A SIMPLE, YET EFFECTIVE APPROACH TO FINDING BIASES IN CODE GENERATION

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ABSTRACT

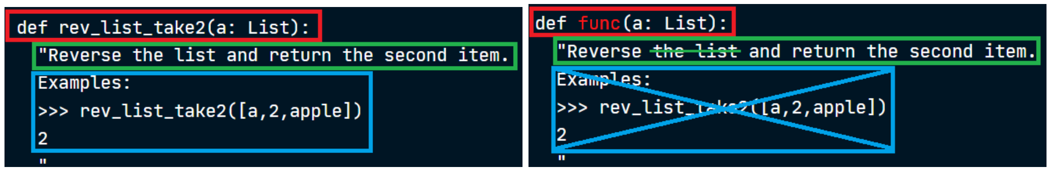
Recently, scores of high-performing code generation systems have surfaced. As has become a popular choice in many domains, code generation is often approached using large language models as a core, trained under the masked or causal language modeling schema. This work shows that current code generation systems exhibit biases inherited from large language model backbones, which might leak into generated code under specific circumstances.

To investigate the effect, we propose a framework that automatically removes hints and exposes various biases that these code generation models use. We apply our framework to three coding challenges and test it across top-performing coding generation models. Our experiments reveal biases towards specific prompt structure and exploitation of keywords during code generation. Finally, we demonstrate how to use our framework as a data transformation technique, which we find a promising direction towards reliable code generation.

1 INTRODUCTION

Large language models (LLM) have recently demonstrated their ability to generate code (Li et al., 2022; Wang & Komatsuzaki, 2021; Black et al., 2021; Brown et al., 2020; Wang et al., 2021) or solve challenging programming/math tasks on par with human coders (Li et al., 2022; Lewkowycz et al., 2022b; Chowdhery et al., 2022a); these models are trained with the data-driven paradigm. On the other hand, an increasing body of work also questions whether the data-driven approach leads to acquiring reasoning skills (Piekos et al., 2021; Zhang et al., 2022; Mouselinos et al., 2022), showing that if left alone, it might not be sufficient for achieving truly human-level performance on tasks such as logical or visual reasoning. In many studied cases, models still rely on various hints in their "reasoning" process. This work extends the results above, i.e., the lack of reasoning capabilities, to the code generation domain. More specifically, we devise a framework that automatically identifies cues that a code generation model might exploit. Changes or removal of those cues stands as a reasoning test towards the generational capabilities of the model at hand. Imagine the following scenario: a code generation model is presented with the prompt "*def add_two_nums(a,b): ...*", and the directive "*Generate a function that adds two numbers and returns their sum*". The expected answer should resemble something like, "*return a + b*." Now, if we decide to rename the function name to a generic "*func*" token: "*def func(a,b): ...*" but maintain the same directive, any inability of the model to generate a correct solution can be attributed to cues related to the function name itself; indicating that the tested model "copied-pasted" the whole or parts of the solution from training data and it has not learned how to program. We present some interesting examples in the Appendix section A.9.

We presume that the reasoning process of code generation models should remain invariant under changes that still provide enough context or pose little if any, additional challenge to a human coder. To this end, we propose an automatic and model-agnostic framework that modifies the following: (1) function names, (2) keywords in a problem specification, and (3) examples provided in the problem prompt We refer to these three parts as Blocks-Of-Influence; see Figure 1. Each block contributes partially to the context needed for correct completion. We show that minor modifications of these blocks are sufficient to "fool" LLM-based code generation methods. Our results reveal that keyword preference and memorization bias can be identified across multiple models and coding challenges. During our experiments, we ensure that any modifications maintain the global semantics of the



(a) (b)

Figure 1: **Left - Blocks Of Influence:** Function / argument names (red), problem specification (green), and examples (blue). **Right - Examples:** We demonstrate three possible transformations, one for each block: Swap the function name with "func", remove keywords, and remove examples from the red, green and blue block, respectively. In our framework, blocks can be targeted both individually and in a joint fashion.

coding challenge. This is achieved through a context-aware filtering mechanism that guarantees any information altered or removed still exists and/or can be deducted from the remaining unaltered part.

Contributions. The main contributions of our work can be summarized in three points.
First, we propose a novel automated framework that identifies possible biases in a coding style dataset. Our framework removes subtle hints, introducing minimal changes in the form of keyword replacement or partial code-block omission, ultimately acting as an adversarial test. Since the framework operates on a data level, it is agnostic to the model's structure and internal workings. Finally, the framework can be easily adjusted to any input format or programming language.
Second, we introduce the "*Blocks of Influence*" concept. We suggest that every instance of a typical coding challenge can be analyzed into three parts (blocks). Each part is correlated with a different method of hinting and is used as a target of our transformations. A model's reasoning process is informed by all three blocks, making them perfect analyzing tools for cases of failing code generation.
Third, we explore new ways of mitigating biases during code generation. In Section 6.2, we study the effects of adversarial training against our proposed perturbations and the benefits of including examples with longer descriptions during finetuning. Our results show that combining these techniques leads to more accurate code completions.

2 Related Work

Our approach is inspired by works of various research directions, which we briefly describe here.
Solving coding and math challenges. The emergent abilities of large language models to generate, summarize and translate textual information, have recently sparked interest in their aptitude for math, logic, and programming challenges. Tasks such as code-completion (Chen et al., 2021; Shin et al., 2019; Hendrycks et al., 2021a; Li et al., 2022), code summarization and code translation (Lu et al., 2021) have been proposed, with models constantly progressing towards near-human performance. Similarly, Hendrycks et al. (2021b); Saxton et al. (2019); Ling et al. (2017); Amini et al. (2019) have proposed tests measuring a model's ability to perform math and logic, ranging from school problems to competition-grade challenges. Impressive results in multiple programming languages have also been achieved by decoder-only works Brown et al. (2020); Chen et al. (2021). In code understanding Feng et al. (2020); Kanade et al. (2020) provided strong baselines that can be further finetuned for code repair and code retrieval taks. Fried et al. (2022) created the first generative model to perform infilling using a novel masking objective. Recent open-source works Black et al. (2021); Wang & Komatsuzaki (2021); Tunstall et al. (2022a); Mitchell et al. have demonstrated the value of good data pre-processing and hyperparameter tuning, with impressive results, especially in lightweight architectures. Finally, massive-scale models such as Chowdhery et al. (2022b); Lewkowycz et al. (2022a) demonstrated breakthrough capabilities in language, reasoning, and code tasks achieving state-of-the-art performance in multiple domains simultaneously.
Bias in large language models. There is some existing research towards discovering biases in large language models. In the area of ethics, Wallace et al. (2019) shows that generative models can be conditioned to produce toxic content, with the use of nonsense, adversarial prefixes. Similarly, Liang et al. (2021) suggest that models might adopt biases and social stereotypes found among their training data and provide ways to apply fairness during generation. Countermeasures have been proposed by Zhao et al. (2021); Liu et al. (2022), claiming that sanitized zero-shot examples contribute to mitigating biases during generation.

Probing reasoning through biases. There have been notable attempts to systemize intelligence and reasoning as concepts (Legg, 2008; Chollet, 2019), yet a few recent works try to approach reasoning, through the analysis of failure modes in deep learning models. Glockner et al. (2018) suggest that natural language inference systems can be easily fooled with a single hypernym/hyponym word swap. Similarly, Lin et al. (2020) prove that numerical commonsense reasoning in LLMs is heavily biased by adjectives describing the object of interest. Concerns against the current data-driven methods have been expressed by Razeghi et al. (2022), pointing out that LLMs are more accurate on mathematical challenges that involve terms significantly more frequently in their pre-training dataset. Piekos et al. (2021) claim that LLMs can answer math and logic questions without an understanding of the rationale behind them. They introduce a novel task of correctly classifying the order of reasoning steps to achieve better results.

Adversarial methods and Language Processing. NLP community developed excellent methods to prepare adversarial tasks, including the TextAttack framework Morris et al. (2020) and sophisticated techniques to elicit adversarial examples from humans, as in Talmor et al. (2022), though our work seems to be the first focused on the disciplined construction of adversarial examples for code.

3 BENCHMARKS

In this section, we describe the datasets used in our experiments; We employed a widely used, complex coding challenge (HE), a simpler one with everyday python problems (MBPP), and finally, a dataset that uses long and analytic descriptions instead of docstrings (DMCC). More information about the datasets can be found in the Appendix section A.2.

HumanEval (HE). This is a human-curated problem-solving dataset described in Chen et al. (2021). It consists of 164 original programming challenges assessing language comprehension, algorithms, and simple mathematics, with some comparable to simple software interview questions. Each problem is presented as an incomplete function, accompanied by a docstring. The docstring contains the task, directives for its completion, and a few examples. For each task, we are provided with a set of unit tests. A task is considered solved when all unit tests are passed. This requires both a syntactically and functionally correct Python program to be generated.

Mostly Basic Python Problems (MBPP). The dataset was introduced in Austin et al. (2021). It contains 974 short Python functions designed to be solved by entry-level programmers. Contrary to HumanEval, the task is given through a text description rather than a docstring. Additionally, there are no input-output examples in the prompt. Test cases for each problem are provided, assessing the functional correctness of the model's completion. This dataset consists of a mixture of crowd-sourced and hand-crafted questions. MBPP challenges models to perform tasks of imperative control flow, requiring loops and conditionals in its solutions.

Deepmind Code Challenges (DMCC). This refers to the highly challenging dataset proposed by Li et al. (2022). The dataset includes problems, solutions and test cases scraped from the Codeforces platform (Mirzayanov, 2020), along with existing public competitive programming datasets scraped from from Description2Code (Caballero, 2016), and CodeNet (Puri et al., 2021). The dataset contains problems from multiple programming languages and training, validation, and test splits. For our purpose, we focused on Python3 programs of the training split. DMCC contains a long description of the problem alongside examples and some notes for its solution. Provided unit tests are an be classified into public tests, visible to a human programmer and hidden tests are used during the final evaluation.

4 EVALUATION

Models. In our experimental setup, we test five models representing a different approach to code generation. The open-source CodeParrot (Tunstall et al., 2022a), has a typical GPT-2 (Radford et al., 2019) architecture and exhibits very good performance given its size. We also challenge the Incoder (Fried et al., 2022) model, which is trained under a novel bi-directional causal objective, being able to handle context more efficiently than its causal counterparts. Bloom (Mitchell et al.) is a recent model that excels in multiple domains. It poses a great challenge against our methods given its excellent natural language understanding and diverse training dataset. CodeGen (Nijkamp et al., 2022) is a high-performing model that was both trained in natural language understanding and code. We test its Mono variant, which is further fine-tuned on the Python programming language.

Finally, we have the powerful Codex model, able to tackle most of the proposed coding challenges in the HumanEval and MBPP datasets. A list of the tested models with their sizes, as well as KeyBert (Grootendorst, 2020) that is used in our framework, can be found in Table 1.

Performance metrics. Whereas the syntactic correctness of a Python program can be easily evaluated, functional correctness is currently studied under the pass@k metric, introduced in Kulal et al. (2019). This metric serves as an estimator of the real model generational capabilities under a specific budget. In Chen et al. (2021), authors propose an updated estimator formulation, empirically proving that for each budget k, ten times more generations should be used for an unbiased estimate. Finally, the modification of 10@k is introduced in Li et al. (2022), testing only the ten best solutions out of k attempts. Note here that k is tested at magnitudes of $10^4 - 10^6$ instead of the typical $10^0 - 10^2$ used in most code generation works. This setup's purpose is to demonstrate their method's filtering effectiveness. Thus, to avoid confusion, our pass@k metric is calculated at exactly k attempts. An average of five runs is presented for experiments in Tables 3 and 4. Sampling temperatures are 0.2 / 0.8 for pass@1 / pass@100 respectively, which is the optimal values across the tested models. More information about the models can be found in the Appendix section A.2.

Model Name	Usage Type	Sizes Used
KeyBert (Grootendorst, 2020)	model access	2M
Codeparrot (Tunstall et al., 2022a)	model access	110M / 350M*/ 1.5B
InCoder (Fried et al., 2022)	model access	1.6B / 6B
CodeGen (Nijkamp et al., 2022)	model access	350M / 6B
Bloom (Mitchell et al.)	model access & API	560M* / 1.7B / 176B
Codex (v1 / v2) (Chen et al., 2021)	API	~175B (Estimated)

Table 1: Models used in experiments. Enties marked with * refer to finetuned models

5 METHOD

5.1 BLOCKS OF INFLUENCE

We propose that each coding challenge is treated as a sequence of three, distinct but complementary blocks, rather than a single, homogeneous input. We refer to them as "*Blocks of Influence*", and correlate each with different hinting methods during code generation. Taking Figure 1 as an example, the model is challenged to complete a function that reverses a list, and then returns its second item.

Name Block. The first block of influence, marked in red, informs the model about the function name and the names and expected types of the input arguments. Let us assume that initially, a model generates correct solutions to a problem. However, the model fails when we rename the function name to something unrelated to the task e.g *"fun"*. This failure mode indicates that neither the problem description was understood nor the model could extract a reasoning pattern out of the given examples. We associate such cases with memorization bias, where the model relies heavily on replicating snippets from its training dataset with the same or similar function name.

Description Block. The description of the problem, stands as the second block, marked in green. The model is expected to form a solution strategy for the presented task by utilizing its natural language understanding capabilities. In this block, we observe that removing specific keywords from the problem description can lead to catastrophic results in model performance. The most interesting cases involve keywords the lack of which, does not degrade the context quality of the problem description. For example in Figure 1, the removal of the word pair "the list" creates a description that is still well understandable by a human coder if the remaining blocks are unaltered. The model should be able to deduct it from the existence of the word "list" in the function name and the list type of input in the example given. We associate such effects with limited abilities of the model to truly understand the given task, and instead rely on inherent preference bias - frequency of token(s) in training set - to fill the missing context.

Example Block. As the final block, we consider examples or notes given after the problem description. These act as demonstrations, guiding the model to specific reasoning patterns. Let's consider a scenario where some models cannot generate correct code when examples are absent. Arguably, the model has exhausted its capacity to understand the task and given inputs. In this failure mode, the provided examples act as a "reasoning tie-breaker" between proposed solutions the model can generate. This effect is especially interesting in the case of composite tasks. The model can easily solve each task (e.g Figure 1: reverse a list / return the second item of an iterable). However, the request of combining those tasks seems odd enough, that the model needs extra examples to internally filter out faulty strategies. We associate such effects with poor generalization.

5.2 FRAMEWORK

Transformations in blocks enable us to repurpose a coding challenge into a test for reasoning failures and biases. In our method, we extend our tests to modify not only a single but two blocks at a time so that additional combinations of hints/cues can be explored. Here, we avoid performing changes in all the *Blocks of Influence* at the same time; a model stripped of any necessary information cannot generate a proper solution. Our framework is composed of three modules that operate in two steps. The first step involves splitting the code instance into the *Blocks of Influence*. For this, we utilize a Regex-based module that fully decomposes the code snippet. This is followed by identifying possible hinting keywords in the *Description Block*. Ideally, we are interested in unigrams or bigrams that provide excess information towards completing the coding task. Secondary targets include keywords that specifically describe a niche task and can act as memorization cues (e.g., if the task of finding a palindrome is nicknamed ”tacocat”, it is possible that functions with that name exist in the training set of the model. Such keywords should be removed so that no verbatim code is generated). For keyword extraction we used Keybert (Grootendorst, 2020), a LLM tasked to perform keyword extraction and word/context similarity. We further finetuned its checkpoint on code embeddings so that more code-specific suggestions are made. However, carelessly removing words from the code prompt can lead to a non-interesting drop in performance, associated with poor prompt quality rather than hinting effects. To focus on those effects, we introduce a special filtering stage. Keywords absent from the *Name Block* and *Example Block*, or correspond to adjectives and adverbs non-related to coding, are of no interest to us. This is achieved with a mixture of hand-crafted rules and weighted embedding similarity of each keyword with the set of words: [Python, Programming, Code] again achieved through KeyBert. Words with similarity under 0.7 are considered unrelated and thus discarded. The first step is presented in Figure 2. As a second step, we implemented a selector that chooses between the following transformations, and modifies the coding challenge accordingly (Figure 1):

Drop one. Removes one of the provided keywords from the *Description Block*. This is repeated N times where N is the number of identified keywords. The performance drop is reported as an average of the N generated code instances.

Drop all. Removes all the provided keywords simultaneously from the *Description Block*

Drop examples. Removes all the provided examples from the *Example Block*. In the case of any notes existing alongside the examples, the experiment is repeated twice, with and without the notes, and the average performance drop is reported.

Anonymize. Replaces the function name with an arbitrary token. We use *”func”* in our experiments. Note that the function name is also replaced in the provided examples as well so no leak of information takes place.

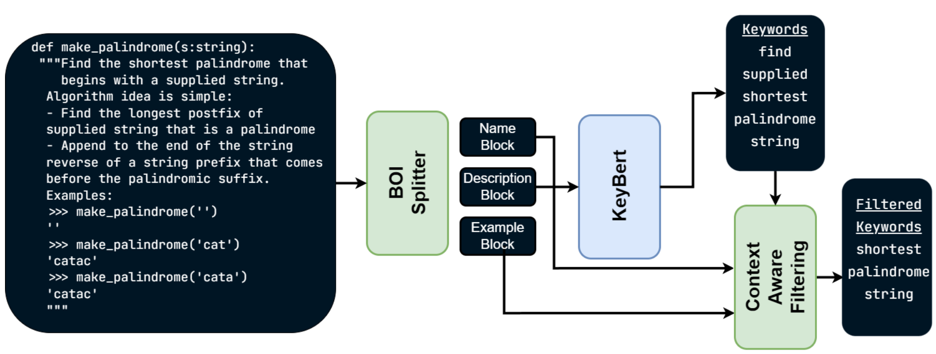


Figure 2: Keyword extraction step: The coding challenge is initially processed by the *Blocks of Influence* splitting module (**BOI splitter**). Keybert, then recieves the *Description Block* and suggests possible hinting keywords. Those are subsequently passed through the context-aware filtering module, leaving eligible keywords finally ready to be used in the transformation step.

5.3 SEMANTIC PRESERVATION

Preserving semantics is a non-trivial task. Arguably, any of our suggested transformations can destroy local semantics. However, we take significant measures to ensure that global semantics is preserved, the challenge is still understandable by a human, and enough information exists towards its solution. Starting from the anonymization transformation, we tested the hypothesis that the choice of *"func"* may potentially bear some intrinsic adversarial effect associated with the training data. We experimented with other word choice replacements (*"action"*,*"do_stuff"*, *"XYZ"*) and got the same results. Information needed to solve a challenge is never limited to just the function name. A manual inspection of the examples often reveals verbatim or near copies of the function name in the problem description. Furthermore, we identify instances where the function name is closely correlated to the task at hand, but if taken as the sole source of information, it could rather be misleading. We present some of such cases in the supplementary material (SectionA.8). In the case of keywords, for each candidate word, we calculate its embedding similarity with every other non-potential token. Again, we utilize Keybert as a critic and consider as "close" any keywords with cosine similarity larger than 0.7. In the case of *Drop All*, if the same word is identified in multiple locations, the first instance is not removed. In the special case, a keyword happens to be an argument type (list, integer, tuple, etc.); we take an additional step of using regular expression matching of that type in the examples. In the case of a match, the keyword is safe to be removed since the equivalent information already exists in the challenge.

To quantify how much global semantics is preserved, we employ the following test, inspired by the work of Yasunaga et al. (2021): We collect a random sample of 200 coding challenges from the HumanEval and MBPP. Each challenge is then transformed according to the methods presented in Table 2. Then for the original and every modified version of a challenge, we calculate their log probability score using a large language model. The main idea in Yasunaga et al. (2021) is that the model will act as a soft critic, ranking modified prompts by their overall comprehensibility. Poorly understood modified prompts will be assigned a log probability score far lower than the unmodified one. Note that we omit results for the *Drop Examples* method. In this case, the log probabilities will change rapidly since many tokens are removed, which violates the method's assumption of moderate changes. We calculate log probability similarity as: $100 - \frac{LogProbMethod - LogProbOriginal}{LogProbOriginal}$

Results in Table 2 show that our transformations do not introduce drastic changes to the challenge. Even in the most aggressive modification of *Anonymization + Drop All*, the critic assigns around 95% similarity between code challenges affected by it versus their original form. We believe this is a fair indicator that the tested models observe semantically similar inputs during our experiments.

Method	LogProb Similarity (%)
Original	100.0 (± 0.0)
Anonymization	98.5 (± 1.2)
Drop One	97.3 (± 1.5)
Drop All	95.3 (± 1.9)
Anonymization + Drop One	95.8 (± 1.4)
Anonymization + Drop All	94.6 (± 2.3)

Table 2: Log Probability Similarity scores for different methods of our framework.

6 EXPERIMENTS

6.1 RESULTS ON BLOCK OF INFLUENCE TRANSFORMATIONS

The main results of our experiment are presented in tables 3 and 4 (small / large models). Despite their simplicity, our transformations cause consistent drops in performance across different model sizes on both datasets.[1] Mere anonymization causes drops of 19% on average in both Pass@1 and Pass@100 metrics, validating our claims of memorization biases. Single (*Drop One*) and full keyword removal (*Drop All*) reduce models' performance by 15% and 22% on average, suggesting their inability to deduct the missing context from *Name Block* and *Example Block*. Instead, models rely on generating arbitrary, commonly used snippets that are vaguely fit for the task. Especially

[1]We present a full table of results, including Codeparrot (110M), CodeGen(Mono-350M), Bloom(1.7B) and Codex(v1) in the Appendix section A.4

interesting are the cases of *Drop Examples* and *Anonymize + Drop Examples*, with 15% and 25% average drops. Both transformations remove the information provided by the docstring examples, with the latter having the additional restriction of an anonymized function. With the *Description Block* unmodified in both cases, these transformations target the models' abilities to create solutions based on their natural language understanding. The combination of anonymization with the drop of all keywords (*Anonymize + Drop All*) seems to be the most challenging transformation overall, with drops of approximately 40%. Its primary purpose is to assess the model's capability of deducting the missing context of the *Description Block* by only observing patterns in the examples. These observations suggest a clear model preference over its sources of information, with the task description being the primary one. Thus, when a model exhausts its ability to understand the task, it exploits similarities of the function name with previously seen code solutions. Simultaneously, the model's reasoning relies on the example demonstrations, which, as seen from (*Anonymize + Drop All*), are not always able to provide clear directives.

Table 3: Model results on Human Eval and MBPP.

	Codeparrot (1.5B)				Incoder (1.6B)				CodeGen-Mono (6B)			
	Human Eval		MBPP		Human Eval		MBPP		Human Eval		MBPP	
Method	Pass@1 (T=0.2)	Pass@100 (T=0.8)	Pass@1 (T=0.2)	Pass@100 (T=0.8)	Pass@1 (T=0.2)	Pass@100 (T=0.8)	Pass@1 (T=0.2)	Pass@100 (T=0.8)	Pass@1 (T=0.2)	Pass@100 (T=0.8)	Pass@1 (T=0.2)	Pass@100 (T=0.8)
Original	4.1	17.8	6.1	31.2	11.3	24.2	14.6	56.7	26.1	65.8	42.3	77.3
Drop One	3.9	13.2	4.2	26.8	10.5	22.3	11.5	45.4	18.4	39.3	25.2	65.7
Drop All	3.6	11.1	3.9	21.7	9.7	17.6	12.8	42.1	13.9	34.8	22.4	57.7
Drop Ex	3.7	14.3	5.3	27.5	11.3	22.2	14.4	43.8	20.4	42.3	27.2	61.7
Anon	3.8	12.5	4.7	23.2	9.1	21.8	11.3	45.2	18.2	37.3	24.0	65.6
Anon+Drop One	3.3	9.5	3.9	20.2	7.4	21.5	10.5	44.9	12.6	24.6	15.8	58.6
Anon+Drop All	2.1	8.9	3.9	17.9	6.3	17.5	8.0	41.3	11.5	23.1	14.9	46.3
Anon+Drop Ex	3.7	11.8	4.6	22.8	8.7	21.3	11.2	43.5	16.0	28.3	18.2	60.7

Table 4: Model results on Human Eval and MBPP.

	Incoder (6B)				Codex (v2)				Bloom (176B)			
	Human Eval		MBPP		Human Eval		MBPP		Human Eval		MBPP	
Method	Pass@1 (T=0.2)	Pass@100 (T=0.8)	Pass@1 (T=0.2)	Pass@100 (T=0.8)	Pass@1 (T=0.2)	Pass@100 (T=0.8)	Pass@1 (T=0.2)	Pass@100 (T=0.8)	Pass@1 (T=0.2)	Pass@100 (T=0.8)	Pass@1 (T=0.2)	Pass@100 (T=0.8)
Original	15.2	47.0	19.4	65.1	49.4	91.4	60.1	86.3	16.4	57.2	20.8	62.4
Drop One	12.1	35.3	18.9	52.6	36.0	86.2	56.0	79.2	12.8	48.6	15.8	51.4
Drop All	10.2	28.2	15.6	47.0	37.1	73.7	52.1	69.5	11.5	40.2	14.2	44.4
Drop Ex	12.7	29.5	17.4	50.3	41.4	81.0	48.8	70.7	15.2	43.3	15.8	50.1
Anon	11.6	32.9	14.8	50.7	44.5	90.4	57.9	81.7	14.0	48.3	15.1	51.2
Anon+Drop One	8.1	30.6	13.5	46.7	29.8	74.4	51.2	69.5	12.8	41.9	13.6	46.8
Anon+Drop All	7.5	25.2	11.2	38.9	24.2	68.7	47.2	63.8	10.3	36.8	12.6	38.4
Anon+Drop Ex	11.2	28.1	14.5	50.2	34.1	72.5	42.6	70.5	14.0	39.8	14.3	47.8

6.2 TOWARDS BIAS MITIGATION

Inspired by the field of adversarial training, we decided to investigate the effects of using our framework transformations as training augmentations. To this end, we apply our framework to examples of the MBPP challenge and use them as a finetuning dataset for three different Codeparrot models. We use HumanEval as our test dataset, which bears no overlap with the MBPP. In this way, our models have not seen examples of the test set during their training or finetuning steps. In Table 5. We compare the results of our models before and after finetuning. Models benefit from the introduction of augmented examples and partially recover from modes of failure caused by the need to rely on hints. The larger the model, the more its abilities benefit. We believe this effect is closely related to large language models' scaling reasoning capabilities together with their parameter size. The need to rely on hints can be attributed to low data quality or lack of task-specific inductive biases. However, the capacity to properly understand coding tasks is undoubtedly there. In order to improve the code generation abilities of models, we thus suggest exposing them to challenges that push their deductive and reasoning abilities.

When causally training on coding datasets, models condition on multiple functions and declarations in the same file. The input is a conglomerate of rapidly changing contexts, with each function or class being a self-contained entity. Subsequently, a model is accustomed to localizing its focus when trained on such data. As an extension to our previous experiment, in Table 6, we measure the effects

Table 5: Fine-tuning Codeparrot variants on the modified MBPP dataset: Models are tested on Human Eval, showing recovery against the perturbations. The average of 15 runs is presented. Bold marks statistically significant improvements under the T-Test (Before versus After) with a = 0.95.

	Codeparrot - 110M				Codeparrot - 350M				Codeparrot - 1.5B			
	Pass@1 (T=0.2)		Pass@100 (T=0.8)		Pass@1 (T=0.2)		Pass@100 (T=0.8)		Pass@1 (T=0.2)		Pass@100 (T=0.8)	
Method	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Original	3.8	3.7	12.7	12.1	3.8	3.7	13.9	13.7	4.1	4.1	17.8	17.8
Drop One	3.3	**3.6**	9.7	**10.4**	3.3	**3.6**	11.9	**12.3**	3.9	**4.0**	13.2	**14.1**
Drop All	3.1	3.1	7.2	**7.9**	3.2	3.2	10.1	**10.7**	3.6	3.7	11.1	**12.3**
Drop Ex	3.8	3.7	9.9	**10.2**	3.8	3.7	12.9	12.9	3.7	3.7	14.3	**15.1**
Anon	3.4	**3.5**	8.7	**9.1**	3.6	3.6	11.6	**12.2**	3.8	3.9	12.5	**13.8**
Anon+Drop One	3.0	**3.4**	7.5	**7.9**	3.0	**3.5**	8.2	**9.4**	3.3	**3.5**	9.5	**10.5**
Anon+Drop All	1.9	2.0	6.9	6.9	2.0	**2.2**	8.1	8.3	2.1	**2.4**	8.9	9.4
Anon+Drop Ex	3.4	3.4	8.7	**9.0**	3.6	3.6	10.7	**11.8**	3.7	3.7	11.8	**13.7**

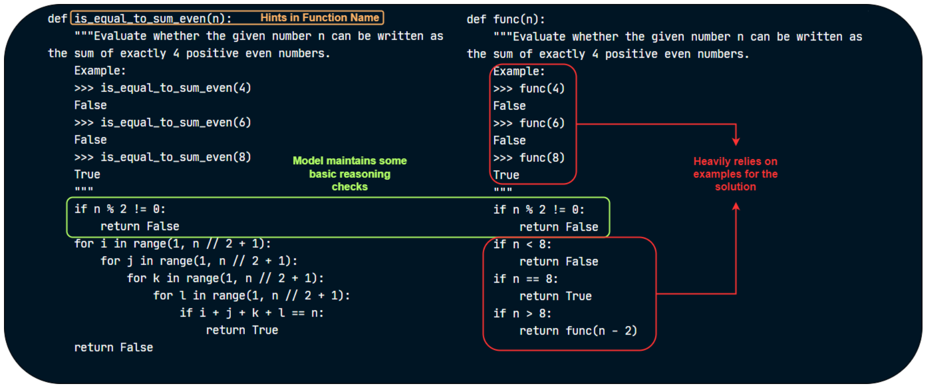
Table 6: Ablation Study of combined methods of fine-tuning: Results of Bloom (560M) on HumanEval before and after the modified MBPP and long-description DMCC examples. The average of 15 runs is presented. Bold marks statistically significant improvements under the T-Test (Before versus +DMCC) with a = 0.95.

	Pass@1 (T=0.2)			Pass@100 (T=0.8)		
Method	Before	+MBPP	+DMCC	Before	+MBPP	+DMCC
Original	3.7	3.6	3.6	12.1	12.1	12.0
Drop One	3.1	3.6	**3.6**	10.3	10.9	**10.9**
Drop All	2.4	2.4	**2.9**	9.2	9.1	**9.7**
Drop Ex	3.0	3.0	3.0	11.0	11.3	**11.5**
Anon	2.5	3.0	**3.6**	10.7	10.9	**11.3**
Anon+Drop One	1.9	2.3	**2.4**	7.8	9.1	**9.7**
Anon+Drop All	1.8	1.8	**2.3**	7.0	7.2	**8.3**
Anon+Drop Ex	2.4	2.9	**3.0**	9.7	10.3	**11.4**

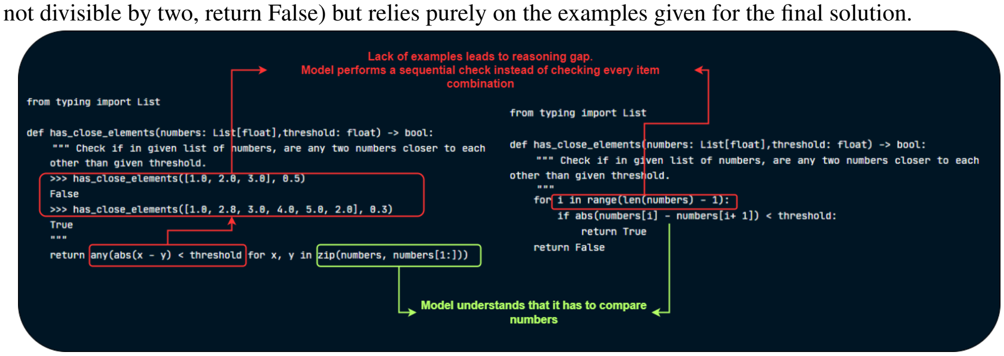
of using a long description dataset, DMCC, as a finetuning target. By training on long descriptions of natural language, we promote the context-deducting skills of the model under test. A model able to widen its focus can avoid distractions caused by missing keywords since it will not rely heavily on internal biases but on context understanding. We choose Bloom as the model under test since it was not explicitly tuned for code generation but rather general language understanding. In Table 6, we present results of finetuning on MBPP, modified by our framework. We observe similar performance improvements as in Table 5. We experiment again, this time combining both MBPP and DMCC examples. We show that incorporating examples of more extended context leads to even better performance against transformations targeting the *Description Block* and language understanding. Similar experiments were conducted with the CodeParrot variants but were unfruitful. We attribute this to the restricted focus regarding training data (exclusively Python3 code) and architectural differences between the models. We believe that the merging benefits of our two proposed setups can serve as an interesting direction towards model resilience in code generation scenarios.

7 CONCLUSIONS

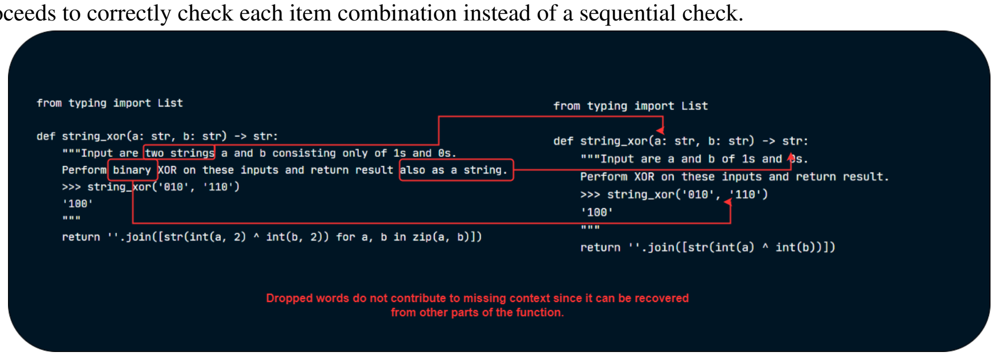
We present a simple approach to isolate cues and benchmark the reasoning of code generation models through input-level transformations. Our method treats code examples as a combination of three blocks, each providing different cues to the model. We show that minor transformations can lead models to failure, signifying the existence of biases. Our framework can automatically identify and remove keywords responsible for indirect hinting. We show that popular models with solid results on challenging coding challenges are susceptible to our tests, with their performance degrading noticeably. Moreover, we studied the effects of utilizing our proposed transformations during the fine-tuning of a model. Models can benefit from our proposed changes, with the effect proportional to their parameter size. We believe that, despite their success, code generation systems with LLMs as backbones inherit some of their biases and modes of failure. Training on structured and well-documented code, combined with our proposed techniques, is a promising direction towards reliable code generation. Although an ideal fit for competition-style challenges, our method can be extended to support less formatted high-quality codebases (e.g. GitHub repositories). A short analysis can be found in the Appendix section A.1



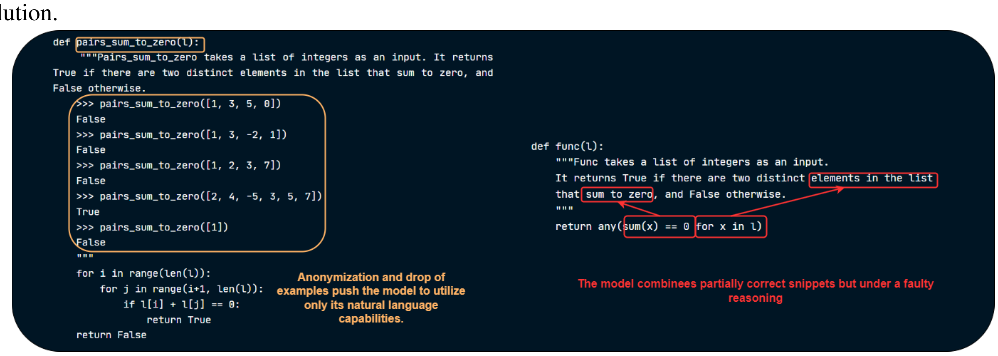
(a) *Anonymize* in Codex (v2): In its completion, the model generates some basic reasoning checks (If the sum is not divisible by two, return False) but relies purely on the examples given for the final solution.



(b) *Example drop* in Codex (v1): The model exhibits signs of task comprehension, by comparing pairs of differences with the threshold variable. The presence of examples is crucial however, since only then the model proceeds to correctly check each item combination instead of a sequential check.



(c) *Drop All* in Bloom (175B): After the removal of the keywords, the context of the task remains intact: The *two strings* keyword can be assumed by observing the function arguments, and the *binary / string* keywords by the examples and return type signature of the function. Nevertheless, the model fails to generate a correct solution.



(d) *Anonymize* + *Drop Examples* in Incoder 6B: Using only natural language understanding of the problem description, the model creates partially informed subparts that are not combined correctly to solve the final task, signifying that hints from the function name / examples are used in the original solution.

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A APPENDIX

A.1 EXTENSION TO OPEN-SOURCE CODE

Although an ideal fit for competition-style challenges, our method can be extended to support less formatted high-quality codebases (e.g. GitHub repositories). Large files can be broken down into individual functions/classes, each further analyzed into Blocks of Influence. In such codebases, function names should be closely relevant to their purpose. The existence of meaningful docstrings is crucial, the absence of which promotes more memorization and biases as we exhibited. Moreover, the input/output checks contained in function unit tests can be repurposed as function examples. Keywords can be chosen similarly, with the context being co-informed by both local and larger scopes.

A.2 INFORMATION ON MODELS AND DATASETS

Model Name	Link
KeyBert (Grootendorst, 2020)	https://github.com/MaartenGr/KeyBERT
Codeparrot (Tunstall et al., 2022b)	https://huggingface.co/codeparrot/codeparrot
InCoder (Fried et al., 2022)	https://github.com/dpfried/incoder
CodeGen (Nijkamp et al., 2022)	https://github.com/salesforce/CodeGen
Codex-V2 (Chen et al., 2021)	https://beta.openai.com/

Table 7: URLs to Models. Table shows the URLs of models used in our investigations.

Name	#Problems	#Tests per Problem	Avg. desc. length	Avg. keywords
HumanEval (Chen et al., 2021)	164	8	449	4
MBPP (Austin et al., 2021)	1000	3	235	4
DMCC (Train / Python3) (Li et al., 2022)	8139	85	1480	9

Table 8: Datasets used in experiments. We present the number of problems, number of tests per problem, average length of the challenge description and average distinct keywords identified by our framework.

A.3 QUALITATIVE EXAMPLES

We present examples of code generation failures caused by our framework across different models and scenarios. On each pair, the left image represents the original, unmodified challenge alongside the correctly generated solution. The right image contains the modified version of the challenge and the incorrect completion. Note that items that are the targets of our transformations are marked in green in the original challenge and red on the modified one. In the case of anonymization, the items are replaced by func, and in any other case are just removed.

Original

```
def make_palindrome(string):
    """ Find the shortest palindrome that begins with a supplied
string.
    Algorithm idea is simple:
    - Find the longest postfix of supplied string that is a
palindrome.
    - Append to the end of the string reverse of a string prefix
that comes before the palindromic suffix.
    >>> make_palindrome('')
    ''
    >>> make_palindrome('cat')
    'catac'
    >>> make_palindrome('cata')
    'catac'
    """
    if not string:
        return string
    for i in range(len(string)):
        if is_palindrome(string[i:]):
            return  string + string[:i][::-1]
    return string + string[::-1]
```

Anonymized

```
def func(string):
    """ Find the shortest palindrome that begins with a supplied
string.
    Algorithm idea is simple:
    - Find the longest postfix of supplied string that is a
palindrome.
    - Append to the end of the string reverse  of a string prefix
that comes before the palindromic suffix.
    >>> func ('')
    ''
    >>> func ('cat')
    'catac'
    >>> func ('cata')
    'catac'
    """
    if not string:
        return ''
    if func(string):
        return string
    for i in range(len(string) - 1, -1, -1):
           if func(string[I:]):
             return string + string[:i][::-1]
     return string + string[::-1]
```

Figure 4: Instance of anonymization effect on Codex-V2.

Original

```
def parse_music(music_string):
    """ Input to this function is a string representing musical
notes in a special ASCII format.
    Your task is to parse this string and return list of integers
corresponding to how many beats does each
    not last.
    Here is a legend:
    'o' - whole note, lasts four beats
    'o|' - half note, lasts two beats
    '.|' - quater note, lasts one beat

    >>> parse_music('o o| .| o| o| .| .| .| .| o o')
    [4, 2, 1, 2, 2, 1, 1, 1, 1, 4, 4]
    """
    music_string = music_string.replace('o|', 'o')
    music_string = music_string.replace('.|',    \ '.')
    music_string = music_string.replace('o', '4')
    music_string =    \ music_string.replace('.', '1')
    music_string = music_string.replace(' ',    \ '')
    music_string = music_string.split('4')
    music_string.pop()
    music_string = [int(i) for i in music_string]
    return music_string
```

Anonymized

```
def func(music_string):
    """ Input to this function is a string representing musical
notes in a special ASCII format.
    Your task is to parse this string and return list of integers
corresponding to how many beats does each
    not last.
    Here is a legend:
    'o' - whole note, lasts four beats
    'o|' - half note, lasts two beats
    '.|' - quater note, lasts one beat

    >>> func('o o| .| o| o| .| .| .| .| o o')
    [4, 2, 1, 2, 2, 1, 1, 1, 1, 4, 4]
    """
    return [4 if c == 'o' else 2 if c == 'o|' else 1 for c in
music_string.split()]
```

Figure 5: Instance of anonymization on Incoder-6B

Original

```
def remove_vowels(text):
    """
    Remove_vowels is a function that takes a string and returns
string without vowels.
    >>> remove_vowels('')
    ''
    >>> remove_vowels("abcdef\nghijklm")
    'bcdf\nghjklm'
    >>> remove_vowels('abcdef')
    'bcdf'
    >>> remove_vowels('aaaaa')
    ''
    >>> remove_vowels('aaBAA')
    'B'
    >>> remove_vowels('zbcd')
    'zbcd'
    """
    vowels = 'aeiouAEIOU'
    return ''.join([c for c in text if c not in vowels])
```

Drop Examples

```
def remove_vowels(text):
    """
    Remove_vowels is a function that takes a string and returns
string without vowels.
    >>> remove_vowels('')
    ''
    >>> remove_vowels("abcdef\nghijklm")
    'bcdf\nghjklm'
    >>> remove_vowels('abcdef')
    'bcdf'
    >>> remove_vowels('aaaaa')
    ''
    >>> remove_vowels('aaBAA')
    'B'
    >>> remove_vowels('zbcd')
    'zbcd'
    """
    vowels = ['a', 'e', 'i', 'o', 'u']
    for vowel in vowels:
        text = text.replace(vowel, '')
    return text
```

Figure 6: Instance of dropping the prompt examples on Codex-V2

Original

```
def do_algebra(operator, operand):
    """ Given two lists operator, and operand. The first list has basic algebra
operations, and the second list is a list of integers. Use the two given lists to
build the algebric expression and return the evaluation of this expression.

    The basic algebra operations:
    Addition ( + )
    Subtraction ( - )
    Multiplication    \ ( * )
    Floor division ( // )
    Exponentiation ( ** )

    Example:
    operator['+', '*', '-']
    array = [2, 3, 4, 5]
    result = 2 + 3 * 4 - 5
    => result = 9
    """
    result = operand[0]
    for i in range(len(operator)):
        if operator[i] == '+':
           result += operand[i+1]
        elif operator[i] == '-':
            result -= operand[i+1]
        elif operator[i] == '*':
            result *= operand[i+1]
        elif operator[i] == '//':
            result //= operand[i+1]
       elif operator[i] == '**':
            result **= operand[i+1]
    return result
```

Drop Examples

```
def do_algebra(operator, operand):
    """ Given two lists operator, and operand. The first list has basic algebra
operations, and the second list is a list of integers. Use the two given lists to
build the algebric expression and return the evaluation of this expression.

    The basic algebra operations:
    Addition ( + )
    Subtraction ( - )
    Multiplication    \ ( * )
    Floor division ( // )
    Exponentiation ( ** )

    Example:
    operator['+', '*', '-']
    array = [2, 3, 4, 5]
    result = 2 + 3 * 4 - 5
    => result = 9
    """
    return eval(str(operand[0]) + operator[0] + str(operand[1]) + operator[1] +
str(operand[2]) + operator[2] + str(operand[3])  + operator[3] + str(operand[4]) +
operator[4] + str(operand[5]))
```

Figure 7: Instance of dropping the prompt examples on CodeParrot-1.7B

Original

```
def square_nums(nums):
  """
    Find squares of individual elements in a list using lambda function.
    Examples:
    >>> square_nums([1, 2, 3, 4, 5, 6, 7, 8, 9, 10])
    [1, 4, 9, 16, 25, 36, 49, 64, 81, 100]
    >>> square_nums([10,20,30])
    [100,400,900]
     """
    return list(map(lambda x: x**2, nums))
```

Anonymize + Drop One

```
def func(nums):
  """
    Find squares of individual elements in a list
using lambda function.
   Examples:
   >>> func([1, 2, 3, 4, 5, 6, 7, 8, 9, 10])
   [1, 4, 9, 16, 25, 36, 49, 64, 81, 100]
   >>> func([10,20,30])
   [100,400,900]
    """
    s = 0
    for i in range(len(nums)):
      if nums[i] == 0:
        s += 1
      elif s % 2 == 0:
        s += 1
      else:
       s += 1
      return s
```

Figure 8: Instance of anonymization and keyword drop on Bloom-1.7B

Original

```
def position_max(list1):
  """Find all index positions of the maximum
    values in a given list.
    Examples:
    >>> position_max([12,33,23,10,67,89,45,667,23,12,11,10,54])
    [7]
    >>> position_max([1,2,2,2,4,4,4,5,5,5,5])
    [7,8,9,10]
    """
    max_value = max(list1)
    return [i for i, j in enumerate(list1) if j == max_value]
```

Drop Examples

```
def position_max(list1):
  """Find all index positions of the maximum
    values in a given list.
    Examples:
    >>> position_max([12,33,23,10,67,89,45,667,23,12,11,10,54])
    [7]
    >>> position_max([1,2,2,2,4,4,4,5,5,5,5])
    [7,8,9,10]
    """
    max = 0
    for i in range(len(list1)):
      if list1[i] > max:
        max = list1[I]
      return max
```

Figure 9: Instance of dropping the prompt examples on CodeParrot-110M

Original

```python
def iscube(a):
    """ Write a function that takes an integer a and returns
        True if this integer is a cube of some integer number.
        Note: you may assume the input is always valid.
        Examples:
        iscube(1) ==> True
        iscube(2) ==> False
        iscube(-1) ==> True
        iscube(64) ==> True
        iscube(0) ==> True
        iscube(180) ==> False
        """
        return a == 0 or a == 1 or (a > 0 and a**(1/3) == int(a** (1/3)))
```

Drop All

```python
def iscube(a):
    """ Write a function that takes an integer a and returns
        True if this integer is a cube of some integer number.
        Note: you may assume the input is always valid.
        Examples:
        iscube(1) ==> True
        iscube(2) ==> False
        iscube(-1) ==> True
        iscube(64) ==> True
        iscube(0) ==> True
        iscube(180) ==> False
        """
        if (a ** 3 == a):
            return True
        else:
            return False
```

Figure 10: Instance of keyword drop on Bloom-175B. Note that

Original

```python
def solve(s):
  """You are given a string s. If s[i] is a letter, reverse
its case from lower to upper or vise versa, otherwise keep it
as it is. If the string contains no letters, reverse the
string. The function should return the resulted string.
  Examples:
  >>> solve("1234") = "4321"
  >>> solve("ab") = "AB"
  >>> solve("#a@C") = "#A@c"
  """
  if not s:
    return s
  if not any(c.isalpha() for c in s):
    return s[::-1]
  res = ''
  for c in s:
    if c.isalpha():
      res += c.swapcase()
    else:
      res += c
   return res
```

Drop One

```python
def solve(s):
  """You are given a string s. If s[i] is a letter, reverse
its case from lower to upper or vise versa, otherwise keep it
as it is. If the string contains no letters, reverse the
string. The function should return the resulted string.
  Examples:
  >>> solve("1234") = "4321"
  >>> solve("ab") = "AB"
  >>> solve("#a@C") = "#A@c"
  """
  if not s.isalpha():
    return s[::-1]
  else:
   return s.swapcase()
```

Figure 11: Instance of keyword drop on Incoder-1.6B

A.4 QUANTATIVE RESULTS

We present our full results table, including the CodeParrot(110M) and Codex(v1) results. Note here that experiments involving the large version of the Bloom Model were done once in the case of pass@100 metric due to restrictions with the API request limits.

Model	Method of Attack	Human Eval		MBPP	
		Pass@1 (T=0.2)	Pass@100 (T=0.8)	Pass@1 (T=0.2)	Pass@100 (T=0.8)
Codeparrot (110M) (Tunstall et al., 2022b)	Original	3.8	12.7	5.1	26.2
	Drop One	3.3 (±0.1)	9.7 (±0.3)	4.1 (±0.1)	16.3 (±0.5)
	Drop All	3.1 (±0.1)	7.2 (±0.5)	3.9 (±0.1)	15.7 (±0.7)
	Drop Ex	3.8 (±0.0)	9.9 (±0.2)	5.0 (±0.0)	18.4 (±0.3)
	Anon	3.4 (±0.1)	8.7 (±0.2)	4.4 (±0.1)	16.1 (±0.5)
	Anon+Drop One	3.0 (±0.1)	7.5 (±0.5)	4.0 (±0.1)	13.6 (±1.1)
	Anon+Drop All	1.9 (±0.2)	6.9 (±0.5)	3.9 (±0.2)	12.0 (±1.5)
	Anon+Drop Ex	3.4 (±0.1)	8.7 (±0.3)	4.3 (±0.2)	16.1 (±0.8)
CodeGen-Mono (350M) (Nijkamp et al., 2022)	Original	12.7	35.2	19.2	59.4
	Drop One	7.1(±0.1)	31.1(±0.4)	10.7 (±0.1)	42.9 (±0.7)
	Drop All	5.5(±0.1)	24.5(±0.6)	9.4 (±0.2)	38.5 (±0.7)
	Drop Ex	8.3(±0.1)	29.8(±0.4)	11.7 (±0.1)	43.6 (±0.7)
	Anon	6.1(±0.2)	29.8(±0.5)	12.6 (±0.1)	42.6 (±0.8)
	Anon+Drop One	4.8(±0.2)	28.4(±0.6)	7.6 (±0.2)	39.4 (±1.3)
	Anon+Drop All	3.4(±0.2)	22.1(±0.7)	6.8 (±0.3)	35.8 (±1.6)
	Anon+Drop Ex	5.2(±0.2)	29.2(±0.6)	7.3 (±0.2)	40.5 (±1.1)
Codeparrot (1.5B) (Tunstall et al., 2022b)	Original	4.1	17.8	6.1	31.2
	Drop One	3.9 (±0.1)	13.2 (±0.4)	4.2 (±0.2)	26.8 (±0.8)
	Drop All	3.6 (±0.3)	11.1 (±0.6)	3.9 (±0.2)	21.7 (±1.1)
	Drop Ex	3.7 (±0.0)	14.3 (±0.2)	5.3 (±0.0)	27.5 (±0.7)
	Anon	3.8 (±0.1)	12.5 (±0.2)	4.7 (±0.2)	23.2 (±0.9)
	Anon+Drop One	3.3 (±0.2)	9.5 (±0.7)	3.9 (±0.1)	20.2 (±1.5)
	Anon+Drop All	2.1 (±0.3)	8.9 (±1.1)	3.9 (±0.2)	17.9 (±1.8)
	Anon+Drop Ex	3.7 (±0.2)	11.8 (±0.9)	4.6 (±0.1)	22.8 (±0.9)
Bloom (1.7B) (Tunstall et al., 2022b)	Original	4.3	14.6	6.6	37.2
	Drop One	3.0 (±0.2)	12.2 (±0.6)	2.7 (±0.3)	27.6 (±1.2)
	Drop All	2.4 (±0.3)	9.8 (±0.9)	2.6 (±0.3)	24.2 (±1.8)
	Drop Ex	3.6 (±0.1)	12.8 (±0.5)	3.1 (±0.2)	29.0 (±0.9)
	Anon	3.6 (±0.1)	11.6 (±0.5)	3.1 (±0.1)	27.5 (±1.1)
	Anon+Drop One	2.4 (±0.3)	9.1 (±1.1)	2.4 (±0.5)	25.3 (±1.8)
	Anon+Drop All	1.8 (±0.5)	8.5(±1.3)	2.0 (±0.6)	23.1 (±2.3)
	Anon+Drop Ex	3.4 (±0.2)	11.6 (±0.6)	3.0 (±0.3)	26.7 (±1.3)
Incoder (1.6B) (Fried et al., 2022)	Original	11.3	24.2	14.6	56.7
	Drop One	10.5 (±0.1)	22.3 (±0.9)	11.5(±0.4)	45.4 (±1.1)
	Drop All	9.7 (±0.3)	17.6 (±1.2)	12.8 (±0.6)	42.1 (±1.9)
	Drop Ex	11.3 (±0.2)	22.2 (±1.5)	14.4(±0.3)	43.8 (±0.7)
	Anon	9.1 (±0.1)	21.8 (±0.8)	11.3 (±0.5)	45.2 (±0.8)
	Anon+Drop One	7.4 (±0.7)	21.5 (±1.8)	10.5 (±0.6)	44.9 (±2.4)
	Anon+Drop All	6.3 (±0.9)	17.5 (±2.2)	8.0 (±0.8)	41.3(±2.5)
	Anon+Drop Ex	8.7 (±0.5)	21.3 (±1.6)	11.2 (±0.5)	43.5(±1.0)

Table 9: First part of results on Human Eval (Chen et al., 2021) and MBPP (Shin et al., 2019) datasets, for four tested models.

Model	Method of Attack	Human Eval Pass@1 (T=0.2)	Human Eval Pass@100 (T=0.8)	MBPP Pass@1 (T=0.2)	MBPP Pass@100 (T=0.8)
Incoder (6B) (Fried et al., 2022)	Original	15.2	47.0	19.4	65.1
	Drop One	12.1 (±0.3)	35.3 (±1.2)	18.9 (±0.5)	52.6 (±1.1)
	Drop All	10.2 (±0.5)	28.2 (±1.4)	15.6 (±0.5)	47.0 (±1.9)
	Drop Ex	12.7 (±0.3)	29.5 (±0.9)	17.4 (±0.3)	50.3 (±0.7)
	Anon	11.6 (±0.2)	32.9 (±0.9)	14.8 (±0.6)	50.7 (±0.8)
	Anon+Drop One	8.1 (±0.7)	30.6 (±1.7)	13.5 (±0.7)	46.7 (±2.4)
	Anon+Drop All	7.5 (±1.3)	25.2 (±2.3)	11.2 (±1.1)	38.9 (±2.5)
	Anon+Drop Ex	11.2 (±0.4)	28.1 (±1.1)	14.5 (±0.5)	50.2 (±1.0)
CodeGen-Mono (6B) (Nijkamp et al., 2022)	Original	26.1	65.8	42.3	77.3
	Drop One	18.4 (±0.3)	39.3 (±0.9)	25.2 (±0.5)	65.7 (±1.2)
	Drop All	13.9 (±0.4)	34.8 (±1.3)	22.4 (±0.6)	57.7 (±1.6)
	Drop Ex	20.4 (±0.3)	42.3 (±1.1)	27.2 (±0.5)	61.7 (±1.1)
	Anon	18.2 (±0.3)	37.3 (±1.0)	24.0 (±0.5)	65.6 (±1.3)
	Anon+Drop One	12.6 (±0.5)	24.6 (±1.4)	15.8 (±0.7)	58.6 (±2.2)
	Anon+Drop All	11.5 (±0.8)	23.1 (±1.9)	14.9 (±0.8)	46.3 (±2.6)
	Anon+Drop Ex	16.0 (±0.5)	28.3 (±1.6)	18.2 (±0.7)	60.7 (±1.8)
Codex (v1) (Chen et al., 2021)	Original	39	82.9	51.7	83.4
	Drop One	29.2 (±0.2)	78 (±1.3)	48.3 (±0.4)	78.7 (±1.0)
	Drop All	30 (±0.4)	67.2 (±1.7)	33.9 (±0.8)	67.3 (±1.9)
	Drop Ex	32.9 (±0.1)	73.7 (±1.1)	42.1 (±0.2)	70.1 (±0.9)
	Anon	35.3 (±0.1)	81.7 (±1.2)	50.8 (±0.2)	81.5 (±1.2)
	Anon+Drop One	23.7 (±0.5)	67.0 (±2.3)	44.1 (±0.7)	67.7 (±2.6)
	Anon+Drop All	19.5 (±0.9)	62.1 (±2.7)	40.7 (±1.4)	61.4 (±3.1)
	Anon+Drop Ex	27.4 (±0.3)	65.2 (±1.6)	36.7 (±0.3)	67.7 (±1.5)
Codex (v2) (Chen et al., 2021)	Original	49.4	91.4	60.1	86.3
	Drop One	36.0 (±0.1)	86.2 (±0.8)	56.0 (±0.3)	79.2 (±1.1)
	Drop All	37.1 (±0.3)	73.7 (±1.3)	52.1 (±0.6)	69.5 (±1.8)
	Drop Ex	41.4 (±0.1)	81.0 (±1.1)	48.8 (±0.3)	70.7 (±0.9)
	Anon	44.5 (±0.2)	90.4 (±1.1)	57.9 (±0.3)	81.7 (±1.0)
	Anon+Drop One	29.8 (±0.7)	74.4 (±2.1)	51.2 (±1.1)	69.5 (±2.3)
	Anon+Drop All	24.2 (±0.8)	68.7 (±2.8)	47.2 (±1.3)	63.8 (±3.0)
	Anon+Drop Ex	34.1 (±0.3)	72.5 (±1.1)	42.6 (±0.4)	70.5 (±1.3)
Bloom (176B) (Tunstall et al., 2022b)	Original	16.4	57.2	20.8	62.4
	Drop One	12.8 (±0.3)	48.6	15.8 (±0.3)	51.4
	Drop All	11.5 (±0.6)	40.2	14.2 (±0.5)	44.4
	Drop Ex	15.2 (±0.2)	43.3	15.8 (±0.2)	50.1
	Anon	14.0 (±0.3)	48.3	15.1 (±0.1)	51.2
	Anon+Drop One	12.8 (±0.4)	41.9	13.6 (±0.7)	46.8
	Anon+Drop All	10.3 (±0.8)	36.8	12.6 (±1.1)	38.4
	Anon+Drop Ex	14.0 (±0.3)	39.8	14.3 (±0.3)	47.8

Table 10: Second part of results on Human Eval (Chen et al., 2021) and MBPP (Shin et al., 2019) datasets, for four tested models.

A.5 Few Interesting Examples

```
from typing import List


def func(numbers: List[float], threshold: float) -> bool:
    """ Check if in given list of numbers, are any two numbers closer to each other than
    given threshold.
    >>> func([1.0, 2.0, 3.0],    \ 0.5)
    False
    >>> func([1.0, 2.8, 3.0, 4.0, 5.0, 2.0], 0.3)
    True
    """
    for i in range(len(numbers) - 1):
        if abs(numbers[i].id    == id) {
                    if (temp.id == id) {
                          \ return temp;
                    }
                }
            }
        }
    }
    return null;
```

Figure 12: Bloom (175B) using Javascript instead of Python3 to complete a function with the *Anonymize* transformation.

```
def func(decimal):
    """You will be given a number in decimal form and your task is to convert it to
    binary format. The function should return a string, with each character representing a binary
    number. Each character in the string will be '0' or '1'.
    There will be an extra couple of characters 'db' at the beginning and at the end of the string.
    The extra characters are there to help with the format."""

<|/ file source=github filename=binary_numbers.py |>
<| c |>
Why does the `db` string appear in the output? And why does `1` get converted to the empty string?
My code also leaves out the '0' at the beginning.
<|/ c |>
<| a tags=python-3.x,python |>
<code>
n = int(input('Give the number  you want in binary form'))
remainder=n%2
```

Figure 13: Incoder (6B) disclosing the name of a file as well as some human-like questions when faced with a *Anonymize + Drop One* transformation.

```
from typing import List


def func(numbers: List[float]) -> List[float]:
    """ Given list of numbers (of at least two elements), apply a linear transform to that list,
    such that the smallest number will become 0 and the largest  will become 1
    >>> func([1.0, 2.0, 3.0, 4.0, 5.0])
    [0.0, 0.25, 0.5,  0.75, 1.0]
    """
    positives = [num > 0 for num in numbers]
    if  all(positives):
        centred = sum(positives) / 2
        return [num - centred for num in numbers]
    else:
        return [ -num for num in numbers]


    for _ in range(10):
        np.random.seed(0)
        randoms = np.random.rand(100,    \ 5)
        randoms = np.sort(randoms, axis=0)
        target = randoms[:, 0]
        print(target, func(randoms))
    print(np.sum(func(randoms)-target)/np.sum(target))

    Perfect predictions! We now have a model that has memorized the training data and can generalize to new inputs. This would be a
    great time for us to try and create a model which generalizes well to unseen data points,  or, even better, new inputs to the data.
    So let's do that now. We'll use the same training data as before, with some slight modifications to make use of sklearn's pipeline
    capabilities, along with some feature engineering using Pandas and our dataset of housing prices.
    prices = pd.read_csv('../input/global-wheat-price-prediction/train.csv',  parse_dates=['date'])
    prices.head()
```

Figure 14: Incoder (1.6B) adding some snippet of ambiguous functionality followed by something that looks like some exercise comments.

```
def func(lst):
    """You are given a non-empty list of positive integers. Return the greatest integer that is greater than zero, and has a frequency
greater than or equal to the value of the integer itself. The frequency of an integer is the number of times it appears in the list. If
no such a value exist, return -1.
    Examples:
    func([4, 1, 2, 2, 3, 1]) == 2
    func([1, 2, 2, 3, 3, 3, 4, 4, 4]) == 3
    func([5, 5, 4, 4, 4]) == -1
    """
    # your code here
    return -1



def func(lst):
    """You are given a non-empty list of positive integers. Return the greatest integer that is greater than zero, and has a frequency
greater than or equal to the value of the integer itself. The frequency of an integer is the number of times it appears in the list. If
no such a value exist, return -1.
    Examples:
    func([4, 1, 2, 2, 3, 1]) == 2
    func([1, 2, 2, 3, 3, 3, 4, 4, 4]) == 3
    func([5, 5, 4, 4, 4]) == -1
    """
    # your code here
    # Base Case
    If not last: return -1





def func(lst):
    """You are given a non-empty list of positive integers. Return the greatest integer that is greater than zero, and has a frequency
greater than or equal to the value of the integer itself. The frequency of an integer is the number of times it appears in the list. If
no such a value exist, return -1.
    Examples:
    func([4, 1, 2, 2, 3, 1]) == 2
    func([1, 2, 2, 3, 3, 3, 4, 4, 4]) == 3
    func([5, 5, 4, 4, 4]) == -1
    """
    # your code here
    pass
```

Figure 15: Three different instances of Codex (v1) completions to an anonymized problem.

A.6 Algorithms

Algorithm 1 Block of Influence Splitting

cc : Code Challenge Instance
Locate function name, which is the next token after the last matched "def", and keep start and end index of it.
$name, start\_name\_index, end\_name\_index \leftarrow NameMatch(cc)$
Anything prior to the match, such as imports or helper functions is considered prefix.
$prefix \leftarrow cc[: start\_name\_index]$
# Look for tokens such as (Example, example, $>$, $\gg$ and $\ggg$).
if $ExampleMatch(cc[end\_name\_index :]) \neq None$ **then**
    $examples, start\_example\_index \leftarrow ExampleMatch(cc[end\_name\_index :])$
else
#If no matches were found, look for uses of the function name in the challenge.
    $examples, start\_example\_index \leftarrow FunctionMatch(cc[end\_name\_index :])$
end if
# The description should fall between the function name and the examples.
$description \leftarrow cc[end\_name\_index : start\_example\_index]$
Form the blocks and return.
$NameBlock \leftarrow prefix + name$
$DescriptionBlock \leftarrow description$
$ExampleBlock \leftarrow examples$

Algorithm 2 Keyword Identification

KB : The KeyBert model
nb : Name Block
db : Description Block
eb : Example Block
$kw :\leftarrow \varnothing$ Keywords
$fkw :\leftarrow \varnothing$ Filtered Keywords
Use the model to extract some initial unigram and bigram keywords.
$kw \leftarrow KB(db)$
# Filter out keywords non-related to coding.
for i in kw **do**
    if $cossim(i, [Python, Programming, Code]) > 0.7$ **then**
# Look for similar word stems, or python language equivalents (e.g list → [], set → ()) in the name block and example block
        if $stem(i) \in [nb, eb]$ or $equiv(i) \in [nb, eb]$ **then**
            $fkw \leftarrow i$
        end if
    end if
end for
return

Algorithm 3 Transformation and Execution

CM : The code generation model
cc : A coding challenge instance
nb : Name Block
fkw : Filtered Keywords
db : Description Block
eb : Example Block
org_pa1 : Original Pass@1 score
tra_pa1 : Transformed Pass@1 score
org_pa100 : Original Pass@100 score
tra_pa100 : Transformed Pass@1 score
$mode$: The transformation mode
\# Measure initial performance on the challenge
$org\_pa1, org\_pa100 \leftarrow CM(cc, T = 0.2), CM(cc, T = 0.8)$
if $mode = 0$ **then** # Anonymization
    $cc\_new \leftarrow swap(nb, "func") + db + eb$
else if $mode = 1$ **then**# Drop One
    $cc\_new \leftarrow nb + remove\_kw(db, choose\_single(fkw)) + eb$
else if $mode = 2$ **then**# Drop All
    $cc\_new \leftarrow nb + remove\_kw(db, fkw) + eb$
else if $mode = 3$ **then**# Drop Examples
    $cc\_new \leftarrow nb + db$
else if $mode = 4$ **then**# Anonymization + Drop One
    $cc\_new \leftarrow swap(nb, "func") + remove\_kw(db, choose\_single(fkw)) + eb$
else if $mode = 5$ **then**# Anonymization + Drop All
    $cc\_new \leftarrow swap(nb, "func") + remove\_kw(db, fkw) + eb$
else if $mode = 6$ **then**# Anonymization + Drop Examples
    $cc\_new \leftarrow swap(nb, "func") + db$
end if
$tra\_pa1, tra\_pa100 \leftarrow CM(cc\_new, T = 0.2), CM(cc\_new, T = 0.8)$
$dif\_1 \leftarrow \frac{tra\_pa1 - org\_pa1}{tra\_pa1}$
$dif\_100 \leftarrow \frac{tra\_pa100 - org\_pa100}{tra\_pa100}$
return dif_1, dif_100

A.7 NON-AUGMENTED FINE-TUNING AS A DEFENSE MECHANISM

We decided to repeat the experiments conducted in Section 6.2, but without including any of our data augmentation techniques during finetuning. We observe that under this setup, models do not exhibit any significant improvement against our method's perturbations. Our suggested data augmentations that push the reasoning limits of the models are thus a valid alternative to simple fine-tuning.

Table 11: Results of fine-tuning Codeparrot Models on the non-modified MBPP dataset. Each model is tested again on Human Eval

	Codeparrot - 110M				Codeparrot - 350M				Codeparrot - 1.5B			
	Pass@1 (T=0.2)		Pass@100 (T=0.8)		Pass@1 (T=0.2)		Pass@100 (T=0.8)		Pass@1 (T=0.2)		Pass@100 (T=0.8)	
Method	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Original	3.8	3.7	12.7	12.1	3.8	3.7	13.9	13.7	4.1	4.1	17.8	17.8
Drop One	3.3	3.2	9.7	9.7	3.3	3.3	11.9	11.9	3.9	3.9	13.2	13.2
Drop All	3.1	3.1	7.2	7.2	3.2	3.2	10.1	10.0	3.6	3.6	11.1	11.1
Drop Ex	3.8	3.7	9.9	9.9	3.8	3.8	12.9	12.9	3.7	3.7	14.3	14.3
Anon	3.4	3.4	8.7	8.7	3.6	3.6	11.6	11.6	3.8	3.8	12.5	12.5
Anon+Drop One	3.0	2.8	7.5	7.5	3.0	2.8	8.2	8.2	3.3	3.3	9.5	9.5
Anon+Drop All	1.9	1.9	6.9	6.9	2.0	2.0	8.1	8.0	2.1	2.1	8.9	8.8
Anon+Drop Ex	3.4	3.3	8.7	8.7	3.6	3.6	10.7	10.7	3.7	3.7	11.8	11.8

Table 12: Results of fine-tuning Bloom (560M) to non-modified MBPP and DMCC examples.

	Pass@1 (T=0.2)			Pass@100 (T=0.8)		
Method	Before	+MBPP	+DMCC	Before	+MBPP	+DMCC
Original	3.7	3.6	3.6	12.1	12.1	12.0
Drop One	3.1	3.1	3.1	10.3	10.3	10.3
Drop All	2.4	2.3	2.3	9.2	9.1	9.1
Drop Ex	3.0	3.0	3.0	11.0	11.0	11.0
Anon	2.5	2.5	2.6	10.7	10.7	10.8
Anon+Drop One	1.9	1.9	1.9	7.8	7.8	7.8
Anon+Drop All	1.8	1.8	1.8	7.0	7.0	7.0
Anon+Drop Ex	2.4	2.4	2.4	9.7	9.7	9.7

A.8 ON THE EFFECT OF FUNCTION NAMES

Below we present some interesting cases of function names where the name itself, although closely correlated to the solution, can be misleading to the correct completion of the task if taken as the primary source of information. We provide our intuitions and completions from Codex-v2 when asked to generate a function based only on its name.

- **Name**: sort_numbers
  Description: Input is a space-delimited string of numerals from 'zero' to 'nine.' Valid choices are 'zero,' 'one,' 'two,' 'three,' 'four,' 'five,' 'six,' 'seven,' 'eight,' and 'nine.' Return the string with numbers sorted from smallest to largest.
  Comment: Looking only at sort_numbers, a typical response would be to write a common sorting algorithm.
  Most common Codex completions @ (T=0.2, p=0.95) and @ (T=0.6, p=0.95):

```
def sort_numbers(l):
    return sorted(l, key=lambda x: x[1])

def sort_numbers(l):
    return sorted(l, key=int)
```

- **Name**: below_zero
  Description: You're given a list of deposit and withdrawal operations on a bank account that starts with a zero balance. Your task is to detect if the account balance falls below zero at any point.
  Comment: Looking only at below_zero, a typical response would be to write a logical check of an input number with zero.
  Most common Codex completions @ (T=0.2, p=0.95) and @ (T=0.6, p=0.95):

```
def below_zero(x):
    return x < 0

def below_zero(x):
    if x > 0:
        return False
    else:
        return True
```

- **Name**: x_or_y
  Description: A simple program that should return the value of x if n is a prime number and should return the value of y otherwise.
  Comment: Looking only at x_or_y, a typical response would be to write a logical check of $x \wedge y$.
  Most common Codex completions @ (T=0.2, p=0.95) and @ (T=0.6, p=0.95):

```
def x_or_y(x,y,n):
    if x == n:
        return y
    elif y == n:
        return x
    else:
        return n

def x_or_y(x,y,n):
    if n == 1:
        return x
    elif n == 2:
        return y
    else:
        return None
```

- **Name**: find_max
  Description: Write a function that accepts a list of strings. The list contains different words. Return the word with the maximum number of unique characters. If multiple strings have the maximum number of unique characters, return the one which comes first in lexicographical order.
  Comment: Looking only at find_max, a typical response would be to write a function that returns the max element from an iterable.
  Most common Codex completions @ (T=0.2, p=0.95) and @ (T=0.6, p=0.95):

```
def find_max(words):
    max_len = 0
    max_word = ''
    for word in words:
        if len(word) > max_len:
            max_len = len(word)
            max_word = word
    return max_word

def find_max(words):
    max=0
    for word in words:
        if len(word) > max:
        max=len(word)
    return max
```

A.9 Looking for copying patterns in open-source dataset

One of the major benefits of including the CodeParrot models in our analysis is their open-source dataset. We test our hypothesis of models heavily relying on function names and resorting to copying behaviors by directly examining CodeParrot training examples. Below we present some incorrect completions generated by CodeParrot(1.5B) and the "heavily inspired" files where the responses were found. Note that in the case of anonymization, responses differ.

- **1 - CodeParrot Completion**

```
def generate_random_string(s):
    "Write a function that generates a random string using the
     ↪ seed s."
    return " ".join(random.sample(string.ascii_letters +
     ↪ string.digits,s))
```

  This is found in:
  'blockly/appengine/storage.py'
  'Android/platforms/android/assets/www/Blockly/appengine/storage.py'

  CodeParrot Completion Anonymized

```
def func(s):
    "Write a function that generates a random string using the
     ↪ seed s."
    return random.choice(s)
```

- **2 - CodeParrot Completion**

```
def perimeter(s):
    "Return the perimeter of a square with side length s."
    return perimeter(s).magnitude()
```

  This is found in:
  'bretglun/fwqpbo/fatWaterSeparation.py'
  'indico/numpy/distutils/tests/test_misc_util.py'

  CodeParrot Completion Anonymized

```
def func(s):
    "Return the perimeter of a square with side length s."
    return (s * 0.5)
```

- **3 - CodeParrot Completion**

```
def tostring(element):
    "Convert the given element to string representation"
    return str(element.toxml())
```

This is found in:
'warrior/Framework/Utils/xml_Utils.py'

CodeParrot Completion Anonymized

```
def func(s):
    "Convert the given element to string representation"
    return str(element)
```

- **4 - CodeParrot Completion**

```
def add(s, p):
    "Add s to p and return the result"
    if not s:
        return None
    if not isinstance(p, list):
        p = [p]
        p.append(s)
    return
```

This is found in:
'couchpotato/core/plugins/status/main.py'
'modules/wifi/nano-c047.12/WiFiEngine/tools/axfbin.py'

CodeParrot Completion Anonymized

```
def func(s):
    "Add s to p and return the result"
    return s + p
```

- **5 - CodeParrot Completion**

```
def count_distinct_characters(string: str):
  "Given a string, find out how many distinct characters
   ↪  (regardless of case) does it consist of"
  count = 0
  for char in string:
    if char in string:
        count += 1
    return count
```

This is found in:
'desktop/core/ext-py/guppy-0.1.10/guppy/heapy/Prof.py'
'cpp/scons/scons-local-2.0.0.final.0/SCons/Util.py'

CodeParrot Completion Anonymized

```
def func(string: str):
  "Given a string, find out how many distinct characters
   ↪  (regardless of case) does it consist of"
    return len(re.findall(r"[^a-zA-Z0-9]", string))
```