Exploring Language Model's Code Generation Ability with Auxiliary Functions

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Abstract

Auxiliary function is a helpful component to improve language model's code generation ability. However, a systematic exploration of how they affect has yet to be done. In this work, we comprehensively evaluate the ability to utilize auxiliary functions encoded in recent code-pretrained language models. First, we construct a human-crafted evaluation set, called HumanExtension, which contains examples of two functions where one function assists the other. With HumanExtension, we design several experiments to examine their ability in a multifaceted way. Our evaluation processes enable a comprehensive understanding of including auxiliary functions in the prompt in terms of effectiveness and robustness. An additional implementation style analysis captures the models' various implementation patterns when they access the auxiliary function. Through this analysis, we discover the models' promising ability to utilize auxiliary functions including their self-improving behavior by implementing the two functions step-by-step. However, our analysis also reveals the model's underutilized behavior to call the auxiliary function, suggesting the future direction to enhance their implementation by eliciting the auxiliary function call ability encoded in the models. We release our code[1] and dataset[2] to facilitate this research direction.

```python
from typing import List


def has_close_elements(numbers: List[float], threshold: float) -> bool:
    """Check if in given list of numbers, are any two numbers
    closer to each other than given threshold.
    >>> has_close_elements([1.0, 2.0, 3.0], 0.5)
    False
    """
    for idx, elem in enumerate(numbers):
        for idx2, elem2 in enumerate(numbers):
            if idx != idx2:
                distance = abs(elem - elem2)
                if distance < threshold:
                    return True
    return False


def has_close_elements_in_array(array: List[List[float]], threshold: float) -> bool:
    """Check if in given array, are any two numbers closer
    to each other than given threshold.
    >>> has_close_elements_in_array([[1.0, 2.0, 3.0], [1.0, 2.0, 3.0]], 0.5)
    True
    """
    return has_close_elements(
      [item for sublist in array for item in sublist], threshold
    )
```

Figure 1: An illustrative example of HumanExtension. The function has_close_elements_in_array delegates their subroutine to the auxiliary function has_close_elements. Red bold text is the reference implementation written by humans.

1 Introduction

Program synthesis, i.e., writing function code by taking natural language descriptions as inputs, has garnered attention in the research community (Yin and Neubig, 2017; Rahit et al., 2020; Austin et al., 2021; Li et al., 2022). With the help of language modeling, several code-pretrained Large Language Models (LLMs) implement functions with prompts that contain target function signatures (Fried et al., 2023; Nijkamp et al., 2023b,a; Allal et al., 2023; Li et al., 2023; Gunasekar et al., 2023). Additional code components, e.g., comment lines (Gao et al., 2023), documents (Zhou et al., 2023c), and other function and class definitions across files (Ding et al., 2023), have been attached to the prompts to boost up their implementation ability.

Auxiliary function is one promising component to improve their code synthesis ability. We define the auxiliary function as a function that handles a subroutine for the target one or performs an easier version of the actual requirements. When this function is included in the prompt, LLMs could call the function to delegate their subroutine or refer to their implementation while synthesizing the target function. However, due to the lack of an evaluation dataset that enables a systematic examination of how these auxiliary functions are utilized, no structured analysis has yet to be conducted.

In this work, we investigate several LLMs' abil-

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[1]https://github.com/sh0416/humanextension
[2]https://huggingface.co/datasets/sh0416/humanextension

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ity to utilize auxiliary functions. To do this, we first construct an evaluation dataset, called HumanExtension, which contains human-crafted examples of two functions that are closely related to each other (Figure 1). Specifically, we guided labelers to extend functions in the HumanEval dataset (Chen et al., 2021). We offer software design concepts related to function extension such as subtyping (Liskov and Wing, 1994) to promote labelers to create realistic function relationships. Additionally, the curated examples are parsed into several components to enable robustness evaluation similar to Wang et al. (2023a).

With the HumanExtension dataset, we conduct systematic analyses to understand how LLMs leverage auxiliary functions. First, we investigate if appending a single auxiliary function to the prompt enhances the likelihood of accurately implementing the target function. Specifically, we design several prompts with auxiliary functions while considering their existence, their functional relevance, and the availability to access auxiliary function implementations. With these prompts, we generate implementations with LLMs and analyze the model behavior focusing on the auxiliary function's effectiveness, robustness, and the models' implementation style. Second, we examine the cases where LLMs can access multiple auxiliary functions for synthesizing target functions. The randomly sampled auxiliary functions are additionally included in the prompts to verify whether LLMs can selectively use the appropriate one. Similar to Liu et al. (2023b), we inspect whether the position of a relevant function affects their code generation ability. This investigation is combined with the implementation style analysis to permit an in-depth analysis through the lens of the auxiliary function call.

Our experimental results show current LLMs' capabilities to utilize auxiliary function and their limitations. First, most LLMs exhibit large performance improvement with proper relevant auxiliary functions. Also, for some advanced LLMs, our evaluation process sheds light on their self-improving behavior by implementing the two functions in a step-by-step manner. However, the ability to utilize auxiliary functions is varied depending on the factors that do not change their functionality, which raises a question about their robustness. In addition, our implementation style analysis results reveal that the models prefer repeating the internal logic in the auxiliary function even when the logic can be easily handled by simply calling them. Finally, our human preference evaluation of their style shows this disparity between model-generated implementation and that of humans, suggesting the future direction of enhancing the ability to delegate their subroutine to the auxiliary functions by calling them.

2 Related work

Several studies have been conducted to evaluate code generation ability (Xu et al., 2022). Neelakantan et al. (2016); Iyer et al. (2018) first introduce neural networks into code completion tasks and evaluate them on traditional metrics, e.g., BLEU. Chen et al. (2021) propose the HumanEval dataset and show LLMs can generate functionally correct implementations by introducing a functional correctness evaluation process. Concurrently, Austin et al. (2021) propose the MBPP dataset for Python basic programs and Hendrycks et al. (2021) release the APPS dataset related to coding contest problems. Consecutive studies have proposed datasets targeted for realistic purposes. Lai et al. (2023) focused on data science problems and Wang et al. (2023b) paid attention to realistic coding queries from StackOverflow and Yu et al. (2024) aimed at Python and Java code generation tasks from real-world open-source projects, and Babe et al. (2023) concentrated on beginning programmers. These work are combined and included in several coding benchmarks (Lu et al., 2021; Khan et al., 2023; Ni et al., 2023). For the metrics, Dong et al. (2023) propose CodeScore to estimate functional correctness and Zhou et al. (2023b) propose CodeBERTScore that utilizes BERTScore (Zhang et al., 2020).

There exists research work that extends the HumanEval dataset to support other features. Cassano et al. (2022); Zheng et al. (2023) extend the dataset to support multiple programming languages and Liu et al. (2023a) propose the HumanEval+ dataset that extends their test case to enable rigorous evaluation of functional correctness. Wang et al. (2023a) focused on prompt robustness by extending the HumanEval dataset. However, an evaluation procedure that enables systematic analysis of how LLMs leverage auxiliary functions has yet to be released in code generation tasks.

3 Dataset

We manually construct a variety of coding examples with corresponding auxiliary functions. To do this, we treat the Python examples in the HumanEval dataset as our base auxiliary functions and employ human experts to create an extended function for each example. We guide them to produce functions that have additional functionalities compared to the given functions. The following aspects are considered to remove the ambiguity inside the concept of extension and enhance their quality.

Extension type There exist two different types of extension, i.e., black-box extension and white-box extension. The black-box extension extends a function by calling the auxiliary function. It does not consider the internal mechanism of the auxiliary function. However, the white-box extension extends them by rewriting the improved internal mechanism. We allow any type of extension, but recommend the black-box one as calling the existing functions if possible is mostly better than rewriting the whole mechanism (Fowler, 2018).

Software engineering concept We show the Liskov-substitution principle and the concept of subtyping (Liskov and Wing, 1994) to the labelers. In doing so, we expect that the curated function could be treated as an extended version of the given function from the software engineering point of view.

Quality control We filtered out some examples in the HumanEval dataset that are not appropriate for using auxiliary functions. We removed the examples that provide the same functionality embedded in Python built-in functions, e.g., sum_to_n, as it already serves through the Python features. Also, the examples that are semantically duplicated with other examples are excluded from the final evaluation set. For example, if the two functions handle the same logic to process symbols but accept brackets or parentheses as their inputs, one of them is removed.

We collect 151 problems representing a function pair that one function extends the other and name it HumanExtension. Additionally, we mechanically parse these code snippets and create features for components for future usage.

4 Experiments

We comprehensively evaluate LLMs' ability to harness auxiliary functions using our HumanExtension dataset. To do this, we designed research questions as follows.

- **RQ1**: Could LLMs properly and robustly utilize different types of auxiliary functions?
- **RQ2**: How do LLMs' implementations vary when they access relevant auxiliary functions?
- **RQ3**: Do current training methodologies enhance the ability to utilize auxiliary functions?

We first examine the effectiveness and robustness of including a single auxiliary function in the prompt and extend this setting into multiple auxiliary functions. Also, we explore their implementation styles and analyze them based on human preference.

4.1 Single auxiliary function experiment

We measure the effectiveness of an auxiliary function in a code synthesis task by designing several prompts varying their existence and type. Currently, the prompt used in the existing work to solve the task is mainly composed of a target function signature with the corresponding import statements (Ben Allal et al., 2022; Cassano et al., 2022; Chen et al., 2021). We attached the auxiliary function signature and their implementation between the import statements and the target function signature to allow LLMs to access the knowledge about auxiliary functions. Our prompts with several types of auxiliary functions are described as follows.

- **No auxiliary function (Direct)**: Prompt consists of a target function signature without auxiliary functions. This setting acts as a baseline in our experiments.
- **Human-written irrelevant auxiliary function (Irrelevant)**: We attached an irrelevant auxiliary function written by humans in the prompt. We constructed an auxiliary function pool with the canonical solutions in the HumanEval dataset (Chen et al., 2021) and sampled an irrelevant function from the pool to construct the prompt.
- **Model-written relevant auxiliary function (Step-by-step)**: We utilize the relevant auxiliary function written by the model in the prompt. Concretely, LLMs first synthesize relevant auxiliary function and then it is attached to the prompt for implementing the target function. Note that

only a relevant auxiliary function signature without their implementation is additionally required for this setting. We utilize the auxiliary function signatures in the HumanEval dataset and the target one in our HumanExtension dataset.

- **Human-written relevant auxiliary function (Oracle)**: We provide a relevant auxiliary function written by humans to the model. The corresponding canonical solutions in the HumanEval dataset are used for human-written relevant auxiliary functions. We consider this setting as an oracle because these functions are currently the best in terms of quality and understandability.

The details about function signature, e.g., type annotation and docstring format, are consistent with the format curated in Cassano et al. (2022).

Language models We collect several LLMs pretrained on code described as follows.

- **Incoder** (Fried et al., 2023) is the early open-source decoder-only generative language model pretrained on public codes and StackOverflow questions and answers.
- **CodeGen** (Nijkamp et al., 2023b) is another open-source language model pretrained on public codes. We use two versions where "Multi" represents pre-training on multiple programming languages and "Mono" is additionally trained on Python codes from the "Multi" checkpoint.
- **BigCode** (Allal et al., 2023; Li et al., 2023) releases two checkpoints, i.e., SantaCoder and StarCoder, pretrained on public codes. They adopt various data-cleaning techniques to enhance the quality of the training corpus.
- **CodeLLaMA** (Rozière et al., 2023) is a variant of LLaMA2 (Touvron et al., 2023) additionally pretrained on code corpus. CodeLLaMAPython and CodeLLaMAInstruct are further trained on Python codes and instruction following datasets, respectively.

Decoding strategy We follow the decoding strategy for LLMs consistent with the existing benchmark (Ben Allal et al., 2022). We use nucleus sampling (Holtzman et al., 2020) with top-p 0.95 and low-temperature scaling, i.e., 0.2, focusing on the correctness of the generated implementation. The models generate at most 512 tokens for each prompt and stop generation when either end of sequence token or predefined stop sequences, i.e., "\ndef", "\nclass", "\nif", "\n#", are generated.

Evaluation criteria The implementations generated by the models are evaluated on functional correctness based on the corresponding test cases. Specifically, an implementation is regarded as functionally correct when it passes all the corresponding test cases. We use the widely used pass@1 metric indicating the proportion of functionally corrected implementations among generated implementations. To reduce the variance of the pass@1 metric, we generate eight implementations for each problem when estimating the model performance.

4.1.1 Performance analysis

We report the performances and the relative improvement compared with the one without auxiliary function in Table 1 and compare them to identify the effectiveness of different auxiliary functions.

Effects on human-written relevant auxiliary function Whole models exhibit remarkable improvement when they access the human-written relevant auxiliary functions (Table 1, Oracle). It implies that most LLMs could utilize the proper relevant auxiliary function. The improvement is observed even for the most recent competitive model, i.e., CodeLLaMAPython 34B, indicating assisting code synthesis with auxiliary function is still a valid approach even as the model size grows.

Effects on model-written relevant auxiliary function Considering the "Step-by-step" column in Table 1, the model-written relevant auxiliary functions contribute to the improvement for some advanced LLMs. CodeLLaMA series, StarCoder, CodeGenMono series, and Incoder 6B properly utilize the auxiliary function written by themselves. It suggests that the models can improve their codes if we provide a two-step plan in the form of function signatures. We attach one successful example that calls the generated auxiliary function during target implementation in Figure 2b. In this sense, this approach is similar to the Least-to-Most prompting (Zhou et al., 2023a) that solves target tasks with the model-generated answer of predefined subtasks.

Effects on human-written irrelevant auxiliary function We observe that providing an irrelevant auxiliary function brings meaningful improvement on few models. To investigate how these functions affect the target implementation, we qualitatively analyze the examples that CodeLLaMAPython 13B successfully generates under both settings, i.e., irrelevant and step-by-step. In Figure 2, we

Model	Direct	Irrelevant	Step-by-step	Oracle
Incoder 1B	0.0373	0.0472 (+26.7%)	0.0364 (-2.2%)	0.2028 (+444.4%)
Incoder 6B	0.0621	0.0762 (+22.7%)	0.0737 (+18.7%)	0.2856 (+360.0%)
CodeGenMulti 2B	0.0969	0.0894 (-7.7%)	0.0778 (-19.7%)	0.2856 (+194.9%)
CodeGenMulti 16B	0.1060	0.1134 (+7.0%)	0.1093 (+3.1%)	0.3568 (+236.7%)
CodeGenMono 2B	0.1068	0.1118 (+4.7%)	0.1366 (+27.9%)	0.3469 (+224.8%)
CodeGenMono 16B	0.1912	0.1912 (0.0%)	0.2127 (+11.3%)	0.4776 (+149.8%)
Santacoder 1B	0.1002	0.1010 (+0.8%)	0.0944 (-5.8%)	0.3104 (+209.9%)
Starcoder 16B	0.1937	0.2310 (+19.2%)	0.2848 (+47.0%)	0.5596 (+188.9%)
CodeLLaMA 7B	0.1738	0.2185 (+25.7%)	0.2219 (+27.6%)	0.5248 (+201.9%)
CodeLLaMA 13B	0.2359	0.2773 (+17.5%)	0.2773 (+17.5%)	0.5712 (+142.1%)
CodeLLaMA 34B	0.2748	0.3262 (+18.7%)	0.3750 (+36.4%)	0.6416 (+133.4%)
CodeLLaMAPython 7B	0.2583	0.2690 (+4.2%)	0.3237 (+25.3%)	0.5919 (+129.2%)
CodeLLaMAPython 13B	0.2657	0.3278 (+23.4%)	0.3957 (+48.9%)	0.5737 (+115.9%)
CodeLLaMAPython 34B	0.3179	0.3460 (+8.9%)	0.4296 (+35.2%)	0.6598 (+107.6%)
CodeLLaMAInstruct 7B	0.2955	0.3088 (+4.5%)	0.3526 (+19.3%)	0.4164 (+40.9%)
CodeLLaMAInstruct 13B	0.3874	0.3791 (-2.1%)	0.4172 (+7.7%)	0.5017 (+29.5%)
CodeLLaMAInstruct 34B	0.4222	0.4214 (-0.2%)	0.4255 (+0.8%)	0.5017 (+18.8%)

Table 1: The pass@1 performance on the HumanExtension dataset. The values in the parentheses represent the relative improvement with the Direct setting.

found that the irrelevant auxiliary function acts as a demonstration like few-shot prompting so that the few models exhibit performance improvement. However, since the given auxiliary function is not relevant to the target function (Figure 2a), no implementation pattern that directly utilizes the auxiliary function is found. On the contrary, the relevant auxiliary functions are successfully utilized by calling in the target function and reduce their implementation difficulty (Figure 2b). Therefore, we conclude there exists a unique advantage of providing relevant auxiliary function although the irrelevant one is helpful to some extent.

Effects on Python specialization We investigate how the additional training with Python corpus affects its ability to utilize auxiliary functions. To do this, we compare the two model families specialized in Python, i.e., CodeGenMono and CodeLLaMAPython. In these model groups, we observed higher pass rates compared to the corresponding base model groups, i.e., CodeGenMulti and CodeLLaMA. Comparing CodeGenMono 2B and CodeGenMulti 2B, the pass rate is similar when no auxiliary function is provided (Direct), but the pass rate of CodeGenMono becomes significantly higher than that of CodeGenMulti when we provide an appropriate auxiliary function (Oracle). Additionally, in the Step-by-step setting, CodeGenMono models show meaningful improvement while CodeGenMulti could not. In the case of CodeLLaMA, CodeLLaMAPython models show higher pass rates in the whole model size. From these experimental evidences, we conclude that additional learning with Python code enhances the ability to utilize auxiliary functions. We speculate that the Python codes used for training contain relevant functions in the same file and the model is trained to jointly consider the functions within the same context.

Effects on instruction tuning We also compare CodeLLaMAInstruct models to determine whether the instruction tuning affects the ability to harness auxiliary functions. In order to use an instruction-tuned model, instructions written in natural language and a prompt template are additionally required. To this end, we apply an approach similar to HumanEvalPack (Muennighoff et al., 2023), where the instructions are automatically generated from the original prompt. We combine these instructions with the CodeLLaMAInstruct template to create a prompt. The prompt is formulated into two consecutive turns where the first turn is about the auxiliary function and the second one is about generating the target function[3].

Our empirical results show that CodeLLaMAInstruct models perform better than CodeLLaMA

[3]Refer to the appendix for the detailed template structure.

```python
def how_many_times(string: str, substring: str) -> int:
    """ Find how many times a given substring can be found in
    the original string. Count overlaping cases.
    >>> how_many_times('aaa', 'a')
    3
    """
    times = 0
    for i in range(len(string) - len(substring) + 1):
        if string[i:i+len(substring)] == substring:
            times += 1
    return times


def change_base_extension(n: str, base_from: int, base_to: int) -> str:
    """Change numerical base of input number n represented as
    string from base_from to base_to. return string representation
    after the conversion. base numbers are less than 10.
    >>> change_base_extension('22', 3, 2)
    '1000'
    """
    # convert to decimal
    decimal = 0
    for i in range(len(n)):
        decimal += int(n[i]) * base_from ** (len(n) - 1 - i)
    # convert to new base
    new_base = ''
    while decimal > 0:
        new_base += str(decimal % base_to)
        decimal //= base_to
    return new_base[::-1]
```

(a) A passed case with irrelevant auxiliary function.

```python
def change_base(x: int, base: int) -> str:
    """Change numerical base of input number x to base.
    return string representation after the conversion.
    base numbers are less than 10.
    >>> change_base(8, 3)
    '22'
    """
    if x == 0:
        return '0'
    if x < 0:
        return '-' + change_base(-x, base)
    digits = []
    while x > 0:
        digits.append(str(x % base))
        x //= base
    return ''.join(digits[::-1])


def change_base_extension(n: str, base_from: int, base_to: int) -> str:
    """Change numerical base of input number n represented as
    string from base_from to base_to. return string representation
    after the conversion. base numbers are less than 10.
    >>> change_base_extension('22', 3, 2)
    '1000'
    """
    return change_base(int(n, base_from), base_to)
```

(b) A passed case with relevant auxiliary function.

Figure 2: The two types of generated implementations from CodeLLaMAPython 13B. Bold purple texts are generated by the model while the others are given. Some examples in the docstring are omitted for brevity.

models when implementing functions without auxiliary functions (Table 1, Direct), which is consistent with previous findings (Rozière et al., 2023). On the other hand, when an appropriate auxiliary function is provided in the prompt (Table 1, Oracle), the base models show better performance than the instruction-tuned models. In addition, the relative improvement in the Step-by-step settings has prominently decreased compared to that of the base models. This suggests that the ability to utilize other functions in the context has been weakened during the instruction tuning process. Therefore, it is necessary to develop an advanced instruction-tuning methodology to incorporate the previously implemented functions, which is our future work.

4.1.2 Robustness analysis

We check whether the model could properly use the given relevant auxiliary function after some components inside the function have been perturbed. We apply two perturbations: (1) replacing the name of the auxiliary function with other function names in the HumanEval dataset or (2) deleting the docstring included in the function. Note that the functionality of the auxiliary function itself does not change because we did not change the function implementation or its input/output format.

Results The experimental results show that even if the functionality of the function does not change,

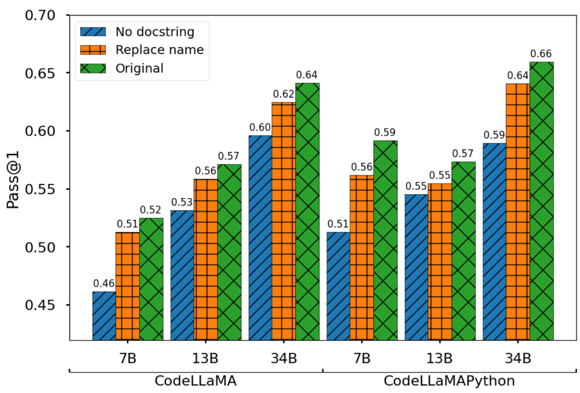


Figure 3: Robustness analysis on two perturbations, renaming auxiliary function and removing docstring.

a performance drop is observed depending on the name of the function or the existence of a docstring (Figure 3). The lack of a docstring had a greater impact than renaming the function, and it is natural in that the docstring contains a more detailed description of its functionality. Despite their usefulness, we want to highlight that LLMs have to understand the function without docstring for their realistic use cases as most practical codes do not include them.[4] The performance drop was not alleviated even when the model size was increased or the model was additionally trained with Python codes. Therefore, there is a need to propose a

[4]In `bigcode/the-stack-smol`, 70.5% of Python functions do not have docstring.

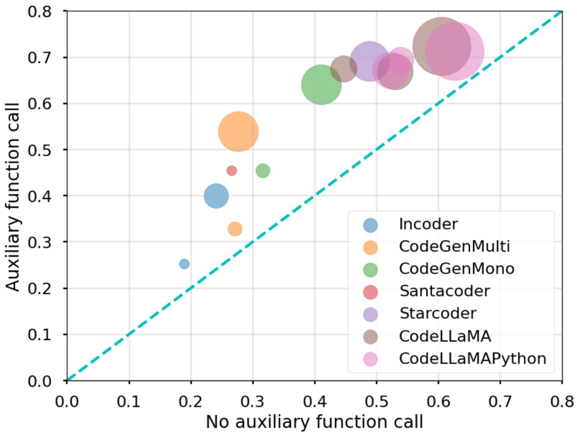


Figure 4: Pass@1 score comparison between black-box implementations (auxiliary function call) and white-box implementations (no auxiliary function call). The scale of dots represents their model size. Aqua dotted line indicates the performance on black-box and white-box implementations are the same.

robust learning methodology that can reduce performance differences caused by such perturbations.

4.1.3 Implementation style analysis

We analyze the generated implementation based on their style and compare preferences between them. In this experiment, we use the implementations generated under the Oracle setting. To identify their implementation style, we apply Python static parser[5] and check whether they called the given auxiliary function. The implementations that call the auxiliary function are regarded as black-box style while the rest as white-box style. The black-box style directly utilizes the auxiliary function as is, while the white-box style mimics the internal mechanism of the auxiliary function.

Results We compute pass@1 scores for each style and model (Figure 4). The results show that all models can implement functions in both styles. Also, we observed that the pass@1 score for the black-box style is higher than that of the white-box style. It implies that calling an auxiliary function is much safer and more accurate if the target function can be implemented by calling the auxiliary function. Currently, up to 40% of the model-generated implementations are implemented in black-box style, even though most examples can be implemented in black-box style.[6] Therefore, it is expected that the pass@1 score can be improved if more examples are implemented in black box style. Furthermore, we would like to emphasize that the improvement of the ability to generate black-box implementations is diminishing as language models evolve. This phenomenon suggests that model developers should consider the model's function call ability when learning their models.

[5] https://docs.python.org/3/library/ast

[6] 147 of 151 human-written reference solutions in the HumanExtension dataset are black-box style.

	Former Win	Tie	Latter Win
Human vs Black box	37.25	56.86	5.88
Human vs White box	88.24	1.96	9.80
Black box vs White box	84.31	5.88	9.80

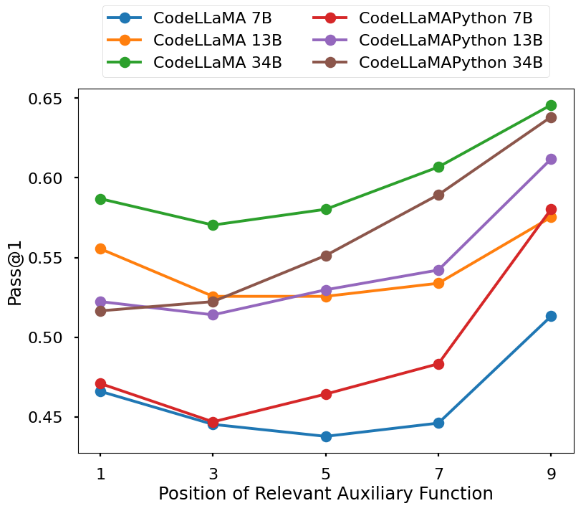
Table 2: Human pairwise preference evaluation results

Human evaluation Further investigating the two different styles, we conduct a human pairwise preference evaluation with human-written implementations (Human), and model-written ones with both styles (Black box and White box). We created a labeling sheet with 17 examples that CodeLLaMAPython 34B implements in both styles correctly. We recruited labelers who have been coding with Python for over five years. For the three possible pairs, labelers were instructed to choose the better implementations according to their preference such as performance or readability.

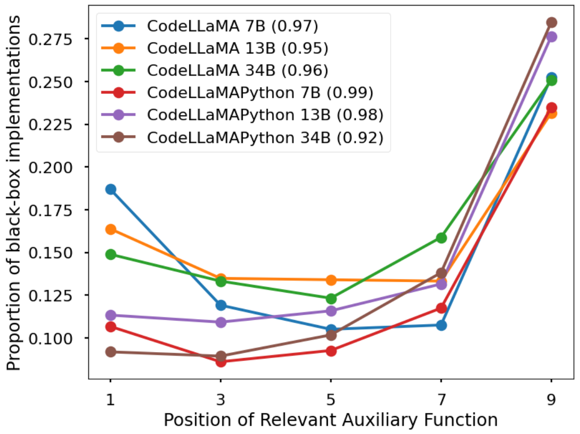
The evaluation results in Table 2 show that implementations that call auxiliary functions are preferred over implementations that do not. After inspecting the result qualitatively, we interpret that most black box implementations were selected due to their clarity and conciseness coming from appropriately delegating subroutines to auxiliary functions. Usually, the model-generated white-box implementations tend to repeat the identical mechanism inside the auxiliary function, which is not preferred in software engineering fields (Hunt and Thomas, 2000). In few cases, white-box implementations are preferred over black-box ones as they are considered as over-engineering. Therefore, training the models to delegate the subroutine to other functions suitably would be the next step for generating realistic code.

4.2 Multiple auxiliary function experiment

We provide several auxiliary functions in the prompt and study whether the model selectively utilizes the appropriate auxiliary function.



(a) Pass@1 scores depending on the position of relevant auxiliary function.



(b) Proportion of black-box style implementations among generated ones. The scores inside the parentheses are Pearson correlation scores between the proportion of black-box style implementations and the pass@1 scores.

Figure 5: Robustness analysis results with multiple auxiliary functions.

4.2.1 Experimental setup

We design a prompt with nine auxiliary functions followed by the target function signature. The functions consist of one relevant auxiliary function and the others are randomly sampled from the auxiliary function pool used in the Irrelevant setting. We change the location of the relevant function in the prompt and measure the pass@1 score and the proportion of black-box style implementations classified as the existence of auxiliary function call.

4.2.2 Result

The experimental results are shown in Figure 5 and we list up empirical findings we observed.

Performance trends We confirmed that CodeLLaMA models and CodeLLaMAPython models show different trends in terms of pass@1 scores (Figure 5a). For CodeLLaMA models, the pass@1 scores showed a U-shape trend, indicating that the performance improved when the related function was located at the first or the last. This result is consistent with the existing findings (Liu et al., 2023b) that, in natural language processing tasks, LLMs can effectively utilize relevant documents when they are located at the beginning or end. On the other hand, for CodeLLaMAPython models, this U-shape trend was weakened and the pass@1 score increased only when the relevant function was located at the end. We conjectured that the two related functions were usually located adjacently in Python codes and this pattern was learned by the model. However, since the location of relevant functions is independent of their functionality, LLMs need to be tuned to robustly utilize them regardless of where they are placed.

Correlation with black-box style implementations We found that there exists a strong correlation between the pass@1 score and the proportion of black-box style implementations. The Pearson correlation scores between the proportion and the pass rate (Figure 5b) are larger than 0.9, indicating that LLMs get higher scores when they try to call appropriate auxiliary functions. However, the black-box style implementations are mostly observed when the relevant auxiliary functions are located at the last, which provides an explanation of why the pass@1 score is higher when the relevant function is located at the last. For CodeLLaMA models, they can call the relevant function if they are located at the first, which causes the U-shape trend in pass@1 scores. Model scaling and additional training with Python codes provide a marginal effect on promoting a model to generate black-box style implementations, suggesting that specialized training for LLMs to call relevant functions similar to invoking general LLMs to use tools (Schick et al., 2023) is needed for enhancing their code synthesis ability.

5 Conclusion

We have explored the ability to utilize auxiliary functions encoded in the LLMs through our newly proposed HumanExtension dataset. The HumanExtension dataset is constructed to contain function relationships while considering the software engineering concepts. Our multi-faceted experiments with the HumanExtension dataset comprehensively show the current LLMs' ability to harness auxiliary functions. Our auxiliary function experiments demonstrate that the LLMs have the ability to utilize auxiliary functions even when the function is implemented by themselves. However, our in-depth analysis discovered that their ability varies depending on the factors that humans might not, i.e., the position of relevant functions, function name, and docstring. Furthermore, our implementation style analysis reveals that, in some cases, the LLMs repeat the mechanism of the given auxiliary function while humans simply call the auxiliary functions, suggesting the future research direction of current code LLMs for auxiliary function calls.

6 Limitations

Although the curated dataset in this study allowed us to evaluate the ability to utilize auxiliary functions from a variety of perspectives, it has some limitations in determining whether multiple relevant auxiliary functions can be jointly utilized. Additionally, our behavioral analyses indicate that the capabilities have been empirically observed, but it might be insufficient to conclude the model truly understands and utilizes the auxiliary function, so additional methods are required to reinforce the statement.

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References

Loubna Ben Allal, Raymond Li, Denis Kocetkov, Chenghao Mou, Christopher Akiki, Carlos Munoz Ferrandis, Niklas Muennighoff, Mayank Mishra, Alex Gu, Manan Dey, Logesh Kumar Umapathi, Carolyn Jane Anderson, Yangtian Zi, Joel Lamy Poirier, Hailey Schoelkopf, Sergey Troshin, Dmitry Abulkhanov, Manuel Romero, Michael Lappert, Francesco De Toni, Bernardo García del Río, Qian Liu, Shamik Bose, Urvashi Bhattacharyya, Terry Yue Zhuo, Ian Yu, Paulo Villegas, Marco Zocca, Sourab Mangrulkar, David Lansky, Huu Nguyen, Danish Contractor, Luis Villa, Jia Li, Dzmitry Bahdanau, Yacine Jernite, Sean Hughes, Daniel Fried, Arjun Guha, Harm de Vries, and Leandro von Werra. 2023. Santacoder: don't reach for the stars!

Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, and Charles Sutton. 2021. Program synthesis with large language models.

Hannah McLean Babe, Sydney Nguyen, Yangtian Zi, Arjun Guha, Molly Q Feldman, and Carolyn Jane Anderson. 2023. Studenteval: A benchmark of student-written prompts for large language models of code.

Loubna Ben Allal, Niklas Muennighoff, Logesh Kumar Umapathi, Ben Lipkin, and Leandro von Werra. 2022. A framework for the evaluation of code generation models. `https://github.com/bigcode-project/bigcode-evaluation-harness`.

Federico Cassano, John Gouwar, Daniel Nguyen, Sydney Nguyen, Luna Phipps-Costin, Donald Pinckney, Ming-Ho Yee, Yangtian Zi, Carolyn Jane Anderson, Molly Q Feldman, Arjun Guha, Michael Greenberg, and Abhinav Jangda. 2022. Multipl-e: A scalable and extensible approach to benchmarking neural code generation.

Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, Dave Cummings, Matthias Plappert, Fotios Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William Hebgen Guss, Alex Nichol, Alex Paino, Nikolas Tezak, Jie Tang, Igor Babuschkin, Suchir Balaji, Shantanu Jain, William Saunders, Christopher Hesse, Andrew N. Carr, Jan Leike, Josh Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. 2021. Evaluating large language models trained on code.

Yangruibo Ding, Zijian Wang, Wasi Uddin Ahmad, Murali Krishna Ramanathan, Ramesh Nallapati, Parminder Bhatia, Dan Roth, and Bing Xiang. 2023. Cocomic: Code completion by jointly modeling in-file and cross-file context.

Yihong Dong, Jiazheng Ding, Xue Jiang, Zhuo Li, Ge Li, and Zhi Jin. 2023. Codescore: Evaluating code generation by learning code execution.

Martin Fowler. 2018. *Refactoring*. Addison-Wesley Professional.

Daniel Fried, Armen Aghajanyan, Jessy Lin, Sida Wang, Eric Wallace, Freda Shi, Ruiqi Zhong, Scott Yih, Luke Zettlemoyer, and Mike Lewis. 2023. Incoder: A generative model for code infilling and synthesis. In *The Eleventh International Conference on Learning Representations*.

Luyu Gao, Aman Madaan, Shuyan Zhou, Uri Alon, Pengfei Liu, Yiming Yang, Jamie Callan, and Graham Neubig. 2023. Pal: Program-aided language models.

Suriya Gunasekar, Yi Zhang, Jyoti Aneja, Caio César Teodoro Mendes, Allie Del Giorno, Sivakanth Gopi, Mojan Javaheripi, Piero Kauffmann, Gustavo de Rosa, Olli Saarikivi, Adil Salim, Shital Shah, Harkirat Singh Behl, Xin Wang, Sébastien Bubeck, Ronen Eldan, Adam Tauman Kalai, Yin Tat Lee, and Yuanzhi Li. 2023. Textbooks are all you need.

Dan Hendrycks, Steven Basart, Saurav Kadavath, Mantas Mazeika, Akul Arora, Ethan Guo, Collin Burns, Samir Puranik, Horace He, Dawn Song, and Jacob Steinhardt. 2021. Measuring coding challenge competence with APPS. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*.

Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. 2020. The curious case of neural text degeneration. In *International Conference on Learning Representations*.

Andrew Hunt and David Thomas. 2000. *The Pragmatic Programmer: From Journeyman to Master*. Addison-Wesley Longman Publishing Co., Inc., USA.

Srinivasan Iyer, Ioannis Konstas, Alvin Cheung, and Luke Zettlemoyer. 2018. Mapping language to code in programmatic context. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1643–1652, Brussels, Belgium. Association for Computational Linguistics.

Mohammad Abdullah Matin Khan, M Saiful Bari, Xuan Long Do, Weishi Wang, Md Rizwan Parvez, and Shafiq Joty. 2023. xcodeeval: A large scale multilingual multitask benchmark for code understanding, generation, translation and retrieval.

Yuhang Lai, Chengxi Li, Yiming Wang, Tianyi Zhang, Ruiqi Zhong, Luke Zettlemoyer, Wen-tau Yih, Daniel Fried, Sida Wang, and Tao Yu. 2023. Ds-1000: A natural and reliable benchmark for data science code generation. In *International Conference on Machine Learning*, pages 18319–18345. PMLR.

Raymond Li, Loubna Ben Allal, Yangtian Zi, Niklas Muennighoff, Denis Kocetkov, Chenghao Mou, Marc Marone, Christopher Akiki, Jia Li, Jenny Chim, Qian Liu, Evgenii Zheltonozhskii, Terry Yue Zhuo, Thomas Wang, Olivier Dehaene, Mishig Davaadorj, Joel Lamy-Poirier, João Monteiro, Oleh Shliazhko, Nicolas Gontier, Nicholas Meade, Armel Zebaze, Ming-Ho Yee, Logesh Kumar Umapathi, Jian Zhu, Benjamin Lipkin, Muhtasham Oblokulov, Zhiruo Wang, Rudra Murthy, Jason Stillerman, Siva Sankalp Patel, Dmitry Abulkhanov, Marco Zocca, Manan Dey, Zhihan Zhang, Nour Fahmy, Urvashi Bhattacharyya, Wenhao Yu, Swayam Singh, Sasha Luccioni, Paulo Villegas, Maxim Kunakov, Fedor Zhdanov, Manuel Romero, Tony Lee, Nadav Timor, Jennifer Ding, Claire Schlesinger, Hailey Schoelkopf, Jan Ebert, Tri Dao, Mayank Mishra, Alex Gu, Jennifer Robinson, Carolyn Jane Anderson, Brendan Dolan-Gavitt, Danish Contractor, Siva Reddy, Daniel Fried, Dzmitry Bahdanau, Yacine Jernite, Carlos Muñoz Ferrandis, Sean Hughes, Thomas Wolf, Arjun Guha, Leandro von Werra, and Harm de Vries. 2023. Starcoder: may the source be with you!

Yujia Li, David Choi, Junyoung Chung, Nate Kushman, Julian Schrittwieser, Rémi Leblond, Tom Eccles, James Keeling, Felix Gimeno, Agustin Dal Lago, Thomas Hubert, Peter Choy, Cyprien de Masson d'Autume, Igor Babuschkin, Xinyun Chen, Po-Sen Huang, Johannes Welbl, Sven Gowal, Alexey Cherepanov, James Molloy, Daniel J. Mankowitz, Esme Sutherland Robson, Pushmeet Kohli, Nando de Freitas, Koray Kavukcuoglu, and Oriol Vinyals. 2022. Competition-level code generation with alphacode. *Science*, 378(6624):1092–1097.

Barbara H Liskov and Jeannette M Wing. 1994. A behavioral notion of subtyping. *ACM Transactions on Programming Languages and Systems (TOPLAS)*, 16(6):1811–1841.

Jiawei Liu, Chunqiu Steven Xia, Yuyao Wang, and LINGMING ZHANG. 2023a. Is your code generated by chatGPT really correct? rigorous evaluation of large language models for code generation. In *Thirty-seventh Conference on Neural Information Processing Systems*.

Nelson F. Liu, Kevin Lin, John Hewitt, Ashwin Paranjape, Michele Bevilacqua, Fabio Petroni, and Percy Liang. 2023b. Lost in the middle: How language models use long contexts.

Shuai Lu, Daya Guo, Shuo Ren, Junjie Huang, Alexey Svyatkovskiy, Ambrosio Blanco, Colin Clement, Dawn Drain, Daxin Jiang, Duyu Tang, Ge Li, Lidong Zhou, Linjun Shou, Long Zhou, Michele Tufano, MING GONG, Ming Zhou, Nan Duan, Neel Sundaresan, Shao Kun Deng, Shengyu Fu, and Shujie LIU. 2021. CodeXGLUE: A machine learning benchmark dataset for code understanding and generation. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 1)*.

Niklas Muennighoff, Qian Liu, Armel Zebaze, Qinkai Zheng, Binyuan Hui, Terry Yue Zhuo, Swayam Singh, Xiangru Tang, Leandro von Werra, and Shayne Longpre. 2023. Octopack: Instruction tuning code large language models.

Arvind Neelakantan, Quoc V Le, and Ilya Sutskever. 2016. Neural programmer: Inducing latent programs with gradient descent. In *International Conference on Learning Representations*.

Ansong Ni, Pengcheng Yin, Yilun Zhao, Martin Riddell, Troy Feng, Rui Shen, Stephen Yin, Ye Liu, Semih Yavuz, Caiming Xiong, Shafiq Joty, Yingbo Zhou, Dragomir Radev, and Arman Cohan. 2023. L2ceval: Evaluating language-to-code generation capabilities of large language models.

Erik Nijkamp, Hiroaki Hayashi, Caiming Xiong, Silvio Savarese, and Yingbo Zhou. 2023a. Codegen2: Lessons for training llms on programming and natural languages.

Erik Nijkamp, Bo Pang, Hiroaki Hayashi, Lifu Tu, Huan Wang, Yingbo Zhou, Silvio Savarese, and Caiming Xiong. 2023b. Codegen: An open large language model for code with multi-turn program synthesis. In *The Eleventh International Conference on Learning Representations*.

K. M. Tahsin Hassan Rahit, Rashidul Hasan Nabil, and Md Hasibul Huq. 2020. Machine translation from natural language to code using long-short term memory. In *Proceedings of the Future Technologies Conference (FTC) 2019*, pages 56–63, Cham. Springer International Publishing.

Baptiste Rozière, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Tal Remez, Jérémy Rapin, Artyom Kozhevnikov, Ivan Evtimov, Joanna Bitton, Manish Bhatt, Cristian Canton Ferrer, Aaron Grattafiori, Wenhan Xiong, Alexandre Défossez, Jade Copet, Faisal Azhar, Hugo Touvron, Louis Martin, Nicolas Usunier, Thomas Scialom, and Gabriel Synnaeve. 2023. Code llama: Open foundation models for code.

Timo Schick, Jane Dwivedi-Yu, Roberto Dessi, Roberta Raileanu, Maria Lomeli, Eric Hambro, Luke Zettlemoyer, Nicola Cancedda, and Thomas Scialom. 2023. Toolformer: Language models can teach themselves to use tools. In *Thirty-seventh Conference on Neural Information Processing Systems*.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023. Llama 2: Open foundation and fine-tuned chat models.

Shiqi Wang, Zheng Li, Haifeng Qian, Chenghao Yang, Zijian Wang, Mingyue Shang, Varun Kumar, Samson Tan, Baishakhi Ray, Parminder Bhatia, Ramesh Nallapati, Murali Krishna Ramanathan, Dan Roth, and Bing Xiang. 2023a. ReCode: Robustness evaluation of code generation models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 13818–13843, Toronto, Canada. Association for Computational Linguistics.

Zhiruo Wang, Shuyan Zhou, Daniel Fried, and Graham Neubig. 2023b. Execution-based evaluation for open-domain code generation. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 1271–1290, Singapore. Association for Computational Linguistics.

Frank F. Xu, Uri Alon, Graham Neubig, and Vincent Josua Hellendoorn. 2022. A systematic evaluation of large language models of code. In *Proceedings of the 6th ACM SIGPLAN International Symposium on Machine Programming*, MAPS 2022, page 1–10, New York, NY, USA. Association for Computing Machinery.

Pengcheng Yin and Graham Neubig. 2017. A syntactic neural model for general-purpose code generation. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 440–450, Vancouver, Canada. Association for Computational Linguistics.

H. Yu, B. Shen, D. Ran, J. Zhang, Q. Zhang, Y. Ma, G. Liang, Y. Li, Q. Wang, and T. Xie. 2024. Codereval: A benchmark of pragmatic code generation with generative pre-trained models. In *2024 IEEE/ACM 46th International Conference on Software Engineering (ICSE)*, pages 417–428, Los Alamitos, CA, USA. IEEE Computer Society.

Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. 2020. Bertscore: Evaluating text generation with bert. In *International Conference on Learning Representations*.

Qinkai Zheng, Xiao Xia, Xu Zou, Yuxiao Dong, Shan Wang, Yufei Xue, Lei Shen, Zihan Wang, Andi Wang, Yang Li, Teng Su, Zhilin Yang, and Jie Tang. 2023. Codegeex: A pre-trained model for code generation with multilingual benchmarking on humaneval-x. In

Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, KDD '23, page 5673–5684, New York, NY, USA. Association for Computing Machinery.

Denny Zhou, Nathanael Schärli, Le Hou, Jason Wei, Nathan Scales, Xuezhi Wang, Dale Schuurmans, Claire Cui, Olivier Bousquet, Quoc V Le, and Ed H. Chi. 2023a. Least-to-most prompting enables complex reasoning in large language models. In *The Eleventh International Conference on Learning Representations*.

Shuyan Zhou, Uri Alon, Sumit Agarwal, and Graham Neubig. 2023b. CodeBERTScore: Evaluating code generation with pretrained models of code. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 13921–13937, Singapore. Association for Computational Linguistics.

Shuyan Zhou, Uri Alon, Frank F. Xu, Zhengbao Jiang, and Graham Neubig. 2023c. Docprompting: Generating code by retrieving the docs. In *The Eleventh International Conference on Learning Representations*.

A Appendix

A.1 HumanExtension dataset card

A.1.1 License & Intended use

We built our dataset with HumanEval dataset distributed under the MIT license.[7] The license allows us to modify HumanEval dataset and distribute our new HumanExtension dataset even though the intended use of HumanEval dataset is model evaluation without changing their content. We plan to release this dataset under the same MIT license.

A.1.2 Potential risk

According to the HumanEval dataset card, no personal and sensitive information was contained in the dataset and we confirmed it by inspecting whole problems. We also conducted a thorough inspection of the newly crafted extended functions and verify that there was no personally identifiable or sensitive information.

A.1.3 Description

This dataset contains Python code snippets that contain target functions and the corresponding auxiliary functions that can assist in their implementation. Additionally, components extracted from abstract syntax parser, e.g., function name and docstring, are included. The primary use of this dataset is to measure the performance change of generating code depending on the existance of auxiliary functions inside the prompt. This dataset contains 151 test examples.

A.1.4 Instruction for crafting problem

The instruction used for crafting extended functions is as follow.

Dear labelers.

Thanks for participating our job about crafting new Python functions. Your task is to design a extended function of the given functions by calling the given function or improving their internal mechanism. There is no constraint about the way for the function extension, but we recommend to read the attached materials [8][9] about the function extension in software engineering fields. You can pass the examples if you think the function is not appropriate for some reasons, e.g., too specific or too general.

We assumes no responsibility or liability for any potential risk in the labeling process. The information for the creation task is provided on an "as is" basis with no guarantees of completeness, accuracy, usefulness or timeliness.

Sincerely.

A.2 CodeLLaMAInstruct prompt template

We follow the template released in their offical github repository [10]. We terminate generation early when eos token or [/PYTHON] is generated. The following text is the template for generating target function with auxiliary function.

```
<s>[INST] Write a Python function
`{auxiliary_function_name}` to
solve the following problem:
{auxiliary_function_docstring}
Your code should start with a
[PYTHON] tag and end with a
[/PYTHON] tag.
[/INST]
[PYTHON]
{auxiliary_function_code}
[/PYTHON]
</s><s>[INST] Write a Python
function `{target_function_name}`
to solve the following problem:
```

[7] https://huggingface.co/datasets/openai_humaneval

[8] https://en.wikipedia.org/wiki/Subtyping

[9] https://en.wikipedia.org/wiki/Liskov_substitution_principle

[10] https://github.com/facebookresearch/codellama

Statistics	Value
Number of examples	151
Number of testcases per examples	3.45
Auxiliary function character length per examples (signature only)	457.05
Auxiliary function character length per examples	638.97
Target function character length per examples (signature only)	443.19
Target function character length per examples	536.44

Table 3: Dataset statistics

```
{target_function_docstring}
 Your code should start with a
 [PYTHON] tag and end with a
 [/PYTHON] tag.
 You can use the above function
 whenever you needed.
 [/INST]
 [PYTHON]
{target_function_signature}
```