable tool for machine-generated code detection in a variety of contexts.

### 6.3 Limitations and Future Directions

The main limitations of our work lie in the following two aspects: Firstly, due to the time and computational constraints, we only focus on a set of LLMs within 7B parameters for both empirical analysis and the machine-generated code detection task. As the landscape of LLMs rapidly evolves, incorporating a wider array of more and larger LLMs could significantly bolster the generalizability and robustness of our findings.

Secondly, our current analysis centers exclusively on Python code, while the features of other programming languages may not be fully explored and the effectiveness of our method on other languages is not verified. However, based on the analysis of our method in Section 6.2, we believe that our method can be effectively generalized to other programming languages, especially where the functionality of code won't be much affected after inserting newlines and spaces like C/C++, Java, and JavaScript.

Looking ahead to future work, we plan to further improve the effectiveness of DetectCodeGPT when detecting machine-generated code at higher levels of generation randomness, such as  $T=1.0$ . We note from Table 4 that although DetectCodeGPT outperforms other baselines at  $T=1.0$ , there is still large room for improvement. Although ensembling multiple detection models may help to improve the detection performance [53], we look forward to exploring more effective perturbation strategies based on code style to further enhance the detection efficacy.

Additionally, the development of watermarking strategies [54] for machine-generated code represents an intriguing avenue for future research. Given that our method can effectively identify machine's code, it could be adapted to assist in the creation of watermarking techniques. For instance, embedding a watermark could be achieved by inserting newlines and spaces in a code-specific pattern, which would increase detectability without compromising functionality.

## 7 RELATED WORK

Recently, there has been much effort in detecting machine-generated text [9], [55]. The two main categories of detection methods are zero-shot and training-based methods, and our DetectCodeGPT falls into the former category, which eliminates the need for training data and brings more generalization ability.

As for zero-shot methods, they are usually based on the discrepancy between likelihood and rank information of human and machine's texts [39], [38], [40]. Leveraging the hypothesis in DetectGPT [11] that machine-generated text often has a negative curvature in the log probability when the text is perturbed, many perturbation based methods have been proposed [11], [45], [56]. These methods usually perturb the text by masking a continuous span of tokens and then

recover the perturbed text using another LLM like T5 [29]. The benefit of these methods is that they are zero-shot and can be applied to any LLM without access to training data. However, the perturbation process is time-consuming and computationally expensive. When it comes to the training-based methods, fine-tuning the RoBERTa[49] or T5 [29] model with data collected from different model families at different decoding settings is a common practice [15], [57], [58]. Additional information like graph structure [59], perplexity from proxy models [60] have been shown to be helpful for detection. Moreover, techniques like adversarial training [61] and contrastive learning [59] have also been proposed to improve the detection performance. The main challenge of training-based methods is that they often lack generalization ability and require access to training data from the target model [11].

However, research on identifying machine-generated code remains relatively scarce and is purported to be more challenging than discerning machine-produced text [13]. GPTSniffer was first proposed to detect machine-generated code with supervised CodeBERT training [47]. And the predominant strategies in current studies largely revolve around watermarking techniques, which embed unique markers into the code either during the training of the model or at the time of code generation [13], [54]. The detection of these watermarks subsequently enables the recognition of code generated by machines. It should be noted, however, that these watermarking methods are primarily designed to address issues related to code licensing and plagiarism [62], [63]. Their reliance on modifications to the generation model renders them unsuitable for general code detection tasks.

## 8 CONCLUSION

In this paper, we have explored the nuanced differences between machine-generated and human-written code to enhance the trustworthiness of software development in the era of AI. By pioneering a comparative analysis across three aspects of code, namely, naturalness, style, and correctness, we have provided new insights into code provenance that machine tends to write more concise and natural code with a narrower spectrum of tokens, towards regularization to programming principles, and the disparity is more pronounced in stylized tokens such as whitespaces. Our proposed detection method, DetectCodeGPT, capitalizes on these insights, specifically targeting the stylized nuances of code with a novel perturbation strategy that is simple yet effective. The empirical success of DetectCodeGPT against several benchmarks confirms its potential to bolster security measures in programming and establish a more symbiotic relationship between human developers and LLMs. Our work marks a significant step towards responsible AI use in software engineering, ensuring clarity in code authorship and maintaining the integrity of code as a craft.

### DATA AVAILABILITY

All the experimental data and source code used in this work are available at <https://github.com/YerbaPage/DetectCodeGPT>.

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