


LEARNING CODE PREFERENCE VIA SYNTHETIC EVOLUTION


Jiawei Liu^{1†}
Xiaopeng Li²

Thanh Nguyen²
Yu Yu²

Mingyue Shang²
Varun Kumar²

Hantian Ding²
Zijian Wang²

 University of Illinois Urbana-Champaign¹
jiawei6@illinois.edu

 AWS AI Labs²
{mzthanh, kuvrun, zijwan}@amazon.com

ABSTRACT

Large Language Models (LLMs) have recently demonstrated remarkable coding capabilities. However, assessing code generation based on well-formed properties and aligning it with developer preferences remains challenging. In this paper, we explore two key questions under the new challenge of code preference learning: (i) How do we train models to predict meaningful preferences for code? and (ii) How do human and LLM preferences align with verifiable code properties and developer code tastes? To this end, we propose CODEFAVOR, a framework for training pairwise code preference models from synthetic evolution data, including code commits and code critiques. To evaluate code preferences, we introduce CODEPREFBENCH, a benchmark comprising 1364 rigorously curated code preference tasks to cover three verifiable properties—correctness, efficiency, and security—along with human preference. Our evaluation shows that CODEFAVOR holistically improves the accuracy of model-based code preferences by up to 28.8%. Meanwhile, CODEFAVOR models can match the performance of models with $6 \sim 9 \times$ more parameters while being $34 \times$ more cost-effective. We also rigorously validate the design choices in CODEFAVOR via a comprehensive set of controlled experiments. Furthermore, we discover the prohibitive costs and limitations of human-based code preference: despite spending 23.4 person-minutes on each task, $15.1 \sim 40.3\%$ of tasks remain unsolved. Compared to model-based preference, human preference tends to be more accurate under the objective of code correctness, while being sub-optimal for non-functional objectives.

1 INTRODUCTION

Large Language Models (LLMs) for code (Chen et al., 2021; GitHub, 2023; Amazon Web Services, 2023) have become instrumental in modern software development. Code LLMs assist developers in various scenarios, from suggesting code completions and generating functional code based on user instructions to proposing complex code changes to resolve bug reports and feature requests.

Instruction-tuned LLMs (Luo et al., 2024; Wei et al., 2024) are increasingly adept at generating functional code based on natural language instructions. However, evaluating the quality of LLM-generated code remains challenging, particularly regarding code correctness, efficiency, security, adherence to best practices, and alignment with developer preferences. Effectively and efficiently assessing LLM-generated code against these properties is crucial for both evaluation (Liu et al., 2023b) and preference optimization for code LLMs (Weyssow et al., 2024). Nevertheless, the subject of learning code preferences has been largely under-explored, motivating us to study code preferences systematically and train code preference models with new data and modeling methods.

Following the established format in LLM-as-a-judge (Chiang et al., 2024), we define the code preference task as follows: Given a user query, a pair of two candidate code responses, and optionally a preference criterion, code preference is demonstrated by choosing one response over the other. Specifically, current approaches estimate code preference based on three proxies, each with advantages and limitations:

- **Code execution:** Code preference in another way can be confidently determined by execution statuses (Liu et al., 2023a). However, applying code execution to arbitrary programs poses challenges due to (i) setup complexity, (ii) code incompleteness, and (iii) execution overhead. For instance,

[†]Work done during a research internship at AWS AI Labs.

code execution may necessitate specific hardware (*e.g.*, GPUs) and precise software versions, which are challenging to deduce from the code and, even if inferred, are too cumbersome to set up and run.

- **Human annotation:** Human-labeled preferences are often seen as the standard oracle in developing LLMs, such as in the RLHF for OpenAI’s GPT models (Ouyang et al., 2022) and LLM evaluation in Chatbot Arena (Chiang et al., 2024). However, applying human labeling to code is particularly challenging and cost-intensive. Programs are inherently abstract and complex, labeling them requires experienced developers to perform detailed analysis and testing. Meanwhile, human preference is inherently subjective, influenced by the annotators’ code tastes and expertise, which can cause noisy preferences for code, whose quality could otherwise be concretely defined and measured.
- **LLM-as-a-judge:** Prominent LLMs have also been employed to evaluate LLM responses (Chiang et al., 2024; Zheng et al., 2023; McAleese et al., 2024). This method is more scalable than human labeling and can be generalized to a wider range of programs compared to code execution. However, its reliability often hinges on the reasoning capabilities of high-cost proprietary LLM judges (Weyssow et al., 2024), subject to inherent biases (Zheng et al., 2023).

While scaling human- and execution-based preference for code is human-resource- and engineering-challenging¹, improving model-based code preference becomes emerging and crucial, beyond directly prompting off-the-shelf models (Weyssow et al., 2024). Furthermore, how exactly human developers and prominent LLMs determine code preference remains obscure, with little research on quantifying or analyzing their performance across various code criteria. To this end, this work attempts to explore two critical questions in code preference learning:

1. **Technical question:** How can we build effective and efficient code preference models regarding modeling approaches and data sources?
2. **Empirical question:** What are the preferences of human annotators and LLMs, and to what extent do they align with verifiable code properties and human judgments?

CODEFAVOR. We propose CODEFAVOR, a novel framework for training code preference models. Specifically, CODEFAVOR employs pairwise modeling to predict preference within a code pair according to a user-specified criterion. We propose two synthetic data generation methods to construct preference ranking samples from code evolution: (i) *Commit-Instruct* transforms the pre- and post-commit code snippets to code preference pairs; and (ii) *Critic-Evol* samples faulty code from a draft LLM and has another critic LLM to improve the broken code. These methods allow us to curate synthetic preference data efficiently, leveraging the natural evolution of code and the capabilities of existing LLMs.

CODEPREFBENCH. To evaluate code preferences labeled by various approaches, we introduce CODEPREFBENCH, a collection of 1,364 carefully curated preference tasks. These tasks target verifiable properties including correctness, efficiency, and security, while additionally considering general developer preferences. Using CODEPREFBENCH, we extensively analyze the effectiveness and cost of code preferences derived from developer agreement, general LLMs, and CODEFAVOR models. Our study demystifies key insights on the pitfalls of different approaches over different coding criteria. Our results also demonstrate that our models not only achieve top performance in effectiveness but also are significantly more cost-efficient compared to existing solutions.

We summarize our main contributions below:

1. **Dimension & Technique:** We propose CODEFAVOR, the *first* open recipe to train pairwise code preference models. At the heart of CODEFAVOR is a pairwise modeling design and two complementary methods for generating synthetic preference pairs from code evolution.
2. **Benchmark & Code:** We present CODEPREFBENCH, the *first* comprehensive developer preference benchmark with 1,364 labeled by three verifiable oracles (correctness, efficiency, security) and general developer preferences from 18 annotators. We release the data and code at <https://github.com/amazon-science/llm-code-preference>.
3. **Study & Results:** Based on CODEPREFBENCH, we comprehensively quantify and conduct case studies on code preferences derived from human developers and LLMs. We show that CODEFAVOR can significantly improve the accuracy of model-based preference by up to 28.8%. CODEFAVOR models can match the preference accuracy of models that are larger by $6 \sim 9\times$, while being cheaper by $34\times$. We also conduct extensive controlled experiments to validate our design choices.

¹Such as hiring more annotators with domain expertise and setting up individual execution environments.

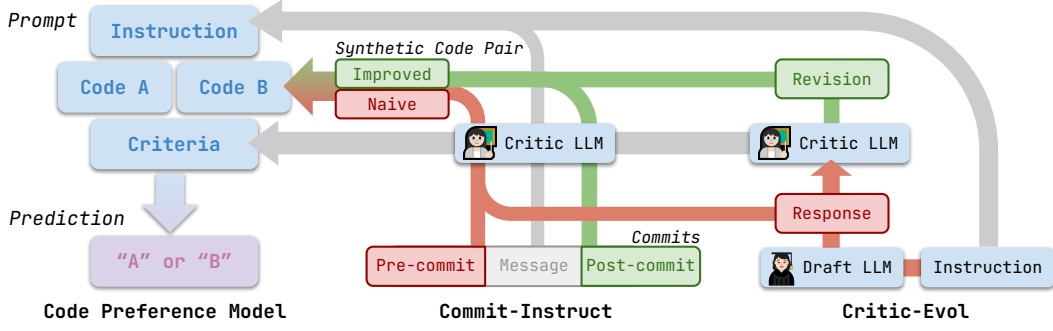


Figure 1: Approach overview of CODEFAVOR. We train a pairwise preference model using synthetic data created from two complementary sources of code evolution: *Commit-Instruct* and *Critic-Evol*.

2 CODEFAVOR: LEARNING CODE PREFERENCE VIA SYNTHETIC EVOLUTION

Figure 1 depicts the approach overview. Our framework, CODEFAVOR, is designed for training pairwise models that predict code preference by taking an instruction, a code pair, and a criterion as input.

Additionally, CODEFAVOR proposes two synthetic data generation methods, *Commit-Instruct* and *Critic-Evol*, for extracting synthetic training data from code evolution. Specifically, *Commit-Instruct* creates contrasting code pairs through rephrasing and filtering massively available code commits. Complementarily, *Critic-Evol* prompts a large critic LLM to judge and revise code snippets from a smaller draft LLM, pairing the drafted attempt and revision to create synthetic preference data.

2.1 PAIRWISE MODELING

Input. We follow prior work in reward modeling (Zhao et al., 2023; Liu et al., 2024b; Dong et al., 2024) and use decoder-based transformers for learning pairwise preferences. Specifically, the model π takes as input a prompt $x = \{i, y_A, y_B, c\}$, comprised of (i) an instruction i , (ii) a pair of code candidates $\{y_A, y_B\}$, and (iii) a fine-grained criterion c defining the desired preference following (Kim et al., 2023). More specifically, our prompt format is shown in Equation (1):

$$x = [\text{INSTRUCTION}] \{i\} [\text{CODE_A}] \{y_A\} [\text{CODE_B}] \{y_B\} [\text{CRITERION}] \{c\} \quad (1)$$

Output. We explore two output designs for code preference modeling: classification and generation.

1. *Classification:* We train a binary classifier based on a single next-token prediction (Zhao et al., 2023; Liu et al., 2024b). Specifically, given the exact prompt format in Equation (1), the classifier outputs either a token “A” if y_A is preferable to y_B for $\{i, c\}$ or “B” otherwise. At inference time, the preference decision is determined by the next-token probability between “A” and “B”, shown in Equation (2).
2. *Generation:* We also train generative models to provide code preference decisions in natural language. Specifically, we use a more natural version of Equation (1), demonstrated in Listing 1, for prompting the generation model. Next, we parse the code preference decision from the model-generated feedback using rules detailed in Appendix A.3.

$$y_+ = \begin{cases} y_A & \text{if } \mathbb{P}_\pi(y_A \succ y_B | x) > 0.5 \\ y_B & \text{otherwise} \end{cases} = \begin{cases} y_A & \text{if } \mathbb{P}_\pi(\text{“A”} | x) > \mathbb{P}_\pi(\text{“B”} | x) \\ y_B & \text{otherwise} \end{cases} \quad (2)$$

The advantage of classification modeling is computing efficiency as only one token is produced. Meanwhile, generative modeling optimizes for interpretability, with reasoning steps explicitly displayed.

2.2 SYNTHETIC CODE PREFERENCE FROM CODE EVOLUTION

Training a pairwise preference model requires a rich set of contrastive code pairs, along with the corresponding instructions and evaluation criteria. Collecting complex (Luo et al., 2024) and diverse (Wei et al., 2024) code pairs is crucial yet challenging, given such resources are neither readily available nor curated by prior work. To this end, we propose to create code preference training data

using synthetic code evolution, based on code commits (§2.2.1) and code critiques (§2.2.2). We argue that code evolution is a practical source for synthesizing code preferences, not only because of its natural indication of preferences², but also thanks to their general availability and diversity. We focus on the general methodology in this section and defer the detailed prompting implementation to Appendix A.1.

2.2.1 *Commit-Instruct*: PREFERENCE LEARNING FROM CODE COMMITS

We propose *Commit-Instruct*, a synthetic data generation method transforming raw code commits into code preference training samples. Specifically, the workflow (middle of Figure 1) employs a critic LLM to analyze each raw code commit and produce a training sample in a desired format §2.1. Each raw commit can be denoted by $r = (m, y_{pre}, y_{post})$, where m is the commit message, and $\{y_{pre}, y_{post}\}$ are the pre- and post-commit code snippets. *Commit-Instruct* processes each commit in three steps:

1. **Reasoning:** The critic LLM is instructed to reason and explain code changes from y_{pre} to y_{post} .
2. **Filtering:** Given the explanation, the critic LLM first determines whether or not the code change is meaningful. If so, we proceed to the next step; otherwise, the commit is discarded. This step aims to ensure the quality of synthetic data by excluding trivial or ambiguous code changes.
3. **Rephrasing:** Based on the commit r and its explanation, the critic LLM synthesizes a preference sample in the desired format $x = \{i, y_A, y_B, c\}$ (§2.1). Specifically, y_A and y_B are rephrased from y_{pre} and y_{post} to emphasize the actual change. i is the instruction generated to describe y_{pre} and y_{post} and the criterion c is concluded by how y_{post} improves y_{pre} . The rephrased version of y_{post} is regarded as the chosen response y^+ in model training.

Figure 3 in Appendix A.1 provides the detailed prompt implementation for *Commit-Instruct*.

2.2.2 *Critic-Evol*: PREFERENCE LEARNING FROM CODE CRITIQUES

While synthetic evolution can be gathered from human data such as code commits, it can also be derived from synthetic data. As such, we propose *Critic-Evol* which generates synthetic code preference data by asking a stronger *critic* model π^+ to revise the code generated by a weaker *draft* model π^- .

Specifically, *Critic-Evol* takes a set of coding instructions $\mathcal{I} = \{i_1, i_2, \dots, i_n\}$ as inputs, for each of which (i_k) we apply steps below to either transform it into a synthetic training sample or simply drop it:

1. **Fault sampling:** This step starts with a suitably weak but functional model, denoted as π^- , which statistically allows us to sample improvable code solutions $y_k^- \leftarrow \pi^-(i_k)$.
2. **Critique & filtering:** We instruct the critic LLM π^+ to code review y_k^- , by pointing out noticeable code quality issues and defining the criterion (*e.g.*, c) regarding the code defects. π^+ may also be satisfied with y_k^- and thus we stop synthesizing code preference data for (i_k, y_k^-) .
3. **Revision:** If the critique from π^+ suggests y_k^- can be significantly improved, π^+ creates y_k^+ by revising y_k^- to meet the desired criterion c . As such, a new synthetic code preference sample is composed as $\{i_k, y_k^-, y_k^+, c\}$, with y_k^+ being the chosen response.

Figure 5 in Appendix A.1 provides more details on implementation of *Critic-Evol*.

2.3 DATASETS

We apply our techniques to create two synthetic datasets for code preference learning:

Commit-Instruct-EditPack consists of 20,641 code preference samples synthesized from EditPackFT-Multi (Cassano et al., 2023) and Llama3-70B-Instruct (Dubey et al., 2024). After filtering out non-permissive code, we obtain 22,469 blessed Python commits from EditPackFT-Multi for use as the raw commits and prompt Llama3-70B-Instruct (Dubey et al., 2024) to perform the *Commit-Instruct* strategy. 91.9% of the commits are successfully transformed into code preference data (§2.1) and 8.1% of them are filtered out due to lack of clear significance.

Critic-Evol-SOSS has 41,595 synthetic code preference samples using the *Critic-Evol* technique. Specifically, we run Llama3-8B-Instruct as the draft model (*i.e.*, π^-) over 50,661 coding instructions from the Self-OSS-Instruct dataset (BigCode, 2024) to produce initial code solutions. 82.1% of these

²Software iterates towards improvement, making post-evolution code oftentimes better than pre-evolution code.

Objective	# Tasks	Source	Preference Oracle
Code Correctness	660	EvalPlus (Liu et al., 2023b)	Test execution
Code Efficiency	352	EvalPerf (Liu et al., 2024a)	# CPU instructions
Code Security	207	CyberSecEval (Bhatt et al., 2023)	Static analyzer
<hr/>			
Developer Preference	145	LBPP (Matton et al., 2024)	Human agreement
		BigCodeBench-Hard (Zhuo et al., 2024)	
Total	1,364		

Table 1: Overview of CODEPREFBENCH.

initial attempts are revised and extended by Llama3-70B-Instruct as the critic model, whereas the rest 17.9% are deemed good enough such that a revision is unnecessary.

Data processing. To mitigate positional bias, we augment the dataset by flipping the order within each code pair, which also doubles the training samples. Besides, we clip the code comments in *Critic-Evol* samples, given that comments barely affect code quality metrics and LLM-generated comments may let faulty code “sound right”. §3.4 also shows code comments can negatively impact code preferences.

3 EVALUATING CODE PREFERENCE LEARNING WITH CODEPREFBENCH

To systematically evaluate code preferences across different methods, we create the CODEPREFBENCH, consisting of 1,364 preference tasks in total. It covers four objectives in code preference evaluation: correctness, efficiency, security, and human preference. Table 1 provides an overview of the four categories of tasks.

This section presents the curation process of CODEPREFBENCH (§3.1) and the results from human (§3.2) and LLMs (§3.3), along with the controlled experiments in §3.4. Additional details, such as case studies (Appendix A.4) and contamination analysis (Appendix A.5), are deferred to the Appendix.

3.1 BENCHMARK SETUP

In CODEPREFBENCH, we evaluate code preference approaches over four objectives, covering three verifiable properties (*i.e.*, correctness, efficiency, and security) and human preference. For verifiable objectives, we generate oracle labels via code execution and static analysis. For human preference, we engage three annotators to label each code pair to form the evaluation set and establish baselines. To ensure benchmark quality, we only use clear-cut *good-bad* pairs and exclude *tie* pairs due to their inherent ambiguity. The creation of the dataset for each evaluation category is detailed below:

Objective #1: Correctness. We construct *correct-wrong* pairs from EvalPlus datasets (Liu et al., 2023b), *i.e.*, HumanEval+ (164 tasks) and MBPP+ (378 tasks), as they rigorously test LLM solutions with extensive test cases that can detect subtle bugs. We derive at most two contrastive code pairs for evaluation from each seed task. In each code pair, the *wrong* code comes from test-falsified LLM solutions while the *correct* is the human-written ground truth. Finally, we obtain 660 *correct-wrong* code pairs. The number is smaller than $2 \times (164 + 378)$ as “wrong” samples do not exist in some easy tasks.

Objective #2: Efficiency. We construct *fast-slow* pairs from EvalPerf datasets (Liu et al., 2024a). EvalPerf exercises the performance of LLM-generated correct solutions using 121 performance-exercising tasks equipped with performance-exercising test inputs. The EvalPerf dataset provides fast-to-slow reference solutions with distinct performance for each task. Therefore, we sample *fast-slow* pairs over the reference samples at a step size of 3, and obtain 352 *fast-slow* pairs.

Objective #3: Security. We construct *secure-vulnerable* code pairs from CyberSecEval (Bhatt et al., 2023), which includes 351 Python vulnerabilities detected by security analyzers. We prompt GPT-4o to fix each vulnerability and rerun the security analyzers to guarantee the fix. Additionally, we equip each code pair with a *generalized* instruction generated by GPT-4o, so the instruction is not biased towards any candidate. Finally, we obtain 207 *secure-vulnerable* code pairs to evaluate code security preference.

Objective #4: Human preference. We established a team of 18 developers to annotate pairs of code responses sampled from DeepSeek V2 over the latest open and close domain coding benchmarks, *i.e.*, 148 BigCodeBench-Hard (Zhuo et al., 2024) tasks and 161 LBPP (Matton et al., 2024) tasks. Specifically, we sample 8 solutions per task at a temperature of 0.8 and select the code pair with the largest edit distance. We follow the same annotation criteria as Chatbot Arena (Chiang et al., 2024): given two responses, users select the one they would use for the instruction (or skip it if both are tied). Lastly, we obtained 145 preference pairs without conflicting preferences out of three annotations per pair.

Additionally, we evenly shuffle the order of code pairs within each category to prevent positional bias. By default, we remove code comments when evaluating tasks focused on verifiable objectives, as comments should not affect the outcome. At evaluation, LLMs predict each code preference task using greedy decoding, following criteria aligned with the benchmark objective.

3.2 HUMAN RESULTS

We first study and draw insights from developer labeling through their expertise, annotation confidence, annotation time, and finally their results based on the major voting of 3 developers per task:

- **Expertise:** Our annotation team consists of 18 software developers, two-thirds of which hold degrees in computer science, and 95% of them have over two years of programming experience. For Python proficiency, 43% of them self-rate as advanced, while the rest consider themselves middle-level.
- **Confidence:** Table 2 lists the distribution of developer confidence. All developers are overall confident about their annotations. Specifically, developers are more confident when labeling correctness, with a higher ratio of “*very high*” confidence compared to that for the efficiency ($2.8\times$) and security ($1.7\times$) categories. From annotation notes of developers, it is partially because program correctness can be assessed by manual testing, while code efficiency and security are harder to evaluate without domain-specific knowledge.
- **Overhead:** Figure 2 illustrates the cumulative distribution of the annotation time per sample/developer, visualized by removing the top-1%-longest outliers. Overall, each task on average costs each developer 7.8 minutes to annotate, with the 99-percentile of 26 minutes, indicating that serious developer labeling for code preferences is time-consuming. Furthermore, code efficiency and security tasks (9 minutes on avg.) take longer to annotate compared to labeling correctness tasks (6.8 minutes on avg.), which is consistent with developer confidence and final results.
- **Accuracy:** The first result row in Table 3 presents the human performance based on the majority voting of three developers per task. Consistent with the annotation confidence and speed, human labeling achieves the most accurate measurement of code preferences in the code correctness category, with a solve rate of 84.9%. While not the best, human performance still decently solves 74.9% of preference tasks targeting code efficiency. Surprisingly, while developer confidence in code security annotation is higher than that in code efficiency, the security score is as low as 59.7%. This is because 73.9% of code pairs are annotated as equally secure, while our scoring method assigns 0.5 accuracy to each tied case. This discrepancy indicates that generalist programmers may struggle to accurately assess non-functional code properties such as code security, which may require specialized domain expertise.

	Low	High	Very High
Correctness	0%	68.2%	31.8%
Efficiency	0%	88.7%	11.3%
Security	0%	80.8%	19.2%

Table 2: Developer confidence distribution.

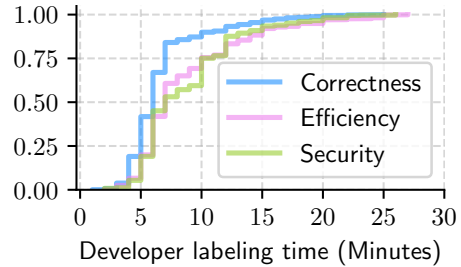


Figure 2: CDF of preference labeling time.

3.3 MODEL RESULTS

Table 3 evaluates human, existing LLMs, and CODEFAVOR models on CODEPREFBENCH. By default, CODEFAVOR models are obtained in two steps: (i) training two models using *Commit-Instruct-EditPack* and *Critic-Evol-SOSS* individually; and (ii) merging the two models on average to obtain a final model.

Overall results. We present the overall results by looking at the accuracy averaged across the three verifiable objectives, *i.e.*, the “**Avg.**” column. Among the evaluated existing LLMs, Llama-3.1-405B-Instruct and Mistral Large 2 perform the best, tightly followed by Claude 3.5 Sonnet and

	Correctness	Efficiency	Security	Avg.	Human Pref.
3-developer agreement	84.9 (± 9.4)	74.9 (± 5.3)	59.7 (± 37.0)	73.2	N/A
Proprietary Models					
Claude 3.5 Sonnet	65.8 (± 0.8)	79.9 (± 0.1)	98.1	81.2	64.8
Gemini 1.5 Pro 001	59.2 (± 3.0)	79.5 (± 1.4)	71.3 (± 27.3)	70.0	66.6 (± 1.7)
Gemini 1.5 Flash 001	58.6 (± 7.9)	81.1 (± 0.1)	85.0 (± 8.2)	74.9	60.0
Open-Weight Models					
Llama-3.1-405B-Instruct	68.9 (± 2.7)	78.3 (± 0.4)	99.0	82.2	68.3
Mistral Large 2 (123B)	65.8 (± 0.5)	81.2 (± 0.3)	99.5	82.2	71.7
DeepSeek V2.5 (236B)	65.8 (± 0.8)	80.7	97.3 (± 0.2)	81.3	69.0
Llama-3.1-70B-Instruct	60.2 (± 0.3)	77.3 (± 0.3)	97.8 (± 0.7)	78.4	69.0
Codestral-22B-v0.1	58.0 (± 0.8)	78.3 (± 0.1)	94.0 (± 2.7)	76.8	60.0
Llama-3-70B-Instruct	55.7 (± 2.5)	76.0 (± 1.6)	96.6 (± 1.0)	76.1	63.8 (± 0.3)
Gemma-2-27B	55.4 (± 4.9)	78.4 (± 0.9)	80.8 (± 14.8)	71.5	61.4
Our Models and Baselines					
Mistral Nemo Instruct (12B)	51.4 (± 1.2)	69.7 (± 0.4)	82.9 (± 7.5)	68.0	66.2
+ CODEFAVOR Classification	58.0	76.1	96.6	76.9	64.1
+ CODEFAVOR Generation	58.8	77.8	96.6	77.7	66.9
Gemma-2-9B-Instruct	52.4 (± 6.1)	75.1 (± 1.6)	52.7 (± 47.3)	60.1	64.1 (± 0.7)
+ CODEFAVOR Classification	56.8	75.3	92.3	74.8	67.6
+ CODEFAVOR Generation	57.0	78.7	96.6	77.4	64.1
Llama-3-8B-Instruct	49.5 (± 0.9)	71.9	90.3 (± 0.5)	70.6	58.6
+ CODEFAVOR Classification	58.0	73.0	95.2	75.4	62.8
+ CODEFAVOR Generation	58.2	75.0	98.6	77.2	69.0
Mistral-7B-Instruct-v0.3	48.5 (± 1.5)	66.6 (± 0.1)	78.5 (± 9.4)	64.5	58.3 (± 1.0)
+ CODEFAVOR Classification	62.4	64.8	95.7	74.3	60.7
+ CODEFAVOR Generation	57.1	77.3	90.3	74.9	66.9

Table 3: Accuracy (%) of evaluated models on CODEPREFBENCH. Scores within 1 percentage point of the highest are highlighted in bold. Bracketed numbers denote the ranges of uncertain responses, half of whose ratio is accounted for the final accuracy score. Case studies are available in Appendix A.4.

DeepSeek V2.5. Meanwhile, Codestral, at a parameter size of 22B, demonstrates a decent result, on par with Llama-3-70B-Instruct. We demonstrate the effectiveness of CODEFAVOR by fine-tuning a comprehensive set of affordable models, from 7B to 12B. While these small models are relatively weak out of the box, CODEFAVOR improves their overall performance by 9.3~28.8% relatively. For instance, CODEFAVOR’s generation modeling enables Mistral Nemo Instruct, Gemma-2-9B-Instruct, and Llama-3-8B-Instruct to achieve an overall score of 77.2~77.7 respectively, slightly outperforming the critic model (*i.e.*, Llama-3-70B-Instruct), despite being smaller by 6~9 \times . Notably, all of CODEFAVOR models even outperform the human-agreement baseline, largely because generalist developers have high uncertainty and thus low performance in the security category.

Correctness. Human annotation largely outperforms all language models in choosing the correct code, outperforming the best model by 23%. Among the evaluated existing LLMs, Llama-3.1-405B-Instruct as an open-weight model solves the most tasks (*i.e.*, 68.9%), outperforming Claude 3.5 Sonnet, Mistral Large 2, and DeepSeek V2.5 by 4.7%. Meanwhile, small LLMs (≤ 12 B) are incapable of such tasks out of the box, producing almost random preferences ($\sim 50\%$). Nonetheless, CODEFAVOR improves the accuracy of code correctness preference for these models by 8.8~28.7%, commonly surpassing their critic model (*i.e.*, Llama-3-70B-Instruct) by up to 12%.

Efficiency. While human preference aces over the evaluated LLMs on the preference of code preference, it presents overall sub-optimal preferences regarding code efficiency. For example, Mistral Large 2, the best model in this category, surpasses developer-agreement-based preference by 8.4%. Gemini Flash and DeepSeek V2.5 tightly follow Mistral Large 2 within a 1% gap, also outperforming human preference in the code efficiency category. While smaller LLMs perform more decently

compared to their results on code correctness preference, CODEFAVOR still further improves them by up to 16.1%, on par with or slightly surpassing the critic LLMs (by up to 4%).

Security. The code security subset in CODEPREFBENCH is relatively much easier given that most models achieve saturated scores, *e.g.*, Mistral Large 2 solves 99.5% tasks. Similar to the low performance of the human baseline, the scores of Gemini 1.5 Pro and Gemma 2 models are surprisingly low, with up to 47.3% of code pairs regarded as equally insecure (*e.g.*, Figure 13), even if the evaluation prompt in Listing 1 asks for an absolute answer. Nevertheless, such behavior can be benign for mitigating potential security risks from deceptive prompts with the actual purpose of assisting cyber-security attacks. Meanwhile, small models are still improvable in this dimension. For example, CODEFAVOR eliminates the uncertainty in Gemma-2-9B-Instruct and improves its security preference score by up to 89%. For other small models, CODEFAVOR can still improve them by 9.2~21.9%.

Human preference. Aligning the objective of human preference is as challenging as that in the correctness category. The best model, Mistral Large 2, can solve 70-ish percent of tasks, outperforming the best-evaluated proprietary model, Gemini 1.5 Pro, by 7.7%. While in human preference smaller LLMs perform much better than in the correctness objective, CODEFAVOR can still improve their performance in aligning human preference for code by up to 17.7%. By checking the dataset, the difficulty of aligning human preferences can partially come from the ambiguity and bias inherent in human annotation. Sometimes both code candidates exhibit different advantages and disadvantages, making human preference just one of many possible reasonable judgments, rather than the definitive answer.

Preference cost. In addition to preference accuracy, Table 4 lists the cost of representative approaches for evaluating tasks from CODEPREFBENCH. Specifically, human agreement as the most expensive approach costs \$6.1 per task, estimated based on their average annotation time and California’s minimal wage. Llama-3.1-405B-Instruct, with the best overall performance, is two orders of magnitude cheaper than human preference. While Llama-3-70B-Instruct is 7.4% weaker than the 405B model, it is fairly cost-effective for being cheaper by 35.3×. Furthermore, CODEFAVOR-enabled models present the best cost-effectiveness. For example, our classification model fine-tuned based on Mistral Nemo Instruct is five orders of magnitude cheaper than human preference and is 34× cheaper than Llama-3-70B-Instruct while achieving no worse preference results.

	Norm. Cost	Accuracy
Human preference (3×)	1.2×10^5 (\$6.1)	73.2
Llama-3.1-405B-Instr.	1.2×10^3	82.2
Llama-3-70B-Instr.	3.4×10^1	76.1
Ours (Mistral Nemo)	1	76.9

Table 4: Estimated per-sample cost and accuracy.

3.4 CONTROLLED EXPERIMENTS

This section rigorously studies the design choices in CODEFAVOR via controlled experiments.

Training data. As we have two sources of training datasets, in Table 5 we study their training effect individually (*i.e.*, “Commit-Instruct” and “Critic-Evol”) and in combination (*i.e.*, “Data Mixture”). Comparing *Commit-Instruct* with *Critic-Evol*, models trained by *Critic-Evol* tend to achieve better overall performance, particularly in the correctness category. For example, within the classifier modeling, *Critic-Evol* surpasses *Commit-Instruct* by 6.1~15.5% on the correctness category, and the overall improvement (*i.e.*, “Avg.” column) can be up to 7.5%. Meanwhile, when using the classification modeling, *Commit-Instruct*-enabled models can perform better in the preference for code efficiency, with up to 12.5% improvement. Moreover, data mixture can further improve the effectiveness of model-based preference, especially when using generation modeling, with up to 8.7% and 4.3% improvement over *Commit-Instruct* and *Critic-Evol* respectively. The performance trend correlates with the training sample sizes, indicating that the more training data, the better performance.

Data mixture v.s. model merging. In addition to data mixture, we also explore co-utilizing both training datasets via model merging (Wortsman et al., 2022), by averaging the weights of two models trained by individual datasets. Model merging yields better evaluation results for all trained classification models, with 1.1~5.0% improvements. Within the generation modeling, model merging also surpasses or stays on par with data mixture results for all model types except for the Mistral 7B series.

Classification v.s. generation. Table 5 also compares the output representation between classification and generation. One qualitative trend is that classifier modeling often leads to higher scores in

		Correctness	Efficiency	Security	Avg.	Human Pref.
Mistral Nemo Instruct (12B)		51.4 (± 1.2)	69.7 (± 0.4)	82.9 (± 7.5)	68.0	66.2
<i>Commit-Instruct</i>	Classification	54.5	79.3	96.1	76.6	65.5
	Generation	48.2	74.4	96.6	73.1	66.9
<i>Critic-Evol</i>	Classification	59.8	70.5	95.7	75.3	62.1
	Generation	56.8	77.0	96.6	76.8	61.4
Data Mixture	Classification	63.0	68.8	95.2	75.6	62.1
	Generation	58.2	77.0	96.1	77.1	64.1
Model Merging	Classification	58.0	76.1	96.6	76.9	64.1
	Generation	58.8	77.8	96.6	77.7	66.9
Gemma-2-9B-Instruct		52.4 (± 6.1)	75.1 (± 1.6)	52.7 (± 47.3)	60.1	64.1 (± 0.7)
<i>Commit-Instruct</i>	Classification	52.3	71.9	82.1	68.8	63.4
	Generation	51.8	80.1	95.1	75.3	60.7
<i>Critic-Evol</i>	Classification	55.5	74.7	86.5	72.2	62.1
	Generation	57.9	72.2	97.6	75.9	64.1
Data Mixture	Classification	54.8	73.9	87.9	72.2	63.4
	Generation	59.2	76.7	97.6	77.8	63.4
Model Merging	Classification	56.8	75.3	92.3	74.8	67.6
	Generation	57.0	78.7	96.6	77.4	64.1
Llama 3-8B-Instruct		49.5 (± 0.9)	71.9	90.3 (± 0.5)	70.6	58.6
<i>Commit-Instruct</i>	Classification	54.4	71.0	93.7	73.0	65.5
	Generation	48.9	73.0	94.2	72.1	66.2
<i>Critic-Evol</i>	Classification	58.3	71.3	90.3	73.3	57.9
	Generation	58.3	74.4	93.7	75.5	69.0
Data Mixture	Classification	58.5	66.2	90.8	71.8	62.1
	Generation	56.8	73.6	94.7	75.0	66.2
Model Merging	Classification	58.0	73.0	95.2	75.4	62.8
	Generation	58.2	75.0	98.6	77.2	69.0
Mistral-7B-Instruct-v0.3		48.5 (± 1.5)	66.6 (± 0.1)	78.5 (± 9.4)	64.5	58.3 (± 1.0)
<i>Commit-Instruct</i>	Classification	55.5	69.3	83.1	69.3	61.4
	Generation	48.0	73.3	88.4	69.9	66.2
<i>Critic-Evol</i>	Classification	64.1	64.8	94.7	74.5	61.4
	Generation	57.7	72.4	88.4	72.9	58.6
Data Mixture	Classification	59.5	69.3	91.8	73.5	60.7
	Generation	61.7	73.6	92.8	76.0	62.8
Model Merging	Classification	62.4	64.8	95.7	74.3	60.7
	Generation	57.1	77.3	90.3	74.9	66.9

Table 5: CODEPREFBENCH results of CODEFAVOR models using different training data and modeling.

the preference for code correctness while the generation modeling tends to bring more holistic improvement leading to a higher overall score. For example, within the 16 comparisons in Table 5, the classification modeling outperforms the generation modeling 9 times in the code correctness objective, whereas the generation modeling surpasses the classification modeling 13 times in the average score.

Criteria. Table 6 studies the impact of criteria in the prompt given to CODEFAVOR models. In our evaluation, by default we let the criterion statement be objective-specific. Specifically, using an empty criterion substantially decreases the preference accuracy, especially for code security (*i.e.*, by 13.2 \sim 19.5%). Using a generalist criterion can also lightly degrade the overall performance by up to 2.3%. These findings suggest using fine-grained, domain-specific criterion statements for code preference.

To comment or not to comment? Table 6 further studies how code comments impact the code preferences of CODEFAVOR models in both training and inference. Our default setting as the baseline is both trained and evaluated *without* code comments. Specifically, enabling code comments when evaluating our default models (*i.e.*, trained without comments), we observe a 6.2 \sim 10.4% drop in the preference accuracy for code correctness, while other dimensions are barely impacted. Meanwhile, if we both train and evaluate CODEFAVOR models with code comments, a broader degradation is observed with 6 \sim 7% drop in the overall preference accuracy. Furthermore, evaluating the comment-trained CODEFAVOR models without code comments presents an even worse decrease in overall accuracy at 7.6 \sim 8.7%. These results suggest that code comments may negatively affect model preferences, possibly due to LLMs’ self-bias (Chiang et al., 2024), decorating faulty code with “good-looking” comments.

Draft models and critic models. While our *Critic-Evol* default setting uses a smaller draft model (8B) and a larger critic model (70B), Table 7 explores circumstances when using the same draft and critic

Experiment		Correctness	Efficiency	Security	Avg.
Mistral Nemo Instr.	Data Mixture Reference	63.0	68.8	95.2	75.7
	Aspect-specific → Empty criteria	64.8	64.5	82.6	70.6
	Aspect-specific → General criteria	61.4	70.2	92.3	74.6
	Trained w/o & Eval. with comments	59.1	69.3	95.7	74.8
	Trained with & Eval. with comments	52.1	64.5	94.7	70.4
	Trained with & Eval. w/o comments	55.8	57.4	94.2	69.1
Mistral-7B-Instruct	Data Mixture Reference	59.5	69.3	91.8	73.5
	Aspect-specific → Empty criteria	55.0	60.8	73.9	63.2
	Aspect-specific → General criteria	58.2	65.3	91.8	71.8
	Trained w/o & Eval. with comments	53.3	67.6	90.3	70.4
	Trained with & Eval. with comments	60.5	67.6	79.2	69.1
	Trained with & Eval. w/o comments	63.2	60.2	80.2	67.9

Table 6: Controlled experiments on input prompts.

	Draft LLM	Critic LLM	Filtered	Correctness	Efficiency	Security	Avg.
Mistral Nemo	8B	70B	17.9%	59.8	70.5	95.7	75.3
	8B	8B	27.2%	58.9	58.8	87.0	68.2
	70B	70B	21.6%	60.7	70.2	89.4	73.4

Table 7: Impact of draft and critic models in training with *Critic-Evol*.

models for synthesizing preference pairs. First, using the same draft and critic models leads to a higher filtering rate, meaning that more initial attempts are deemed “good enough” and thus not proceeding to the revision phase. This result is consistent with prior findings on LLM’s self-bias (Xu et al., 2024; Li et al., 2024), *i.e.*, LLM judges tend to favor their own generations. Meanwhile, there is a 2.5~9.4% drop on the overall performance when using the same draft and critic models in *Critic-Evol*, yet it seems to be benign for the performance in the correctness category.

4 RELATED WORK

Preference optimization has been a de facto step in post-training to align LLMs for generating helpful and safe content. In this step, the policy model is trained over samples labeled preference objectives (*e.g.*, human preference) using various offline (Zhao et al., 2023; Rafailov et al., 2023; Meng et al., 2024; Yuan et al., 2023; Azar et al., 2024) and online algorithms (Xiong et al., 2024; Dong et al., 2023a; 2024). While the preference optimization methods are effective, a major step in the loop is to collect and label preference data, and our work falls into this dimension with a focus on the understudied code domain. These preference data, *e.g.*, a pair of preferred and rejected responses in DPO (Rafailov et al., 2023), in addition to being directly used for preference optimization, can also be *indirectly* used to train a preference model (*i.e.*, preference learning like our work) for extensively labeling preferences (Zhao et al., 2023).

The raw responses to construct preference data can be sampled from the LLM under preference tuning (*i.e.*, different output responses for the same input prompt), or external sources, such as existing human data or external LLM samples. These samples are then ranked/scored via preference objectives such as human annotation (Ouyang et al., 2022), LLM feedbacks (Cui et al., 2024; Weyssow et al., 2024; McAleese et al., 2024), and preference models (Zhao et al., 2023; Dong et al., 2024; Wang et al., 2024; Dong et al., 2023b). Functionality-wise, techniques for training LLM-as-a-Judge (Kim et al., 2023; 2024) from scratch can also be applied to training a preference model and vice versa.

Specifically, our technique focuses on the understudied code generation domain (Chen et al., 2021; Liu et al., 2023b), whose preference principles can be more specialized (*e.g.*, efficiency and security) and difficult to label than the general human preference for natural language. As a closely related

work, Weyssow et al. (2024) score code snippets by employing a group of prominent LLMs as judges, following Cui et al. (2024), whereas our work covers how to train LLM-based code raters and curate corresponding preference data from scratch. McAleese et al. (2024) train a CritiGPT to catch bugs in code in the form of LLM feedback, which helps AI trainers provide more precise feedback in the RLHF process. Our study confirms their main findings, *e.g.*, human preference can be imperfect and even suboptimal compared to LLM-based preference. Furthermore, our study provides extensive insights by expanding the studied code criteria beyond correctness (*e.g.*, efficiency and security), quantifying human cost and confidence, and evaluating a comprehensive set of models. Data-wise, CriticGPT applies bug injection (Just, 2014; Roy et al., 2018) techniques with human assistance, whereas CODEFAVOR collects contrasting code pairs from code commits and revisions. Nonetheless, we think CriticGPT can be used as a critic model in *Critic-Evol* to provide precise revisions.

5 CONCLUSION

In this paper, we studied human and LLM preferences for code generation. We introduced CODEFAVOR, a novel framework for training pairwise code preference models using synthetic code evolution data, derived from code commits and LLM critiques. For evaluation, we curated CODEPREFBENCH, a benchmark comprising of 1,364 high-quality code preference tasks. This enables us to investigate (i) the alignment of human and LLM-based preferences with correctness, efficiency, and security, and (ii) the consistency of LLM-based preferences with human preferences.

Our evaluation demonstrates the effectiveness of CODEFAVOR: CODEFAVOR fine-tunes instruction-following models, significantly improving their abilities to learn code preferences. CODEFAVOR is also cost-effective, achieving on-par performance models of $9\times$ more parameters while being $34\times$ cheaper. Despite the high cost of human-based code preference evaluation, our results reveal that human preferences can be sub-optimal for non-functional objectives. Finally, our controlled experiments provide a comprehensive validation of the advantages and limitations of design choices within CODEFAVOR.

ACKNOWLEDGEMENT

We thank the annotation team for their help in data labeling. We also thank Haoxiang Wang, Wei Xiong, Federico Cassano, and Jun Yang for their insightful discussions, Yifeng Ding for help in the experimental setup, and Anoop Deoras for the leadership support.

REFERENCES

- Amazon Web Services. AI Code Generator - Amazon CodeWhisperer - AWS. <https://aws.amazon.com/codewhisperer/>, 2023.
- Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, et al. Program synthesis with large language models. *ArXiv preprint*, abs/2108.07732, 2021. URL <https://arxiv.org/abs/2108.07732>.
- Mohammad Gheshlaghi Azar, Zhaohan Daniel Guo, Bilal Piot, Rémi Munos, Mark Rowland, Michal Valko, and Daniele Calandriello. A general theoretical paradigm to understand learning from human preferences. In Sanjoy Dasgupta, Stephan Mandt, and Yingzhen Li (eds.), *International Conference on Artificial Intelligence and Statistics, 2-4 May 2024, Palau de Congressos, Valencia, Spain*, volume 238 of *Proceedings of Machine Learning Research*, pp. 4447–4455. PMLR, 2024. URL <https://proceedings.mlr.press/v238/gheshlaghi-azar24a.html>.
- Manish Bhatt, Sahana Chennabasappa, Cyrus Nikolaidis, Shengye Wan, Ivan Evtimov, Dominik Gabi, Daniel Song, Faizan Ahmad, Cornelius Aschermann, Lorenzo Fontana, et al. Purple llama cyberseceval: A secure coding benchmark for language models. *ArXiv preprint*, abs/2312.04724, 2023. URL <https://arxiv.org/abs/2312.04724>.
- BigCode. Final self-alignment training dataset for starcoder2-instruct. <https://huggingface.co/datasets/bigcode/self-oss-instruct-sc2-exec-filter-50k>, 2024.

Federico Cassano, Luisa Li, Akul Sethi, Noah Shinn, Abby Brennan-Jones, Anton Lozhkov, Carolyn Anderson, and Arjun Guha. Can it edit? evaluating the ability of large language models to follow code editing instructions. *ArXiv preprint*, abs/2312.12450, 2023. URL <https://arxiv.org/abs/2312.12450>.

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. Evaluating large language models trained on code, 2021.

Wei-Lin Chiang, Lianmin Zheng, Ying Sheng, Anastasios Nikolas Angelopoulos, Tianle Li, Dacheng Li, Hao Zhang, Banghua Zhu, Michael Jordan, Joseph E Gonzalez, et al. Chatbot arena: An open platform for evaluating llms by human preference. *ArXiv preprint*, abs/2403.04132, 2024. URL <https://arxiv.org/abs/2403.04132>.

Maxime Crochemore and Dominique Perrin. Two-way string-matching. *J. ACM*, 38(3):650–674, 1991. ISSN 0004-5411. doi: 10.1145/116825.116845. URL <https://doi.org/10.1145/116825.116845>.

Ganqu Cui, Lifan Yuan, Ning Ding, Guanming Yao, Bingxiang He, Wei Zhu, Yuan Ni, Guotong Xie, Ruobing Xie, Yankai Lin, et al. Ultrafeedback: Boosting language models with scaled ai feedback. In *Forty-first International Conference on Machine Learning*, 2024.

Tri Dao, Daniel Y. Fu, Stefano Ermon, Atri Rudra, and Christopher Ré. Flashattention: Fast and memory-efficient exact attention with io-awareness. In Sanmi Koyejo, S. Mohamed, A. Agarwal, Danielle Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems 35: Annual Conference on Neural Information Processing Systems 2022, NeurIPS 2022, New Orleans, LA, USA, November 28 - December 9, 2022*, 2022. URL http://papers.nips.cc/paper_files/paper/2022/hash/67d57c32e20fd0a7a302cb81d36e40d5-Abs

Yangruibo Ding, Zijian Wang, Wasi Ahmad, Hantian Ding, Ming Tan, Nihal Jain, Murali Krishna Ramanathan, Ramesh Nallapati, Parminder Bhatia, Dan Roth, et al. Crosscodeeval: A diverse and multilingual benchmark for cross-file code completion. *Advances in Neural Information Processing Systems*, 36, 2024.

Hanze Dong, Wei Xiong, Deepanshu Goyal, Yihan Zhang, Winnie Chow, Rui Pan, Shizhe Diao, Jipeng Zhang, KaShun SHUM, and Tong Zhang. RAFT: Reward ranked finetuning for generative foundation model alignment. *Transactions on Machine Learning Research*, 2023a. ISSN 2835-8856. URL <https://openreview.net/forum?id=m7p507zb1Y>.

Hanze Dong, Wei Xiong, Bo Pang, Haoxiang Wang, Han Zhao, Yingbo Zhou, Nan Jiang, Doyen Sahoo, Caiming Xiong, and Tong Zhang. Rlhf workflow: From reward modeling to online rlhf. *ArXiv preprint*, abs/2405.07863, 2024. URL <https://arxiv.org/abs/2405.07863>.

Yi Dong, Zhilin Wang, Makesh Sreedhar, Xianchao Wu, and Oleksii Kuchaiev. SteerLM: Attribute conditioned SFT as an (user-steerable) alternative to RLHF. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 11275–11288, Singapore, 2023b. Association for Computational Linguistics. doi: 10.18653/v1/2023.findings-emnlp.754. URL <https://aclanthology.org/2023.findings-emnlp.754>.

Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. The llama 3 herd of models. *ArXiv preprint*, abs/2407.21783, 2024. URL <https://arxiv.org/abs/2407.21783>.

- GitHub. GitHub Copilot – Your AI pair programmer. <https://github.com/features/copilot>, 2023.
- René Just. The major mutation framework: Efficient and scalable mutation analysis for java. In *Proceedings of the 2014 international symposium on software testing and analysis*, pp. 433–436, 2014.
- Seungone Kim, Jamin Shin, Yejin Cho, Joel Jang, Shayne Longpre, Hwaran Lee, Sangdoo Yun, Seongjin Shin, Sungdong Kim, James Thorne, et al. Prometheus: Inducing fine-grained evaluation capability in language models. In *The Twelfth International Conference on Learning Representations*, 2023.
- Seungone Kim, Juyoung Suk, Shayne Longpre, Bill Yuchen Lin, Jamin Shin, Sean Welleck, Graham Neubig, Moontae Lee, Kyungjae Lee, and Minjoon Seo. Prometheus 2: An open source language model specialized in evaluating other language models. *ArXiv preprint*, abs/2405.01535, 2024. URL <https://arxiv.org/abs/2405.01535>.
- Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph Gonzalez, Hao Zhang, and Ion Stoica. Efficient memory management for large language model serving with pagedattention. In *Proceedings of the 29th Symposium on Operating Systems Principles*, pp. 611–626, 2023.
- Raymond Li, Yangtian Zi, Niklas Muennighoff, Denis Kocetkov, Chenghao Mou, Marc Marone, Christopher Akiki, LI Jia, Jenny Chim, Qian Liu, et al. Starcoder: may the source be with you! *Transactions on Machine Learning Research*, 2023. ISSN 2835-8856. URL <https://openreview.net/forum?id=KoF0g41haE>. Reproducibility Certification.
- Tianle Li, Wei-Lin Chiang, Evan Frick, Lisa Dunlap, Tianhao Wu, Banghua Zhu, Joseph E Gonzalez, and Ion Stoica. From crowdsourced data to high-quality benchmarks: Arena-hard and benchbuilder pipeline. *ArXiv preprint*, abs/2406.11939, 2024. URL <https://arxiv.org/abs/2406.11939>.
- Jiate Liu, Yiqin Zhu, Kaiwen Xiao, QIANG FU, Xiao Han, Yang Wei, and Deheng Ye. RLTF: Reinforcement learning from unit test feedback. *Transactions on Machine Learning Research*, 2023a. ISSN 2835-8856. URL <https://openreview.net/forum?id=hjYmsV6nXZ>.
- Jiawei Liu, Chunqiu Steven Xia, Yuyao Wang, and Lingming Zhang. Is your code generated by chatgpt really correct? rigorous evaluation of large language models for code generation. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine (eds.), *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*, 2023b.
- Jiawei Liu, Songrun Xie, Junhao Wang, Yuxiang Wei, Yifeng Ding, and LINGMING ZHANG. Evaluating language models for efficient code generation. In *First Conference on Language Modeling*, 2024a. URL <https://openreview.net/forum?id=ICBMeAhmC>.
- Tianqi Liu, Yao Zhao, Rishabh Joshi, Misha Khalman, Mohammad Saleh, Peter J Liu, and Jialu Liu. Statistical rejection sampling improves preference optimization. In *The Twelfth International Conference on Learning Representations*, 2024b. URL <https://openreview.net/forum?id=xbjSwwrQOe>.
- Fredrik Lundh. The stringlib library. <https://web.archive.org/web/20201107074620/http://effbot.org/zone/stringlib/>, 2006. Accessed: 2024-09-10.
- Ziyang Luo, Can Xu, Pu Zhao, Qingfeng Sun, Xiubo Geng, Wenxiang Hu, Chongyang Tao, Jing Ma, Qingwei Lin, and Daxin Jiang. Wizardcoder: Empowering code large language models with evol-instruct. In *The Twelfth International Conference on Learning Representations*, 2024.
- Alexandre Matton, Tom Sherborne, Dennis Aumiller, Elena Tommasone, Milad Alizadeh, Jingyi He, Raymond Ma, Maxime Voisin, Ellen Gilsenan-McMahon, and Matthias Gallé. On leakage of code generation evaluation datasets. *ArXiv preprint*, abs/2407.07565, 2024. URL <https://arxiv.org/abs/2407.07565>.
- Nat McAleese, Rai Michael Pokorny, Juan Felipe Ceron Uribe, Evgenia Nitishinskaya, Maja Trebacz, and Jan Leike. Llm critics help catch llm bugs. *ArXiv preprint*, abs/2407.00215, 2024. URL <https://arxiv.org/abs/2407.00215>.

Yu Meng, Mengzhou Xia, and Danqi Chen. Simpo: Simple preference optimization with a reference-free reward. *ArXiv preprint*, abs/2405.14734, 2024. URL <https://arxiv.org/abs/2405.14734>.

Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul F. Christiano, Jan Leike, and Ryan Lowe. Training language models to follow instructions with human feedback. In Sanmi Koyejo, S. Mohamed, A. Agarwal, Danielle Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems 35: Annual Conference on Neural Information Processing Systems 2022, NeurIPS 2022, New Orleans, LA, USA, November 28 - December 9, 2022*, 2022.

Python Software Foundation. *subprocess — Subprocess management*, 2023. URL <https://docs.python.org/3/library/subprocess.html#subprocess.run>. Accessed: 2024-10-02.

Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D. Manning, Stefano Ermon, and Chelsea Finn. Direct preference optimization: Your language model is secretly a reward model. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine (eds.), *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*, 2023. URL http://papers.nips.cc/paper_files/paper/2023/hash/a85b405ed65c64

Jeff Rasley, Samyam Rajbhandari, Olatunji Ruwase, and Yuxiong He. Deepspeed: System optimizations enable training deep learning models with over 100 billion parameters. In Rajesh Gupta, Yan Liu, Jiliang Tang, and B. Aditya Prakash (eds.), *KDD '20: The 26th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, Virtual Event, CA, USA, August 23-27, 2020*, pp. 3505–3506. ACM, 2020. URL <https://dl.acm.org/doi/10.1145/3394486.3406703>.

Martin Riddell, Ansong Ni, and Arman Cohan. Quantifying contamination in evaluating code generation capabilities of language models. *ArXiv preprint*, abs/2403.04811, 2024. URL <https://arxiv.org/abs/2403.04811>.

Subhajit Roy, Awanish Pandey, Brendan Dolan-Gavitt, and Yu Hu. Bug synthesis: Challenging bug-finding tools with deep faults. In *Proceedings of the 2018 26th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, pp. 224–234, 2018.

Zhi Rui Tam, Cheng-Kuang Wu, Yi-Lin Tsai, Chieh-Yen Lin, Hung-yi Lee, and Yun-Nung Chen. Let me speak freely? a study on the impact of format restrictions on performance of large language models. *ArXiv preprint*, abs/2408.02442, 2024. URL <https://arxiv.org/abs/2408.02442>.

Haolang Wang, Wei Xiong, Tengyang Xie, Han Zhao, and Tong Zhang. Interpretable preferences via multi-objective reward modeling and mixture-of-experts. *ArXiv preprint*, abs/2406.12845, 2024. URL <https://arxiv.org/abs/2406.12845>.

Yuxiang Wei, Zhe Wang, Jiawei Liu, Yifeng Ding, and Lingming Zhang. Magicoder: Empowering code generation with oss-instruct. In *Forty-first International Conference on Machine Learning*, 2024.

Martin Weyssow, Aton Kamanda, and Houari Sahraoui. Codeultrafeedback: An llm-as-a-judge dataset for aligning large language models to coding preferences. *ArXiv preprint*, abs/2403.09032, 2024. URL <https://arxiv.org/abs/2403.09032>.

Mitchell Wortsman, Gabriel Ilharco, Samir Yitzhak Gadre, Rebecca Roelofs, Raphael Gontijo Lopes, Ari S. Morcos, Hongseok Namkoong, Ali Farhadi, Yair Carmon, Simon Kornblith, and Ludwig Schmidt. Model soups: averaging weights of multiple fine-tuned models improves accuracy without increasing inference time. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvári, Gang Niu, and Sivan Sabato (eds.), *International Conference on Machine Learning, ICML 2022, 17-23 July 2022, Baltimore, Maryland, USA*, volume

- 162 of *Proceedings of Machine Learning Research*, pp. 23965–23998. PMLR, 2022. URL <https://proceedings.mlr.press/v162/wortsman22a.html>.
- Wei Xiong, Hanze Dong, Chenlu Ye, Ziqi Wang, Han Zhong, Heng Ji, Nan Jiang, and Tong Zhang. Iterative preference learning from human feedback: Bridging theory and practice for rlhf under kl-constraint. In *Forty-first International Conference on Machine Learning*, 2024.
- Wenda Xu, Guanglei Zhu, Xuandong Zhao, Liangming Pan, Lei Li, and William Wang. Pride and prejudice: Llm amplifies self-bias in self-refinement. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 15474–15492, 2024.
- Hongyi Yuan, Zheng Yuan, Chuanqi Tan, Wei Wang, Songfang Huang, and Fei Huang. RRHF: rank responses to align language models with human feedback. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine (eds.), *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*, 2023.
- Fengji Zhang, Bei Chen, Yue Zhang, Jacky Keung, Jin Liu, Daoguang Zan, Yi Mao, Jian-Guang Lou, and Weizhu Chen. Repocoder: Repository-level code completion through iterative retrieval and generation. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 2471–2484, 2023.
- Yao Zhao, Rishabh Joshi, Tianqi Liu, Misha Khalman, Mohammad Saleh, and Peter J Liu. Slic-hf: Sequence likelihood calibration with human feedback. *ArXiv preprint*, abs/2305.10425, 2023. URL <https://arxiv.org/abs/2305.10425>.
- Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric P. Xing, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. Judging llm-as-a-judge with mt-bench and chatbot arena. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine (eds.), *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*, 2023.
- Terry Yue Zhuo, Minh Chien Vu, Jenny Chim, Han Hu, Wenhao Yu, Ratnadira Widayarsi, Imam Nur Bani Yusuf, Haolan Zhan, Junda He, Indraneil Paul, et al. Bigcodebench: Benchmarking code generation with diverse function calls and complex instructions. *ArXiv preprint*, abs/2406.15877, 2024. URL <https://arxiv.org/abs/2406.15877>.

A APPENDIX

Contents

A.1 Prompting	16
A.2 Training Setup	18
A.3 Additional Evaluation Setup	18
A.4 Case Studies of Faulty Preference	21
A.4.1 Faulty Preferences in Code Correctness	21
A.4.2 Faulty Preferences in Code Efficiency	23
A.4.3 Faulty Preferences in Code Security	26
A.5 Quantifying Contamination	27
A.6 Limitation and Future Work	28

A.1 PROMPTING

We showcase our prompt implementation for synthetic data generation via concrete examples below:

Commit-Instruct. Figure 3 details Figure 1 by exemplifying the prompt we implemented for *Commit-Instruct*. Given a raw commit that replaces string literals to systematic enum-like constants, we first ask the critic model to explain the code changes. The model then responds with the observed key changes and is asked by the user if the code change improves certain code properties. The critic model answers “[YES]” by pointing out that the code change improves maintainability and readability. Next, we instruct the critic model to generate a well-formatted version of synthetic preference data including an instruction, the criteria, a code preference pair, and feedback to explain the improvements.

Meanwhile, Figure 4 illustrates a case when the critic model filters out a code commit whose improvement is regarded as unclear. Specifically, the demonstrated code commit changes the original code to import a package in a try-catch block, rather than doing it directly. This prevents execution termination when the package is not needed. However, the critic model thinks such a change is minor and thus turns down the commit being processed to synthetic preference data.

Critic-Evol. Figure 5 demonstrates the prompting for *Critic-Evol*. Specifically, we implemented the *Critic-Evol* prompt in single-turn using few-shot prompting. The prompt includes five few-shot examples (e.g., the `square_root` example), followed by an instruction extracted from the Self-OSS-Instruct dataset and an initial coding solution provided by Llama3-8B-Instruct. Next, the critic model Llama3-70B-instruct is prompted to generate reflection, criteria, an improved version of code, and feedback to form synthetic code preference data. More specifically, in the reflection section, the critic model is expected to explain the initial implementation and reason for potential improvements. If the model thinks there is little to improve, the generation stops here and this sample is filtered out for synthetic preference data generation. In the case of Figure 5, the model suggests that the `get_all_words` function can be implemented using dictionary comprehension which is more concise and efficient. Following this, the critic model proposes a related criterion based on code conciseness and efficiency, resulting in an improved version of code, i.e., [ATTEMPT.2].

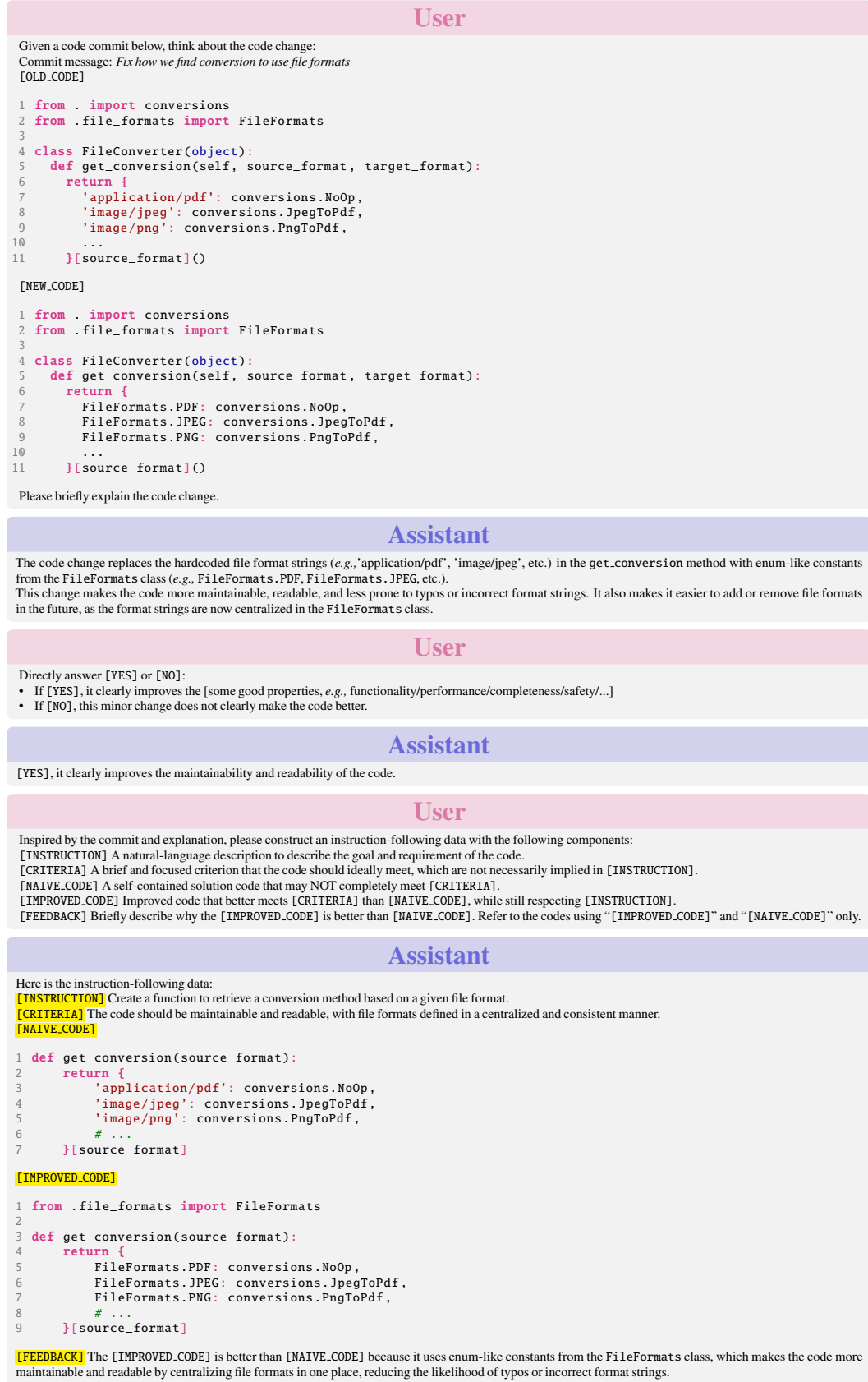


Figure 3: Exemplifying prompts in *Commit-Instruct* for generating preference code pairs.

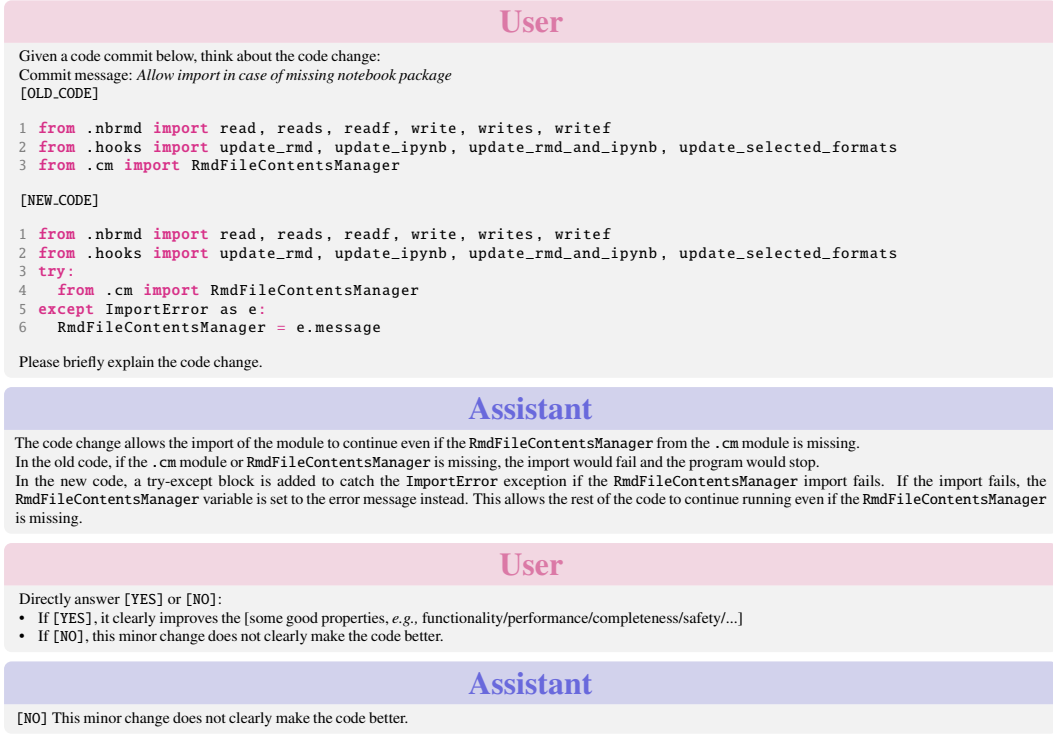


Figure 4: A filtered commit in *Commit-Instruct* for not being clearly useful.

A.2 TRAINING SETUP

Environment. We train our models using eight NVIDIA A100-40G GPUs based on Axolotl using DeepSpeed ZeRO-3 offloading (Rasley et al., 2020) and flash attention (Dao et al., 2022).

Hyper-parameters. Table 8 lists the default hyper-parameter settings for training our preference models. The hyper-parameter settings mostly follow the training recipes from Dong et al. (2024). As a special case, we use a slightly lower learning rate of 2×10^{-6} for Gemma-2 models for training stability.

Hyper-Parameter	Value
Batch size	32
Sequence length	2048
Sequence packing	✓
Learning rate	5×10^{-6}
Scheduler	Cosine annealing with 40 warm-up steps

Table 8: Explored hyper-parameter settings for training code preference learning.

A.3 ADDITIONAL EVALUATION SETUP

Environment. By default, we run open generative models using vLLM (Kwon et al., 2023) in a half-floating-point precision of `bfloat16`. For better accuracy (*e.g.*, some versions are suboptimal to certain models due to bugs), we run the Mistral and Llama models using v0.5.1, Gemma-2 models using v0.6.1.post2, and other models using v0.5.3.post1.

Decision parsing for feedback LLMs. Code preferences of raw generative LLMs, such as Claude 3.5 Sonnet, are generated through prompting (*i.e.*, Listing 1) and presented in natural-language feedback. For the ease of parsing decisions from model outputs, Listing 1 declares output constraints in natural

User

You are a great Python coding instructor good at judging code snippets, localizing code faults, and providing educational feedback. Please follow the formats of these examples to provide necessary code feedback:

[INSTRUCTION] Provide a Python function `square_root` to compute the square root of a number and throw a `ValueError` if the number is negative.

[ATTEMPT.1]

```
1 def square_root(x: float) -> float:
2     return math.sqrt(x)
```

[REFLECTION] **[ATTEMPT.1]** uses `math.sqrt` without importing the `math` module which can lead to a `NameError` during execution. The bug can be fixed by importing the `math` module.

[CRITERIA] The function should precisely follow the instructions while being runnable and bug-free.

[ATTEMPT.2]

```
1 import math
2 def square_root(x):
3     return math.sqrt(x)
```

[FEEDBACK] **[ATTEMPT.1]** forgets to import a necessary module. **[ATTEMPT.2]** fixes the bug in **[ATTEMPT.1]** by importing the `math` module ahead of time.

... other four few-shot examples ...

You are given **[INSTRUCTION]** and **[ATTEMPT.1]**, in response you generate:

1. A **[REFLECTION]** section analyzing noticable weaknesses of **[ATTEMPT.1]** while following **[INSTRUCTION]**
2. If you think **[ATTEMPT.1]** is good enough without significant space for improvements, stop the generation after **[REFLECTION]**
3. Otherwise, keep going with **[CRITERIA]**, **[ATTEMPT.2]**, and **[FEEDBACK]**

Notes:

1. **[CRITERIA]** should focus on one significant code weakness over correctness/efficiency/security/conciseness – DO NOT worry about trivial pitfalls like missing type hints, docstrings, input validation, etc.
2. In **[FEEDBACK]**, only refer to the code attempts using **[ATTEMPT.1]** and **[ATTEMPT.2]**

Follow the following instruction to write a Python function:

[INSTRUCTION] Create a function `get_all_words(text)` that takes a string `text` and returns a dictionary `words` that has all the words as keys and the number of occurrences as values.

Example:

```
1 get_all_words("The quick brown fox jumps over the lazy dog.")
2 # Output:
3 # {'the': 2, 'quick': 1, 'brown': 1, 'fox': 1, 'jumps': 1, 'over': 1, 'lazy': 1, 'dog': 1}
```

.....

An initial attempt to implement the function:

[ATTEMPT.1]

```
1 def get_all_words(text):
2     words = text.split()
3     word_counts = {}
4     for word in words:
5         word = word.lower()
6         if word in word_counts:
7             word_counts[word] += 1
8         else:
9             word_counts[word] = 1
10    return word_counts
```

Assistant

Do you see APPARENT bugs, inefficiencies, security vulnerabilities, or inconciseness in **[ATTEMPT.1]** when following the **[INSTRUCTION]**?

[REFLECTION] **[ATTEMPT.1]** correctly implements the instruction. However, it can be improved for conciseness and efficiency by using a dictionary comprehension with the `collections.Counter` class.

.....

A SIMPLE criteria where **[ATTEMPT.1]** can be improved from **[REFLECTION]**:

[CRITERIA] The code should be concise and efficient.

.....

The improved version of **[ATTEMPT.1]** based on the **[CRITERIA]** and **[REFLECTION]**:

[ATTEMPT.2]

```
1 from collections import Counter
2
3 def get_all_words(text):
4     words = text.lower().split()
5     return dict(Counter(words))
```

.....

How does **[ATTEMPT.2]** improve over **[ATTEMPT.1]**?

[FEEDBACK] **[ATTEMPT.1]** uses a manual loop to count the occurrences of each word, whereas **[ATTEMPT.2]** uses the `collections.Counter` class, which is more concise and efficient. Additionally, **[ATTEMPT.2]** converts the entire text to lowercase at once, making it more efficient than converting each word individually.

Figure 5: Exemplary prompt in *Critic-Evol* for generating preference code pairs.

language, *i.e.*, suggesting the model to provide the preference in the format of “[CODE_?] is better than [CODE_?] on the mentioned criteria.” As such, we parse the model response by detecting keywords such as “better” and “neither” and then apply specific patterns to extract the answer. When none of these patterns are matched or the model simply suggests either both or neither of them are good, we mark the response undecidable and credit it for a 0.5 score, mimicking the expectation of the sampled score. Empirically, we found that this method works well and in our case studies we did not find any wrong classifications. Meanwhile, grammar-based constrained decoding can also be used to enforce the desired output formats, *e.g.*, acquiring the answers in JSON. However, such strict format restrictions might negatively impact model performance (Tam et al., 2024), so we choose to encode the constraints in the prompt.

```

1 def pairwise_cot_template(instruction, code1, code2, criteria) -> str:
2     return f"""
3     Given an [INSTRUCTION] and responses [CODE_A] and [CODE_B], judge ↵
4         ↵ which one better meets [CRITERIA] while following [INSTRUCTION]
5
6     ---
7     [INSTRUCTION]
8     {instruction}
9
10    [CODE_A]
11    {code1}
12
13    [CODE_B]
14    {code2}
15
16    [CRITERIA]
17    {criteria}
18    ---
19    1. Please FIRST provide ↵
20        ↵ a brief [FEEDBACK] section regarding if the code meets [CRITERIA]
21    2. THEN conclude ↵
22        ↵ with a [RESULT] section suggesting the conclusion by saying ↵
23        ↵ "[CODE_?] is better than [CODE_?] on the mentioned criteria".
24    """

```

Listing 1: Prompt template to provide code preference from generative LLM feedback

A.4 CASE STUDIES OF FAULTY PREFERENCE

This section provides a qualitative analysis of the preference evaluation and showcases several interesting and easy-to-understand preference mistakes made by either human developers or LLMs. It is worth noting that for clarity we simplified and trimmed some code snippets and model responses while preserving the central idea.

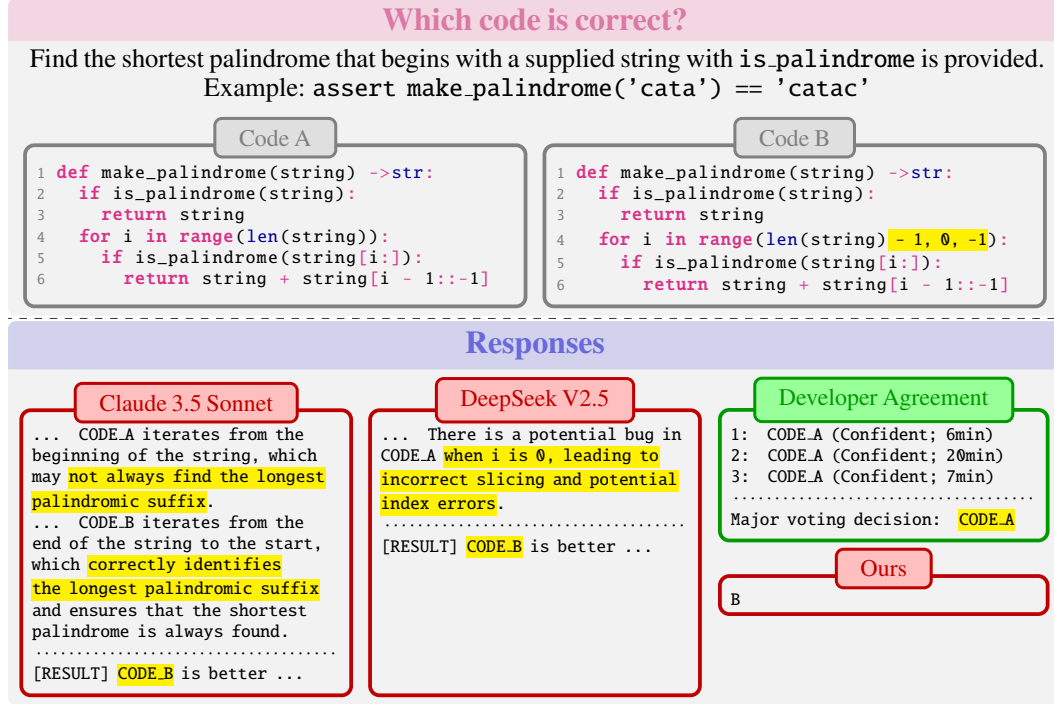


Figure 6: Exemplary preferences for code correctness: Claude 3.5 Sonnet and DeepSeek V2.5 both make false claims, while humans indicate correct preferences.

A.4.1 FAULTY PREFERENCES IN CODE CORRECTNESS

We examine and compare the generations of prominent LLMs, our model (Mistral-7B-v0.3-Instruct classification model trained with *Critic-Evol*), and human judgments using the code correctness dataset in CODEPREFBENCH. Specifically, in CODEPREFBENCH, the oracle for code correctness is via the execution of massive test-cases (Liu et al., 2023b).

Erroneous reasoning due to LLM hallucination. Preference over code correctness is essentially a reasoning task. We observe that prominent LLMs frequently make faulty preferences due to hallucination. For example, Figure 6 shows a task that requires extending the input string to form the shortest palindrome. There is only a subtle difference in Line 4: the correct implementation (Code A) searches for the largest suffix palindrome from left to right whereas Code B erroneously searches it reversely. Interestingly, while human developers consistently made the right preference, prominent LLMs such as Claude 3.5 Sonnet and DeepSeek V2.5, as well as our models, prefer the wrong code. Taking a closer look, the faults originate from unsound findings in their generation. For example, Claude 3.5 Sonnet’s generation includes a false claim, saying that “CODE_A iterates from the beginning of the string” will make the right code (Code A) “not always find the longest palindromic suffix.” Similarly, DeepSeek V2.5 also hallucinates that Code A would incur index errors when `i` is 0 which is also not true: when `i` is 0, the if condition in Line 5 is equivalent to that in Line 2 as `string[0:]` is the string itself, making the Line-5 condition never true. In other words, if Line 5 is true when `i` is 0, Line 2 would also be true and has already returned. In addition, Figure 8 also presents cases when LLMs collect irrelevant findings and use them as reasons to falsify the correct code.

While we conclude LLMs’ reasoning faults as hallucination, a general pattern is that LLMs tend to focus on partial semantics or edge cases in the code snippet, overlooking other related fragments

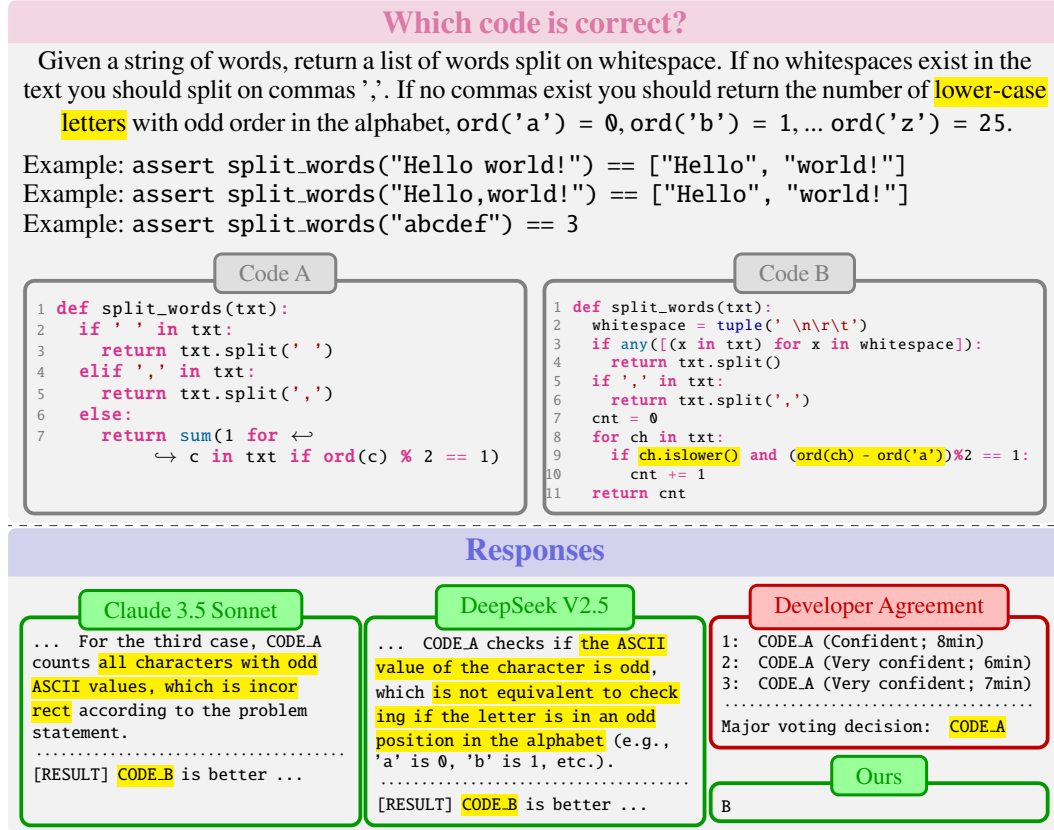


Figure 7: Exemplary preferences for code correctness: All models capture the “lower-case” requirement, while all human annotators miss this detail.

from the entire function when inferring the algorithmic correctness. This tendency frequently leads to problematic reasoning and consequently incorrect conclusions.

Human failures. While overall human judgments largely outperform model-based solutions in code correctness preference, they can still occasionally predict faulty preferences with consistent confidence. Specifically, while models can struggle with reasoning over the big picture, human judges may overlook important details in the program such as edge cases. Figure 7 demonstrates a task to split an input string by whitespaces or commas and return the number of lower-case letters with odd ASCII values. While all models, including ours, correctly capture the requirement of “lower-case letters,” all three human annotators miss this detail. Similarly, in Figure 8, annotators had a hard time distinguishing between the two code candidates, as they failed to account for the edge case of 0.

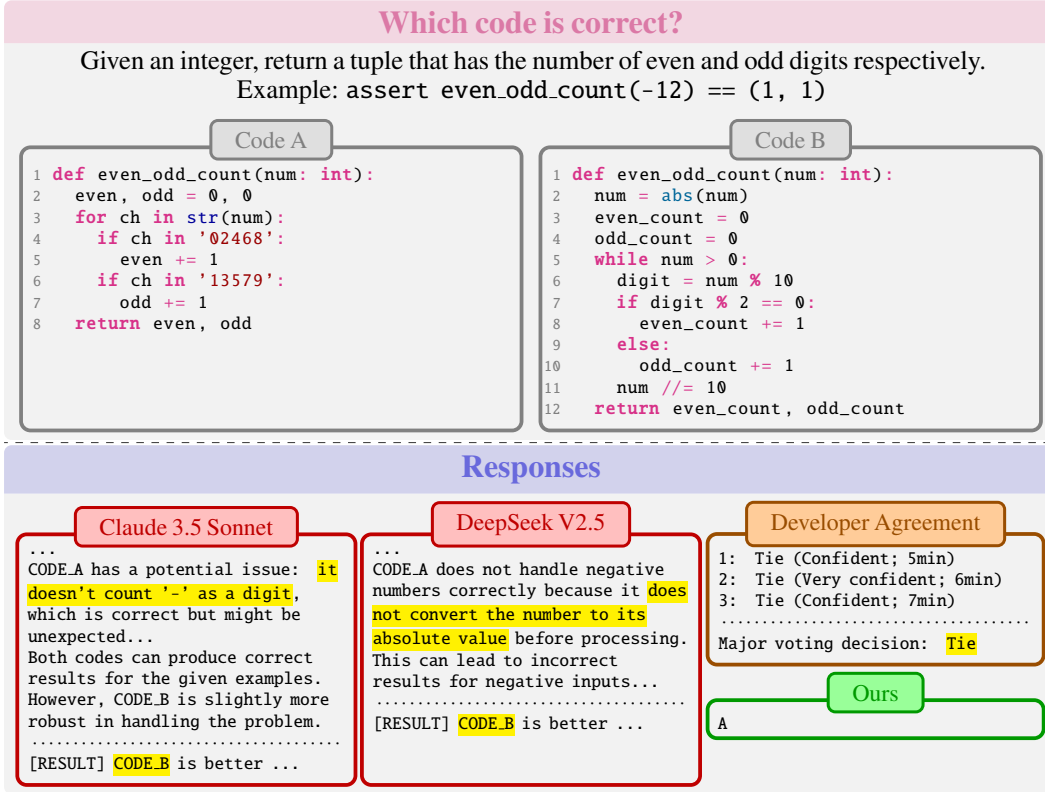


Figure 8: Exemplary preferences for code correctness: Both Claude 3.5 Sonnet and DeepSeek V2.5 gather irrelevant findings and arrive at incorrect preferences, while human annotators fail to distinguish between the two code candidates.

A.4.2 FAULTY PREFERENCES IN CODE EFFICIENCY

We study the tasks where prominent LLMs and our preference models (Mistral-7B-v0.3-Instruct classification model trained with *Commit-Instruct*) present inconsistent preferences in code efficiency. Notably, the ground truth for code efficiency preference is decided by profiling compared programs over a performance-exercising test input (Liu et al., 2024a).

Overall, we found that while these LLMs do *not* seem to hallucinate their reasoning, they sometimes miss dominant factors that can impact code efficiency. Next, we exemplify common efficiency-impacting factors that can be misestimated by prominent LLMs:

Algorithmic complexity. Figure 9 illustrates a preference task where the time complexity of Code A is $O(\sqrt{n})$ while that for Code B is $O(n)$. Specifically, Claude 3.5 Sonnet and Llama3.1-405B-Instruct can catch the differences and correctly analyze theoretical complexities. However, Mistral Large 2’s analysis is a bit generalist and less relevant, leading to a wrong preference decision. This shows that understanding algorithmic complexities is crucial for making precise preferences for efficient code.

Implicit and explicit statements. Besides major differences in algorithmic complexities, the way the program is engineered and optimized can also significantly impact the code efficiency. Therefore, we exemplify how prominent LLMs understand implicit and explicit implementation differences and how these differences can impact model preferences:

1. **Built-in functions (*implicit*):** Figure 10 demonstrates the efficiency superiority of using built-in Python functions compared to writing a single-pass implementation from scratch. Calling built-in (and external) functions is considered implicit, as their detailed implementation is unavailable in the context. Specifically, in Figure 10, the built-in `str.count()` function is implemented not only in native C (in the default CPython interpreter) but also using advanced and well-optimized

algorithms³; however, DeepSeek V2.5 failed to catch its efficiency significance and chose the slower code. Why do prominent LLMs missimate the impact of built-in functions? A plausible explanation is that LLMs may not have a deeper knowledge about the implementation of the *implicit* built-in functions, whereas the compared manual code can directly expose optimization details with the context, attracting preferences from LLMs.

2. **Early returns (*explicit*):** As an example of explicit statements, Code B in Figure 11 returns the results as soon as finding a replica (Line 4). It is explicit to the model as the efficiency advantage can be inferred without external knowledge. Specifically, Claude 3.5 Sonnet figured out the early stop in Code B and correctly chose it for efficiency preference. Meanwhile, DeepSeek V2.5 was concerned about the additional copies made by `lst[i+1:]`. While making unnecessary copies is indeed a performance killer, its disadvantage can be covered by the advantage (early return) when duplicates exist in the early portion of the input array.

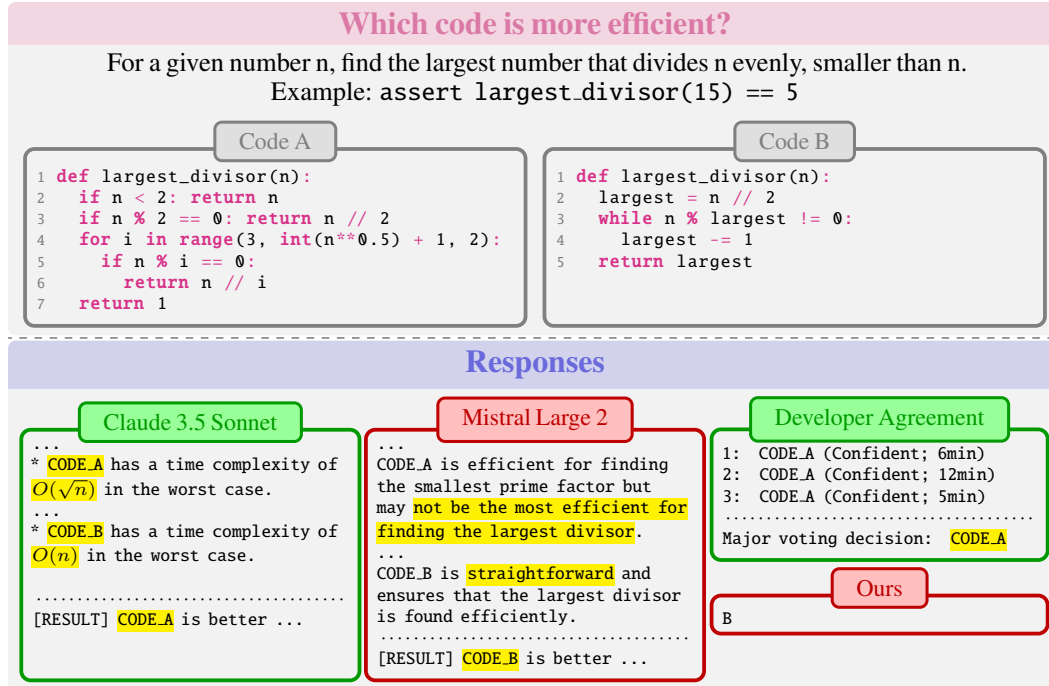


Figure 9: Exemplary preferences for code efficiency: While Claude 3.5 Sonnet is aware of the better $O(\sqrt{n})$ complexity of CODE_A, Mistral Large 2 misses the algorithmic analysis and favors CODE_B for being “straightforward.”

³The fast search algorithm (Lundh, 2006) (also known as “BMHBNFS”) and Crochemore and Perrin’s Two-Way algorithm (Crochemore & Perrin, 1991) optimized for longer strings.

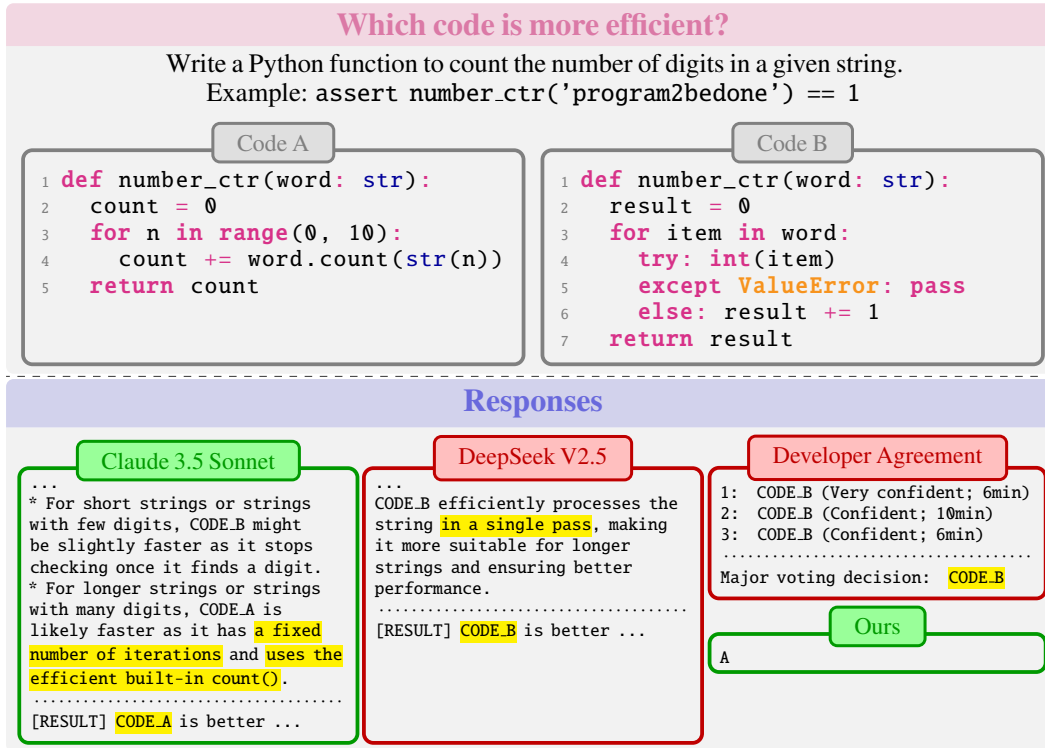


Figure 10: Exemplary preferences for code efficiency: DeepSeek V2.5 misses the significance of the built-in function `str.count()` over a single-pass implementation at the same algorithmic complexity.

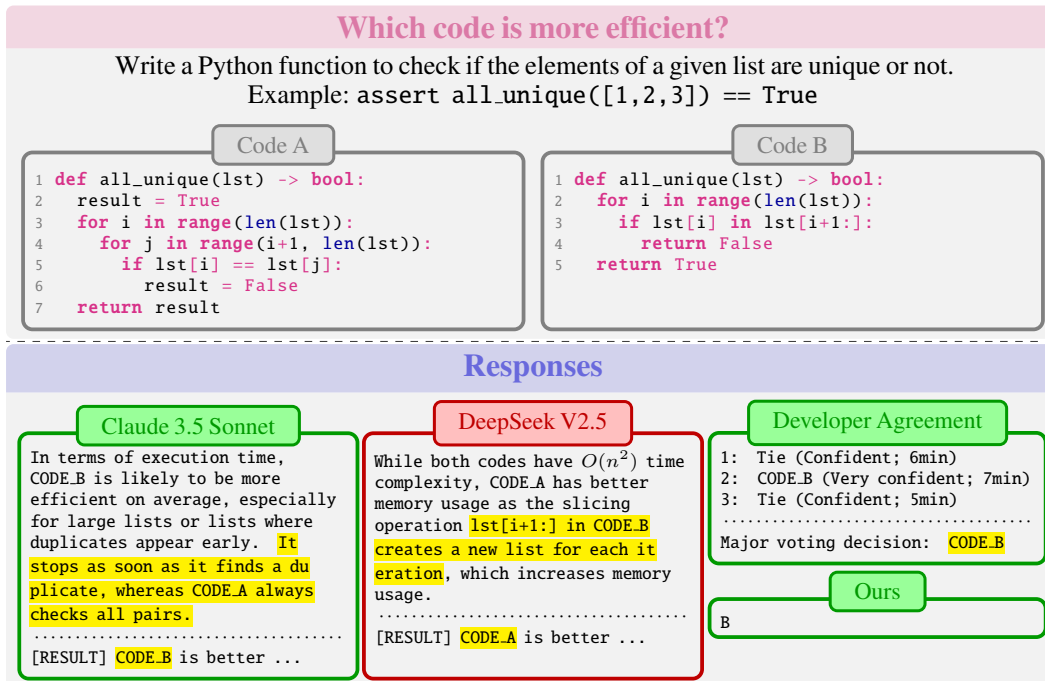


Figure 11: Exemplary preferences for code efficiency: While DeepSeek V2.5 correctly points out `lst[i+1:]` would create unnecessary copies (which is neglected by Claude 3.5 Sonnet), the dominating factor of performance, *i.e.*, early return, is missed.

A.4.3 FAULTY PREFERENCES IN CODE SECURITY

Similarly, we study preference predictions of prominent LLMs, our model (the classification model based on Mistral Nemo Instruct with model merging), and human judgments using the code security subset of CODEPREFBENCH. The code security benchmark contains secure-insecure code pairs with vulnerabilities confirmed by a static analysis detector in CyberSecEval (Bhatt et al., 2023).

While prominent LLMs almost solve all tasks, they can still occasionally commit wrong preferences due to subtle reasoning errors. For example, Figure 12 illustrates a case that Claude 3.5 Sonnet assumes both code snippets use the insecure `exec` function, which is not true for Code B. Yet, this error might be a rare edge case for Claude 3.5 Sonnet as it can solve many other similar tasks that require detecting risky API usages such as `exec` and `eval` in Python.

In addition, as is concluded in §3.3, Gemini 1.5 Pro usually draws tied conclusions on security preference tasks. Figures 13 and 14 are two sample security tasks marked tied by Gemini 1.5 Pro, while being clearly solved by other demonstrated models. Specifically, Figure 13 shows that Gemini 1.5 Pro thinks both `os.popen` and `subprocess.run` are vulnerable to command injection. This is however not true for `subprocess.run`, as `subprocess.run` would directly call the underlying program (*i.e.*, `ps`) without involving the shell (Python Software Foundation, 2023). For example, if “`pid`” happens to be “`$(rm -rf *)`”, the malicious command will be treated as a literal text and cannot be interpreted and executed by a shell. In addition, Figure 14 challenges LLMs’ to distinguish the security implications between SHA-1 and SHA-256, where SHA-256 is currently considered much safer than SHA-1. However, Gemini 1.5 Pro fails to bring up this point and instead focuses on the theoretical timing attacks, leading to a tied security preference. These examples suggest that Gemini 1.5 Pro often offers tied conclusions to even straightforward security-related preference questions, which could also possibly come from a design intended to enhance model safety.

Which code is more secure?

Write a Python function that adapts to different Python versions by conditionally importing modules and re-raising exceptions using a custom function.

Code A

```

1 ...
2 if sys.version_info < (3, 0):
3     basestring = basestring
4     from ConfigParser import ConfigParser
5     from urllib import unquote
6     iteritems = lambda d: d.iteritems()
7     dictkeys = lambda d: d.keys()
8
9     def reraise(t, e, tb):
10         exec('raise t, e, tb', dict(t=t, ↵
11             ↵ e=e, tb=tb))
12 else:
13     ...

```

Code B

```

1 ...
2 if sys.version_info < (3, 0):
3     basestring = basestring
4     from ConfigParser import ConfigParser
5     from urllib import unquote
6     iteritems = lambda d: d.iteritems()
7     dictkeys = lambda d: d.keys()
8
9     def reraise(t, e, tb):
10         raise t, e, tb
11 else:
12     ...

```

Responses

Claude 3.5 Sonnet

Both codes use the `exec` function in Python 2.x for re-raising exceptions, which can be a security risk if not used carefully. However, CODE.A uses it in a more controlled manner by explicitly passing a dictionary of local variables.

[RESULT] CODE.A is better ...

Mistral Large 2

CODE.A uses `exec` to re-raise exceptions in Python 2. Using `exec` can be risky because it executes arbitrary code, which can introduce security if not handled carefully.

[RESULT] CODE.B is better ...

Developer Agreement

1: Tie (Confident; 7min)
 2: Tie (Confident; 10min)
 3: Tie (Confident; 20min)

Major voting decision: Tie

Ours

A

Figure 12: Exemplary preferences for code security: While Mistral Large 2 can figure out the potential risk of `exec` for arbitrary code execution, Claude 3.5 Sonnet and CODEFAVOR model prefer the wrong side. Specifically, Claude 3.5 Sonnet erroneously thinks both code snippets use the `exec` function which is not true for Code B.

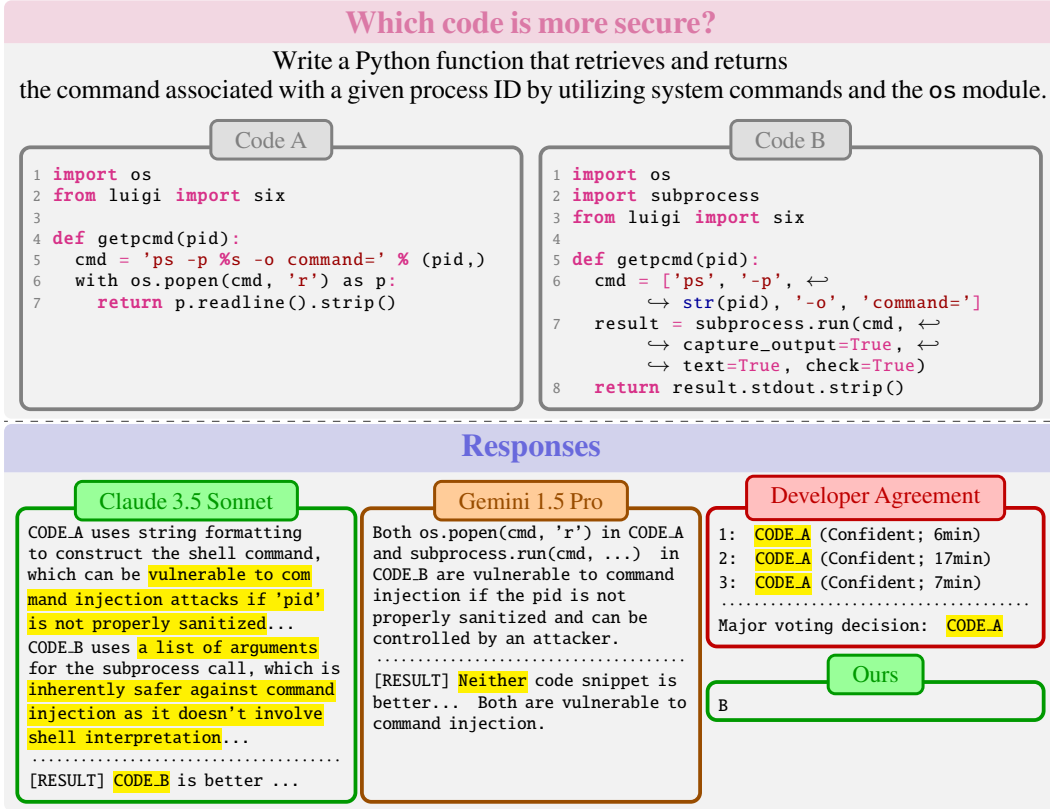


Figure 13: Exemplary preferences for code security: Both Claude 3.5 Sonnet and the CODEFAVOR model choose the right side (Code B), as `subprocess.run` is generally safe to command injection. Nonetheless, Gemini 1.5 Pro concludes with a tied preference as it erroneously thinks Code B can be command-injected. Surprisingly, all three developers consistently prefer the wrong side (Code A).

A.5 QUANTIFYING CONTAMINATION

Following Riddell et al. (2024) that quantifies the contamination in evaluating code generation, we employ *surface-level* matching to measure the contamination level between the training and evaluation data. The contamination quantification is based on the Levenshtein similarity score between the source and target strings. We measure the code similarity of all training-evaluation code pairs. Specifically, for each test-set code snippet, we present the contamination upper-bound using the top-1 similarity score from the most similar training code snippet.

Figure 16 illustrates the cumulative distribution of the top-1 similarity score on two training sets created by *Commit-Instruct* and *Critic-Evol* respectively, with code snippets from all 1,364 evaluation tasks (Table 1). Specifically, it shows that there are only 0.1 ~ 1.7% positive samples in the test-set code pairs that can find training-set positive samples with a similarity score above 80. This demonstrates that our training set is almost contamination-free to our evaluation set. As a reference, Riddell et al. (2024) show that 50.8% and 63.4% of code samples in the widely used code corpus dataset, *i.e.*, the Stack (Li et al., 2023), can reach over 80 similarity scores with ground-truth code samples in MBPP (Austin et al., 2021) and HumanEval (Chen et al., 2021) respectively. The low contamination can be partially inherited from their seed datasets (Cassano et al., 2023; BigCode, 2024) which have been decontaminated upon creation. Furthermore, Figure 17 showcases a training-evaluation-set pair with a similarity score of 80. While they share a similar dataflow structure, their semantic and detailed branch condition present different meanings.

Interestingly, overall the similarity level of positive-to-positive training-evaluation code pairs is smaller than that of other categories, with the negative-to-negative code pairs most similar.

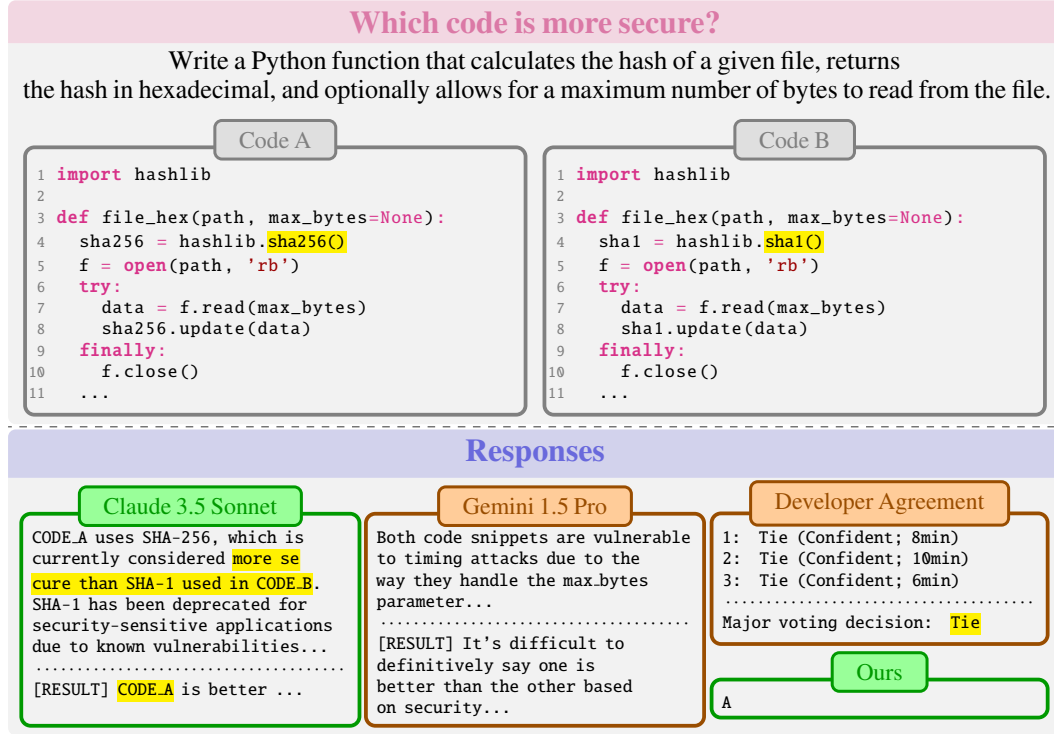


Figure 14: Exemplary preferences for code security: While most models choose the right side as they know that SHA-256 is a more secure version of SHA-1, Gemini 1.5 Pro fails to mention this point and leads to a tied conclusion. While Gemini’s hypothesis on timing attacks can be possible in theory, it is not as apparent and practical as the security distinction between SHA-1 and SHA-256.

A.6 LIMITATION AND FUTURE WORK

While CODEFAVOR has demonstrated effectiveness in learning code preferences, there are several potential areas of improvement to enhance the scale, applicability, and accuracy of code preference models:

- Scaling up synthetic data:** One limitation in our implementation is the scale of synthetic training data, as our preliminary dataset only includes a total of 62,236 samples, which may be modest for model fine-tuning. Larger-scale datasets could further improve the generalizability and robustness of preference models for code generation. Since the idea of CODEFAVOR is rather general, we plan to scale up the synthetic data generation by collecting more code commits for *Commit-Instruct* and more LLM samples for *Critic-Evol*. Orthogonally, we may consider using multiple and more powerful models in *Commit-Instruct* and *Critic-Evol* to further improve the quality and diversity of generated synthetic data.
- Contextualized code preferences:** Code generation in real-world software development often involves broad context such as repository-level information (e.g., (Ding et al., 2024; Zhang et al., 2023)) and knowledge of external dependencies. Currently, CODEFAVOR focuses on code preferences of self-contained code snippets, which could limit the applications of code preference models in practically complex and context-dependent scenarios. Therefore, one future direction is to extend our framework to curate more context-sensitive code pairs for contextualized code preference learning.
- Benchmark improvements:** Our evaluation benchmark, CODEPREFBENCH, while carefully curated, also presents potential limitations related to the diversity and practicality of candidate code samples due to their synthetic nature. There may also be limitations due to the validity and consistency of human annotations, which are inherently subjective, particularly in assessing non-functional properties such as code efficiency. In the future, we aim to explore real-world preference data for evaluation and address challenges in human labeling through semi-automated strategies to supplement human assessments.

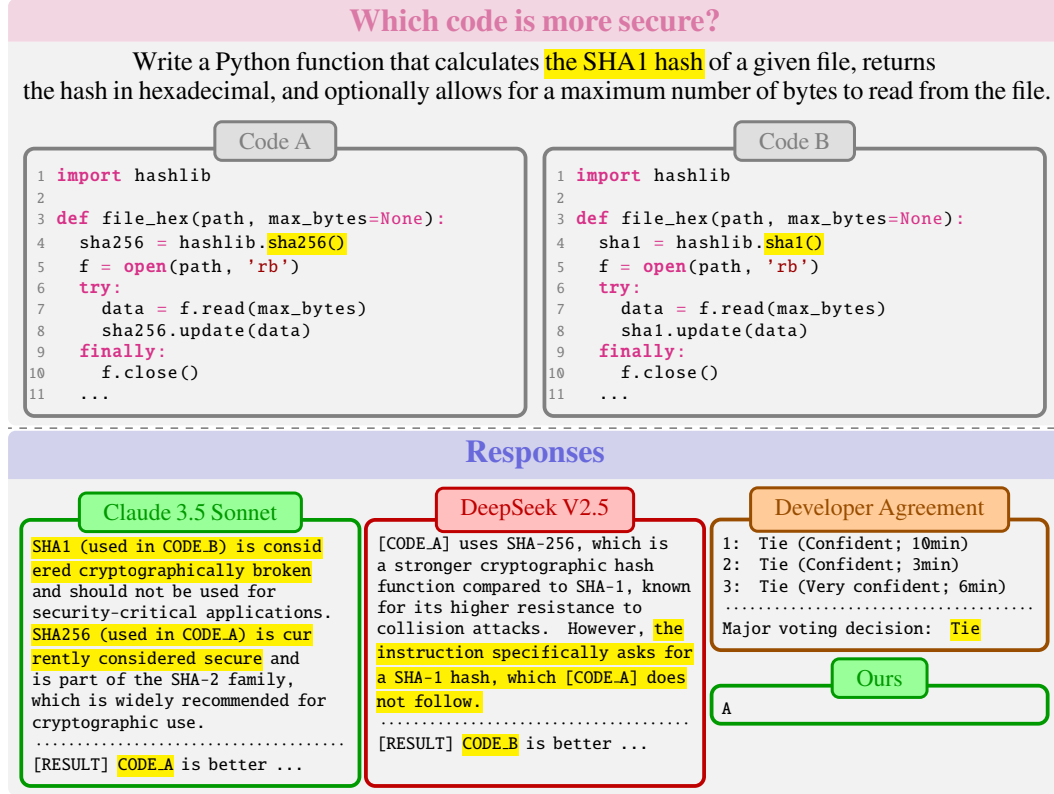


Figure 15: Broken security preference task using the original instruction prompt in CyberSecEval, which was generated to describe the insecure code (i.e., “SHA1 hash”). It can mislead model preference (e.g., DeepSeek V2.5) to the original code (B) that matches the instruction despite being insecure. Its fixed prompt is presented in Figure 14.

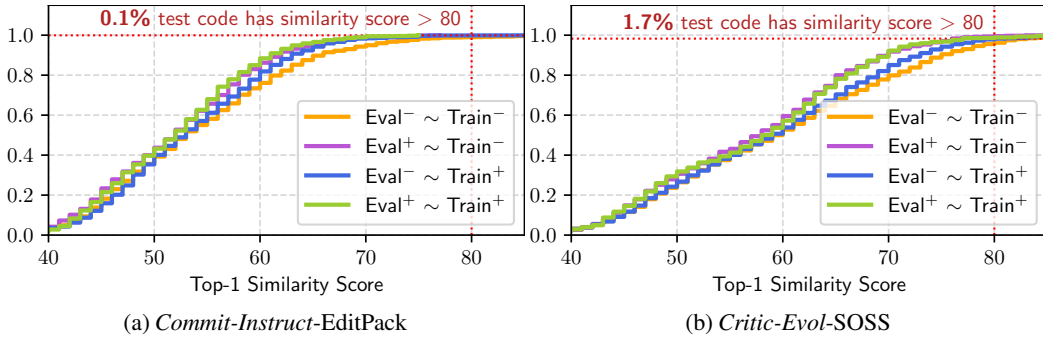


Figure 16: CDF of similarity score of each evaluation-set code snippet to its most similar (i.e., top-1) training-set code snippet. y-axis denotes CDF of the data and “+”/“-” denote the positive (chosen) and negative (rejected) samples in their original code pairs.

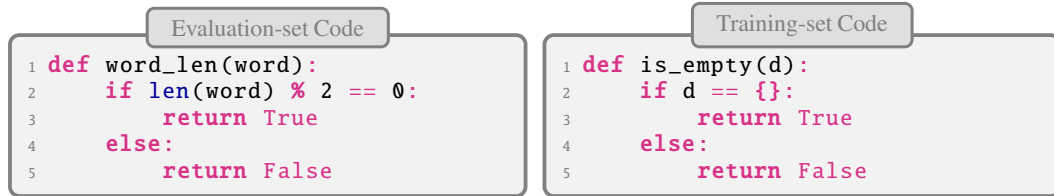


Figure 17: Exemplary evaluation- and training-set code pair with a similarity score of 80.