ON CODE-INDUCED REASONING IN LLMS

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ABSTRACT

Code data has been shown to enhance the reasoning capabilities of large language models (LLMs), but it remains unclear which aspects of code are most responsible. We investigate this question with a systematic, data-centric framework. We construct parallel instruction datasets in ten programming languages and apply controlled perturbations that selectively disrupt structural or semantic properties of code. We then finetune LLMs from five model families and eight scales on each variant and evaluate their performance on natural language, math, and code tasks. Across 3,331 experiments, our results show that LLMs are more vulnerable to structural perturbations than semantic ones, particularly on math and code tasks. Appropriate abstractions like pseudocode and flowcharts can be as effective as code, while encoding the same information with fewer tokens without adhering to original syntax can often retain or even improve performance. Remarkably, even corrupted code with misleading signals remains competitive when surface-level regularities persist. Finally, syntactic styles also shape task-specific gains with Python favoring natural language reasoning and lower-level languages such as Java and Rust favoring math. Through our systematic framework, we aim to provide insight into how different properties of code influence reasoning and inform the design of training data for enhancing LLM reasoning capabilities.

1 INTRODUCTION

There has been substantial interest in the last several years in engineering language models that can tackle challenging reasoning tasks (Huang & Chang, 2023). Language reasoning tasks, such as math word problems or logic puzzles, tend to require multi-step, structured "thinking" in order to produce the correct answer. Recent work has found that training the language model on code, either during pre-training (Fu & Khot, 2022; Ma et al., 2023b) or during post-training (Zhang et al., 2024b), can improve its skill at reasoning tasks, even ones that are unrelated to programming. These prior works have hypothesized that the properties of code data, such as its logical consistency, compositional structure, and reduced ambiguity compared to natural language, provide effective signals that benefit reasoning. Despite the broad effectiveness of code data in training, we still lack a systematic understanding of which aspects of code drive these improvements: is it the its syntactic regularity, structural abstractions, or linguistic styles?

In this work, we aim to provide such an account by systematically investigating which aspects of code serve as effective training signals. To this end, we construct parallel instruction datasets in both natural language and code, and further expand the code dataset into language-specific variants by generating responses in ten widely used programming languages. This design allows us to examine how structural differences across languages affect downstream reasoning. In addition, we introduce controlled perturbations to the code data to isolate contributing factors: (1) *rule-based* transformations such as whitespace removal or comment shuffling, and (2) *generative* transformations where GPT-4o-mini rewrites or reformats the code (e.g., with augmented comments, pseudocode, or flowcharts). We then fine-tune language models on each dataset variant, and evaluate them across natural language and general knowledge, math, as well as code understanding and generation tasks. Our contributions are:

- We introduce a systematic framework to disentangle what aspects of code data improve reasoning, combining parallel instruction data construction, controlled perturbations, and large-scale evaluation across five model families and eight scales.
- We design a comprehensive and controlled suite of perturbations spanning rule-based edits and generative rewritings.

- We provide new insights into the role of code in reasoning to inspire guidance on leveraging its structural and linguistic properties in future training data design.

2 Related Work

Code data for LLM reasoning Recent work has increasingly demonstrated that incorporating code data can substantially improve the reasoning abilities of LLMs. Prior studies show that adding code during pretraining or instruction tuning consistently improves model performance across reasoning tasks, domains, model scales and architectures (Ma et al., 2023a; Zhang et al., 2024a; Yang et al., 2025b; Aryabumi et al., 2024). Several works further explore the synergy between code and reasoning and highlight how code's structured and verifiable properties support logical decomposition and intermediate step generation (Bi et al.; Yang et al., 2024). This effect has been observed in multilingual contexts as well, where code-augmented training improves structured reasoning in under-resourced languages (Li et al., 2024). Complementary research focuses on code's impact for alignment and reward modeling, where pretraining with code-preference pairs or code-based intermediate steps can improve model calibration for reasoning-intensive tasks (Yu et al., 2024). The closest line of research to our work explores stress-testing LLMs with structural and semantic code perturbations (Lam et al., 2025), which shows that small corruptions can significantly reduce reasoning performance.

Data impact on LLM performance The performance of LLMs are tied to the vast amounts of training data, but the quality, composition, and characteristics of this data greatly shape their abilities (Wang et al., 2024; Li et al., 2023; Lee et al., 2022). For example, extensive analyses by Longpre et al. (2024) have shown that pretraining data curation decisions for dataset age, composition, and content filtering have systematic impact on downstream performance, and that these effects persist even after fine-tuning steps. Zhang et al. (2024c) demonstrate that poisoning as little as 0.1% (and even 0.001%) can produce persistent behavioral changes that survive instruction tuning and alignment. In addition, Havrilla & Iyer (2024) showed that LLMs are sensitive to global, accumulative errors in chain-of-thought-structured training data, and that it is critical to filter out documents containing large amounts of dynamic, global noise during both pretraining and fine-tuning.

3 Methodology

We design a controlled experimental framework to understand what aspects of code improve reasoning in language models. Our methodology consists of three stages: constructing parallel natural language and code instruction datasets (Section 3.1); applying systematic modifications to code instruction data (Section 3.2); and fine-tuning various language models on each dataset variant and then conducting evaluation (Section 3.3). An overview of this framework is shown in Figure 1.

3.1 Instruction Data Generation

We construct two parallel instruction datasets: one in natural language and the other in code, each containing 120,000 instruction-response pairs. We collect instructions from publicly available datasets, carefully process and filter them through deduplication and language-agnostic filtering, and augment the code data in a controlled way. This construction enables a more controlled comparison of natural- and code-based instruction following under a unified training framework.

Code instructions We aggregate code instructions from Codeforces-CoT (Penedo et al., 2025), Code-Instruction-122K (TokenBender, 2024), Evol-Instruct-Code-80k-v1 (nickrosh, 2024), Code-Instruction (red1xe, 2023), Code-Instruct-Sets (AtlasUnified, 2023), and Code-Instruct-Alpaca-Vicuna-WizardLM (rombodawg, 2024). We aim to construct instruction data that is high-quality, diverse, and language-agnostic.

To ensure generality and eliminate redundancy, we first remove all exact-match duplicates across the datasets. We then filter out instructions that are explicitly programming-language-specific (e.g., "Translate this code from Python to java") or whose solutions are inherently tied to particular domains, such as web development or databases (e.g., "webpage", "website", "SQL", "HTML").

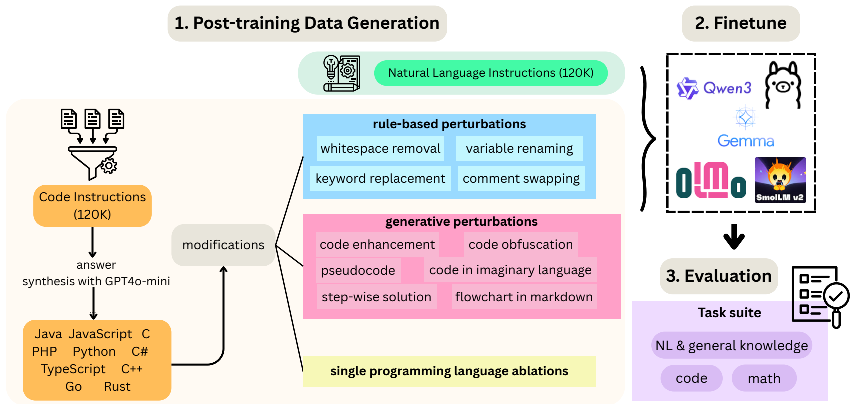

Figure 1: We construct parallel code and natural language instruction datasets, apply targeted modifications (rule-based and generative-based perturbations, single programming language ablations), and fine-tune a separate LLM on each modified dataset. We then evaluate the resulting models across general natural language, code, and math reasoning tasks.

For each instruction, we prompt GPT-4o-mini* to generate answers in ten widely used programming languages: Java, JavaScript, PHP, Python, C#, TypeScript, C, C++, Go, and Rust. To create these variants, we design 20 language specification templates that explicitly request a solution in a given programming language (Table 6). For every instruction, we randomly select a template, instantiate it with one of the target languages, and combine it with the general generation instructions to form a complete prompt (Figure 8). From these generations, we sample 120K instruction–response pairs with valid outputs, evenly distributed across all ten languages.

To assess the quality of our synthesized code instruction–response pairs, we perform a comprehensive syntax and compilation check across all ten programming languages. For each instance, we extract the generated code block and apply standard syntax or compilation tools (e.g., `ast.parse` for Python, `gcc -fsyntax-only` for C, `javac` for Java). As shown in Appendix Table 3, the majority of samples compile or execute successfully, with pass rates ranging from 64.08% (TypeScript) to 99.25% (Python) and an average pass rate of 82.59% across all languages. These results indicate that most generated instructions correspond to syntactically valid and executable code.

Natural language instructions We sample 120K examples from the OpenHermes 2.5 corpus (Teknium, 2023). We exclude instruction-response pairs associated with categories unrelated to general-purpose instruction following, such as "agent" and "summarization", as well as those labeled "coding" to ensure the dataset is entirely natural language. To maintain linguistic consistency, we further filter out non-English examples. This filtered natural language subset complements our code instruction data, enabling a fair comparison between code and natural language instructions.

3.2 Systematic Perturbation Design

To understand which specific structural and semantic properties are responsible for changes in reasoning task performances, we systematically perturb different aspects of the code dataset. We design the perturbations through two ways: *rule-based* (deterministic transformations) and *generative* (model-generated augmentations). Notably, our perturbation strategies do not alter the number of examples in the dataset. We illustrate an examples of these perturbations in Table 1, with extended examples and token statistics in Appendix Table 2.

3.2.1 Rule-Based Perturbations

Rule-based perturbations apply deterministic transformations to the code. They are designed to disrupt superficial patterns or semantic signals that may influence model predictions without altering the core logic of the code. We describe five such perturbations below:

*Responses are generated with temperature 0.6 and API-default decoding parameters.

Table 1: An example of perturbations (Section 3.2) applied to the same original snippet.

Full Original Snippet	Type	Strategy	Original Excerpt	Perturbed Excerpt

`def process_string(input_string):`
`  vowels = "aoyeuiAOYEUI"`
`  result = []`
 	
`  for char in input_string:`
`    if char not in vowels:`
`      result.append('.' +`
`char.lower())`
 	
`  return ''.join(result)`
 	
`# Read input`
`input_string = input().strip()`
`# Process and print the result`
`print(process_string(input_string))`
	Rule-based	Whitespace Removal	`result.append('.' + char.lower())`	`result.append('.'+char.lower())`

		Variable Renaming	`for char in input_string: ...`	`for var_4 in var_1: if var_4 not in var_2: ...`
		Keyword Replacement (Nonsense)	`if char not in vowels:`	`garply i not in baz`
		Keyword Replacement (Non-English)	`for char in input_string:`	`para ch en entrada`
		Comment Swapping (Local)	`# Read input`	`# Walking`
		Comment Swapping (Global)	`# Process and print the result`	`// Queue for processing nodes`
		Comment Removal	`# Read input`	`/* all comments removed */`
	Generative	Pseudocode	`for char in input_string: if char not in vowels`	*FOR EACH character IF not vowel THEN append '.'+lowercase*
		Step-by-Step	`result.append('.' + char.lower())`	*Append '.' before consonants and convert to lowercase*
		Flowchart	`if char not in vowels:`	`[Read char] → {Vowel?} → [Append '.'+lower]`
		Code in Imaginary Language	`result.append('.' + char.lower())`	*glorf add '.' ⊕ lower(chr)*
		Comment Enhancement	`# Process and print the result`	*# Removes vowels and prefixes consonants with '.'*
		Comment Obfuscation	`# Read input`	*# WARNING: Code may summon aliens; # TODO: handle quantum vowels*

Whitespace removal All whitespace characters are removed from the code. This tests whether models rely on formatting heuristics, such as indentation or visual grouping of blocks, as implicit structural cues, particularly in languages like Python where whitespace is semantically meaningful.

Variable renaming We replace user-defined variables, function names, and class names with canonical placeholders of the form `var_i`, where $i \in [0, n)$ and n is the total number of unique identifiers in the code snippet. This removes semantic cues conveyed by meaningful identifier names (e.g., `counter`, `isSorted`).

Programming language keyword replacement For each of the ten programming languages in our dataset, we identify its reserved keywords (e.g., `if`, `return`, `def` in Python) and substitute all occurrences of them using two strategies. The first replaces keywords with nonsense tokens (e.g., *foo*, *quux*), which have no semantic meaning in any language. In the second strategy, we use non-English but valid words (e.g., *amigo*, *fleur*), which are real words in various languages but semantically unrelated to the programming context. These perturbations aim to challenge models' reliance on syntactic and semantic cues from familiar language constructs.

Comment removal We remove all inline and block comments from each code snippet. Code comments often provide useful semantic signals for program comprehension (Buse & Weimer, 2009; De Souza et al., 2005). This perturbation tests whether models largely leverage such auxiliary natural-language cues.

Comment swapping We introduce local and global swapping that misplace code comments to disrupt the semantic alignment between code and documentation. In local swapping, comments within a snippet are randomly reordered, preserving their content but misaligning them with the relevant code segments. In global swapping, we first collect a global pool of comments from the entire dataset. Then, for each comment in a snippet, we replace it with a randomly sampled comment from this pool. This results in documentation that is entirely mismatched to the surrounding code.

3.2.2 Generative Perturbations

We create generative perturbations by prompting GPT-4o-mini[†] to produce alternative versions of code responses generated according to Section 3.1. These rewrites preserve the original intent of the code while introducing more diverse variations beyond what rule-based edits can achieve, allowing

[†]We use temperature of 0.6 and default settings.

us to test model sensitivity and robustness to semantically equivalent inputs expressed in different forms. The full set of prompts used is available in Appendix A.6.

Comment enhancement We prompt GPT-4o-mini to regenerate the code with high-quality documentation and inline comments (Figure 9). The prompt emphasizes two forms of annotation: (1) comprehensive documentation comments for all functions, classes, and key code blocks to describe their purpose, parameters, return values, and assumptions; and (2) informative inline comments that clarify complex or non-obvious logic. These annotations follow the conventions of the target programming language (e.g., Python docstrings, JavaDoc). Unlike the often sparse comments in unperturbed data, the enhanced versions provide consistent, high-quality annotations, which enables us to test the effect of documentation quality on model performance.

Comment obfuscation Here, we generate deliberately misleading, irrelevant, or nonsensical comments, while preserving the code's functionality (Figure 10). These include (1) inaccurate, off-topic, or absurd documentation (e.g., references to astrology, cooking, or fictitious technologies) and (2) chaotic inline comments that contradict the code's functionality, reference imaginary bugs or features, and use distracting styles such as ALL-CAPS, emojis, and fabricated jargon. This perturbation tests model robustness to extreme noise and deceptive annotations.

Pseudocode We convert code into high-level pseudocode while preserving its logical structure (Figure 11). The model is instructed to replace language-specific syntax with pseudocode constructs (e.g., `IF...THEN...ENDIF`, `FOR EACH`, etc.), remove low-level implementation details (e.g., type declarations or library calls), and maintain the original control flow and indentation. This perturbation evaluates whether models can reason over algorithmic intent without relying on concrete syntax, which offers insight into generalization across abstraction layers in code representation.

Flowchart in Markdown We generate a control flow diagram using Mermaid syntax in Markdown for a given code snippet (Figure 12). The diagram captures all major control structures, such as loops, branches, function calls, and return points, using minimal but descriptive labels. This transformation renders executable code as a graphical abstraction, allowing us to understand whether models can reason over symbolic control flow and align it with underlying program semantics.

Step-by-step solution We rewrite code as a numbered list of natural language steps (Figure 13). Each step preserves the program's logic and execution order but uses declarative, language-agnostic phrasing (e.g., "Define a function named...", "Check if the input is valid"). Unlike pseudocode or flowchart formats, this version entirely removes code or symbolic notation and instead emphasizes procedural understanding in purely narrative form.

Code in imaginary language We translate real code into a fictional language that preserves structure and control flow but replaces all syntax and identifiers with invented tokens (Figure 14). The result is semantically consistent yet entirely ungrounded in real languages. This perturbation allows us to examine whether models rely on surface-form familiarity (e.g., recognizing logical patterns.

To assess the correctness of the perturbed data, we conduct a human evaluation with two annotators, randomly sampling 30 examples per perturbation type (13 total: 7 rule-based and 6 generative). For the rule-based perturbations and comment enhancement/obfuscation, annotators verify that each transformation strictly follows the intended perturbation rule while leaving all unrelated content unchanged. For the generative perturbations (pseudocode, step-by-step instructions, flowchart, imaginary language), which express the original code in alternative forms, annotators verify that the conveyed semantics remain faithful to the original program. Across all 390 sampled instances, 351 were judged correct (90% overall). Rule-based perturbations achieved 176/210 $\approx$ 84% correctness, while generative perturbations achieved 175/180 $\approx$ 97% correctness.

3.3 Model Training and Evaluation

We train a suite of decoder-only LLMs using supervised fine-tuning (SFT) on our instruction–response datasets detailed in Section 3.1, along with their perturbed variants described in Section 3.2. To assess the effect of language-specific patterns, we additionally finetune models on subsets of the code data restricted to a single programming language. This allows us to examine how the syntactical diversity of programming languages influences reasoning performance. Each instruction–response pair is treated as a single input–output sequence, and models are trained to autoregressively predict the response tokens conditioned on the instruction and prior context. All models are fine-tuned from the same pre-trained backbone under supervised fine-tuning (SFT) objective to ensure comparability across experimental conditions. Let $x = (x_1, x_2, \ldots, x_m)$ be the instruction tokens and $y = (y_1, y_2, \ldots, y_n)$ be the response tokens. The SFT objective is defined as:

$$\mathcal{L}_{\text{SFT}} = -\sum_{t=1}^{n} \log P_\theta(y_t \mid x, y_{<t}) \tag{1}$$

where P_θ denotes the model's conditional probability distribution parameterized by θ, and $y_{<t}$ represents the prefix of the response up to position $t-1$.

Models We choose a diverse set of pre- and post-trained language models ranging from 0.6B to 8B parameters. Specifically, we experiment with models from five major families: Qwen3 (Yang et al., 2025a), LLaMA-3 (Grattafiori et al., 2024), Gemma3 (Team et al., 2025), OLMo2 (OLMo et al., 2024), and SmolLM2 (Allal et al., 2025). For each model family, we select representative sizes (e.g., $<$1B, $\sim$1B, $\sim$3-4B, $\sim$7-8B)[‡] to evaluate performance across different scales.

Training data configurations Our base training set consists of 120K instruction–response pairs spanning both code and natural language formats detailed in Section 3.1. From this, we construct several configurations: (1) 100% code-only, (2) 100% natural language-only, and (3) mixed data with varying code-to-language ratios. In addition, we train models on each perturbed variant introduced in Section 3.2. Finally, we include programming-language-specific subsets, training separate models on data from each of the ten languages ($\sim$12K examples per language) to assess the effect of language specialization. The implementation details are in Section A.5.

Evaluation tasks We evaluate model performance across three categories: natural language and general knowledge, math, and code (Table 4).

For natural language and general knowledge, we evaluate across commonsense reasoning, science and textbook-style QA, logical reasoning, and instruction-following. All tasks are evaluated using accuracy. For math, we include both elementary and advanced problem-solving datasets (e.g., GSM8K, HRM8K), as well as arithmetic and math-related subsets of MMLU. Open-ended tasks (GSM8K, HRM8K) use exact match, while arithmetic and MMLU (math) are scored with accuracy.

For code, we evaluate both code understanding and generation. Based on preliminary experiments, we adopt the LLM-as-Judge paradigm (Gu et al., 2025) instead of execution-based evaluation (Huang et al., 2022). Our relatively small, perturbed models often fail to produce fully executable code, making execution-based metrics unreliable. More importantly, our goal is to assess code quality and reasoning under perturbations, not just execution success.

Thus, we prompt *GPT-4o-mini* to first generate an instance-specific rubric on a 1–10 Likert scale given the original instruction, which is expected to capture nuanced quality variation across outputs. The same model is then prompted as a judge to provide a brief reasoning step ("thought") and assign a score based on that rubric. Examples of the rubric-generation prompt and judging prompt are shown in Appendix A.6 (Figures 15 and 16). For the main results, we use *GPT-4o-mini* as the judge due to its strong judging quality and favorable cost–performance tradeoff. To assess the reliability of our LLM-as-judge setup, we additionally conduct an extensive cross-judge analysis using multiple models. The results in Appendix Table 7 demonstrate that our evaluation is stable across judges.

4 Results and Discussion

RQ1: Does incorporating code in finetuning improve task performance? First, we validate prior findings that finetuning on code data can enhance downstream reasoning. Following the training setup in Section 3.3, we compare performance across four settings: zero-shot, full code finetuning ("code-ft"), full natural language finetuning ("nl-ft"), and mixed data finetuning with equal proportions of code and natural language instructions ("mixed-ft"). Across model families and scales, code-ft and mixed-ft generally achieve leading or competitive performance across tasks (Figure 2, and Figures 17–21), with the trend particularly consistent on code generation.

[‡]Due to resource constraint, the larges model we could finetune is 8B.

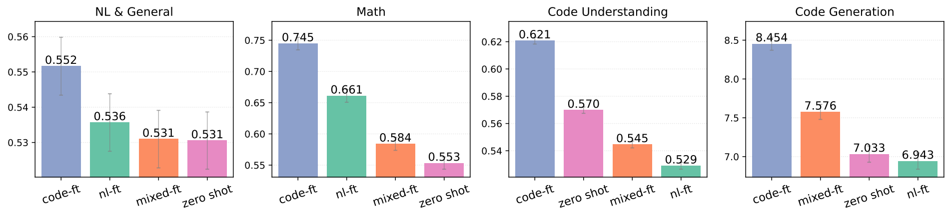

Figure 2: Performance (with stderr bars) of Qwen3-4B-Base across zero-shot, full code finetuning (code-ft), full natural language finetuning (nl-ft), and 50-50 code to NL data ratio finetuning (mixed ft). Incorporating code improves performance across tasks.

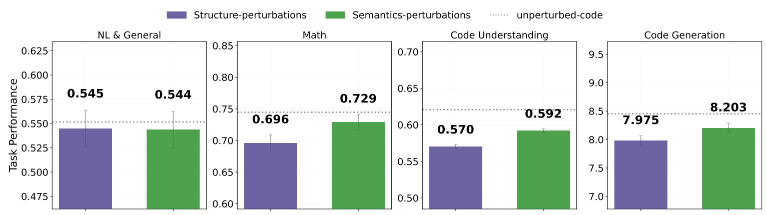

Figure 3: Aggregated performance (with stderr bars) under structural perturbations (e.g. removing whitespace) vs. semantics perturbations (e.g. modifying the comments) of Qwen3-4B-Base. Semantic perturbations tend to be more harmful to performance than semantic ones.

Overall, across the 14 model bases, either code-ft or mixed-ft achieves the best performance on 64% of natural language tasks, 86% of math and code understanding tasks, and all code generation tasks. Motivated by this, we further examine the effect of varying the proportion of code in mixed finetuning (Figure 22). We find that higher fractions of code data generally improve performance across most tasks, with math tasks most sensitive to mixture ratios.

RQ2: How do our systematic perturbations affect performance?

Section Findings

- Structural perturbations hurt more than semantic ones, especially for math and code.
- Appropriate abstractions such as pseudocode and flowcharts can substitute for explicit code structure in reasoning.
- Models don't need verbose code: reduced-token variants perform well as long as core information is preserved.
- LLMs can reason effectively from corrupted code by exploiting surface-level regularities.

Next, we analyze task performance under the perturbations introduced in Section 3.2. Based on the properties of each perturbation, we group them into distinct analysis axes that allow us to systemati-

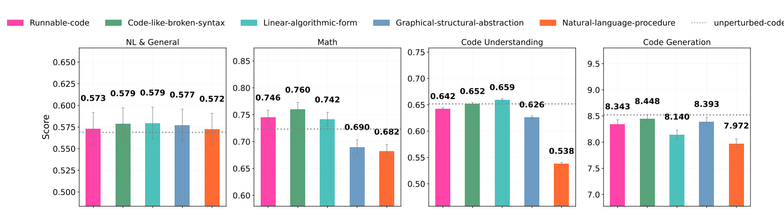

Figure 4: Aggregated performance (with stderr bars) under levels of explicitness of code structure (less explicit going from runnable code to NL procedure) of Qwen3-8B-Base. Certain algorithmic and graphical abstractions benefit reasoning.

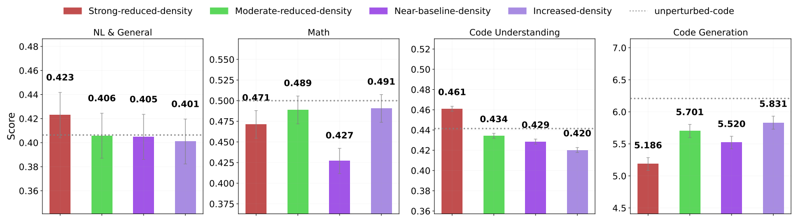

Figure 5: Aggregated performance (with stderr bars) of Qwen3-0.6B-Base with various of token counts wrt to unperturbed code. Reductions can perform comparable or even better than the baseline.

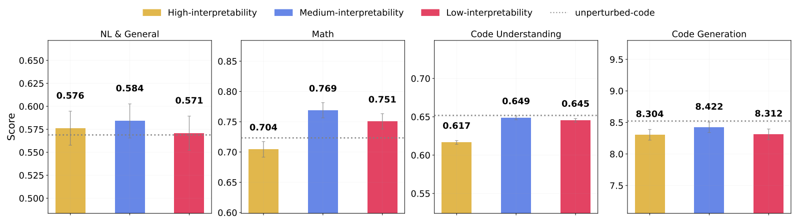

Figure 6: Aggregated performance of Qwen3-8B-Base (with stderr bars), depending on how much the perturbed code data is readable to humans. Low-interpretability with misleading signals can match or perform better than other configurations.

cally probe their effects. The grouping details are in Table 5. We illustrate performance of individual perturbations in Appendix A.7.6.

Structural vs. Semantics Perturbations. We define structural perturbations as edits that alter the syntactic scaffolding or formatting of code (e.g., whitespace removal, pseudocode, flowcharts), while semantic perturbations modify meaning-bearing tokens such as identifiers, keywords, or comments without disrupting the underlying structure. Across model families and scales (Figures 23 – 27), nearly all perturbations reduce performance compared to the unperturbed code-fineturned baseline. More importantly, structural perturbations consistently degrade performance more severely than semantic ones, especially for math and code tasks (e.g., Figure 3). The discrepancy is more evident as models scale up (e.g., Figure 23). This resembles prior work that reasoning structure rather than content is more critical to the learning process (Li et al., 2025). We hypothesize that tasks such as math and code rely more heavily on formatting and layout cues to shape reasoning.

Explicitness of Code Structure. Building on the importance of structure, we examine perturbations along a spectrum of how explicitly they preserve code structure: from runnable or code-like forms, through intermediate abstractions such as pseudocode and flowcharts, to natural language step-by-step procedures. For code generation, where executable outputs are required, it is natural that perturbations that preserve explicit code structure, whether runnable or not, lead to the best performance. For other tasks, however, certain abstractions such as pseudocode or flowcharts often match or even surpass unperturbed code, as they highlight algorithmic structure while removing superficial syntax. By contrast, the most implicit form, natural language procedures, provides little advantage and generally performs worst across tasks (e.g. Figure 4, Figures 28–32).

Relative Information Density. Because our constructed instruction datasets are parallel, the amount of information they convey about the code is comparable across perturbations. We define relative information density as (number of tokens in perturbed dataset) $\div$ (number of tokens in the original code-ft dataset), which reflects how compactly the same content is represented. Perturbations differ in how they adjust density: some produce highly compact forms that strip away most tokens but preserve the algorithmic skeleton (e.g., flowcharts, pseudocode), others moderately reduce density by removing comments or using imaginary languages, while others preserve or even increase density through verbose variable renamings or enriched documentation. We find that strong or moderate reductions in density often perform close to, and sometimes better than, the baseline (e.g. Figure 5, Figures 33–37). However, this advantage doesn't extend to code generation, where preserving richer surface detail is important. In addition, smaller models are more sensitive to density differences, whereas larger models remain robust. Overall, this suggests that the benefit of code for reasoning doesn't lie in its verbosity but but in the efficiency with which essential information is preserved.

Human Interpretability. We also examine perturbations through the lens of human readability: high-interpretability (enriched explanations and visual scaffolds), medium (local edits leaving most code intact), and low (obscured readability or misleading signals). Interestingly, low-iterpretability variants, despite adding noise or distortion, often do not degrade performance too much from the unperturbed baseline, and often match or even surpass medium-interpretability ones (e.g. Figure 6, Figures 38–42). This counterintuitive trend suggests that the models could exploit surface-level regularities and recurring structural cues that persist even in noisy or opaque forms.

RQ3: How does performance vary across programming languages?

Section Findings

- Lower-level languages benefit math tasks.
- Python aligns best with NL tasks, while Java and Rust often rank among the top for math.

The strong impact of structure in RQ2 motivates the question of whether syntactic regularities in programming languages also influence model performance. To explore this, we group the ten programming languages into high-scripting (Python, PHP, JavaScript, TypeScript), intermediate (Java, C#), and low-system (C, C++, Rust, Go) according to their abstraction level. Overall, differences across groups are small. On NL and code tasks, the impact of language groups is largely model-dependent. However, on math tasks, most high-scripting languages consistently underperform relative to intermediate and low-system ones (e.g. top Figure 7, Figures 48–51a). We hypothesize that richer structural detail in lower-level languages provides beneficial signals for mathematical reasoning.

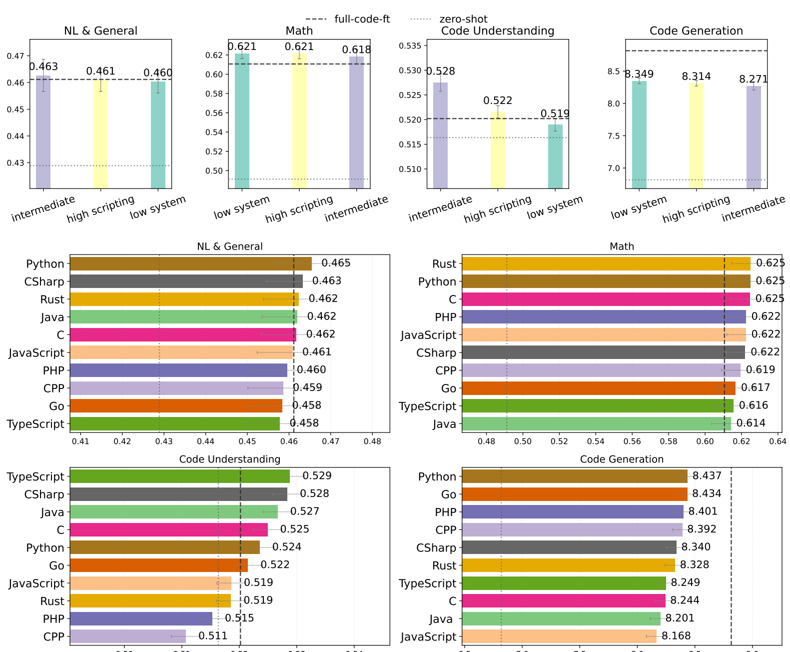

Figure 7: Performance (with stderr bars) of Qwen3-1.7B. *Top:* grouped by abstraction level (low-system, intermediate, high-scripting). Low-system and intermediate languages outperform on math. *Bottom:* individual programming languages. Python aligns best with NL, Rust leads on math.

For code generation, finetuning on any single language improves over zeroshot but lags behind full code finetuning, which suggests the benefit of multi-language diversity for code generation. At the individual language level (e.g. bottom Figure 7, Figures 49–51b), across models, Python often leads on NL tasks, probably due to its surface form being closer to natural language. Aligning with the group-level results, lower-level languages such as Java and Rust often rank among the top for math. For code tasks that span multiple languages, results are more mixed, with no clear leaders, and performance gaps remain relatively small.

5 Conclusion

In this work, we aim to understand what aspects of code enhance reasoning in LLMs and which aspects matter most. Through 3,331 finetuning experiments spanning five model families, eight scales, ten programming languages, and a suite of systematic perturbations, we arrive at four central conclusions. First, structural properties of code are critical: disrupting them leads to consistent performance drops, especially on math and code tasks. Second, appropriate abstractions and efficient encodings can be just as effective as raw code. Moreover, models remain surprisingly robust even to corrupted or low-interpretability code, exploiting statistical regularities that persist despite surface distortions. Finally, lower-level programming languages provide more benefits for math tasks. Together, we want to provide a more precise account of how code supports reasoning and point toward practical design principles for constructing effective training data beyond executable programs.

6 Limitations

Our study focuses on small- to mid-scale base models due to resource constraints. Future work could extend our framework to larger models. Our perturbations, although diverse, may still not cover enough and leave out other factors like code complexity and data diversity. Finally, although we evaluate across a broad suite of reasoning tasks, our benchmarks still capture only part of the reasoning spectrum, and future work could extend the analysis to additional domains.

7 Reproducibility Statement

We provide extensive details throughout the paper and supplementary materials. Section 3.1 describes the construction and processing of both the code and natural language datasets. Section A.5 outlines model training and implementation details. Appendix A.6 includes all prompts used for data generation, perturbations, and LLM-as-Judge evaluation.

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A Appendix

A.1 Extended details of perturbation data

See Table 2.

Table 2: Extended examples of the perturbation dataset and token statistics for each perturbation category.

Perturbation	Original Excerpt	Perturbed Excerpt	Total Tokens	Avg Tokens per Instruction
whitespace removal	`for char in input_string:`	`forcharininput_string:`	78,553,430	654.61
variable renaming	`for char in input_string:`	`for var_4 in var_1:`	87,619,500	730.16
keyword replaced with non-sense	`if c not in vowels:`	`garply c not in vowels:`	87,123,587	726.03
keyword replaced with non-English	`if c not in vowels:`	`père c not in vowels:`	88,078,906	733.99
comment removal	`# Read input`	–	80,238,050	668.65
local comment swapping	`# Read input`	`# Process and print the result`	85,324,436	711.04
global comment swapping	`# Process and print the result`	`// Queue for processing nodes`	85,329,862	711.08
flowchart (Markdown)	`if char not in vowels:`	`[Read char] → {Vowel?} → [Append '.' + lower]`	67,553,461	562.95
step-by-step explanation	`result.append('.' + char.lower())`	`Append '.' before consonants ...`	84,250,378	702.09
pseudocode	`for char in input_string:`	`FOR EACH character IF not vowel THEN`	73,722,933	614.36
imaginary language	`result.append('.' + char.lower())`	`gloff add '.' ⊕ lower(chr)`	81,011,032	675.09
comment enhancement	`# Process the result`	`# Removes vowels and prefixes consonants ...`	119,399,621	994.99
comment obfuscation	`# Read input`	`# WARNING: Code may summon aliens ...`	111,771,640	931.43

A.2 VERIFICATION OF QUALITY OF SYNTHETIC CODE DATA

See Table 3.

Table 3: Syntax and compilation check results across all ten programming languages. The majority of samples successfully compiled or executed, with a mean pass rate of 82.59%

Language	Total	% Passed
C	11,998	81.49
PHP	12,009	94.81
JavaScript	11,996	91.57
Python	11,993	99.25
C++	11,997	83.20
TypeScript	12,001	64.08
Rust	11,995	66.71
C#	11,996	81.06
Go	12,012	77.77
Java	12,003	88.94

A.3 EVALUATION SUITE DETAILS

See Table 4.

A.4 CATEGORIZATION OF PERTURBATIONS FOR RQ2 ANALYSIS

See Table 5.

A.5 IMPLEMENTATION DETAILS

We train all models under identical hyperparameter settings to ensure a fair comparison across model sizes and data configurations. All experiments are conducted using full finetuning in *BF16* precision with a maximum sequence length of 2048 tokens. We run all experiments on 4×A100 80G node. Models are trained for 2 epochs with a cumulative batch size of 64 for most experiments, except for language-specific settings, where the batch size is reduced to 32. The learning rate is fixed at $1\mathrm{e}{-5}$ and follows a cosine decay schedule with a warmup ratio of 0.1. For memory-efficient parallelism and distributed training, we use *DeepSpeed ZeRO Stage 3* (Ren et al., 2021). All models are trained using the LLaMA-Factory framework (Zheng et al., 2024). All other parameters and configurations follow the default setting unless otherwise specified.

Table 4: Evaluation suite spanning natural language and general knowledge, math, and code tasks.

Task Type	Topic	Benchmarks	Metric
Natural Language & General Knowledge	Commonsense	PIQA (Bisk et al., 2019)	Accuracy
	Science / Textbook	ARC-Easy (Clark et al., 2018) ARC-Challenge (Clark et al., 2018) OpenBookQA (Mihaylov et al., 2018) MMLU (non-math) (Hendrycks et al., 2021)	
	Logic-Heavy	LogiQA (Liu et al., 2020)	
	Instruction Following	IFEval (Zhou et al., 2023)	Prompt-level Accuracy
Math	–	GSM8K (Cobbe et al., 2021) HRM8K (Ko et al., 2025)	Exact Match
	–	Arithmetic (Brown et al., 2020) MMLU (math) (Hendrycks et al., 2021)	Accuracy
Code	Code Understanding	CodeMMLU (Manh et al., 2024)	Accuracy
	Code Generation	HumanEvalX (Zheng et al., 2023)	LLM-as-Judge

Table 5: Categorization of perturbations across four analysis axes: structural vs. semantic (S/S) perturbations, explicitness of code structure (ECS), relative information density (RID), and human interpretability (HI).

Perturbation	S/S Perturbations	ECS	RID	HI
Whitespace removal	Structural	Broken syntax	Moderate-reduced	Medium
Pseudocode		Algorithmic	Strong-reduced	High
Imaginary		Broken syntax	Moderate-reduced	Low
Step-by-step		NL procedure	Moderate-reduced	High
Flowchart		Graphical	Strong-reduced	High
Comment removal	Semantic	Runnable	Moderate-reduced	Medium
Variable renaming		Runnable	Increased	Medium
Keyword repl. (nonsense)		Broken syntax	Increased	Low
Keyword repl. (non-Eng.)		Broken syntax	Increased	Low
Comment swap (global)		Runnable	Near-baseline	Low
Comment swap (local)		Runnable	Near-baseline	Low
Comment enhancement		Runnable	Increased	High
Comment obfuscation		Runnable	Increased	Low

A.6 PROMPTS

Standard generation prompt We provide the standard prompt to generate code for a given instruction in a specific language in Figure 8. , where the *instruction* can be instantiated using one of the templates in Table 6.

Comment enhancement prompt The prompt to enhance the quality and readability of a given code snippet by adding detailed documentation is shown in Figure 9.

Comment obfuscation prompt The prompt used to generate obfuscated versions of code from a given instruction is presented in Figure 10.

Pseudo generation prompt We illustrate the prompt designed to produce pseudocode for a given instruction in Figure 11.

Flowchart generation prompt The prompt for generating a flowchart-style representation of an instruction is provided in Figure 12.

Table 6: Language specification templates with placeholders that can be instantiated with different programming languages.

Generate the code in {language}.	Provide code in {language}.	Write the code in {language}.
Build the code using {language}.	Create the code using {language}.	Draft the code in {language}.
Produce a code snippet in {language}.	Develop the code using {language}.	Generate a solution in {language}.
Create a script in {language}.	Implement the code in {language}.	Design the code in {language}.
Construct the code using {language}.	Format the code in {language}.	Write a program in {language}.
Prepare a code snippet in {language}.	Write a function in {language}.	Deliver the code in {language}.

Code Instruction Data Generation Prompt

You are tasked with generating code based on a specified programming language and instruction. Your goal is to generate code that follows the syntax and semantics of the specified language. If the instruction is invalid (e.g., contradicts the language's rules or references functions or constructs from a different language), you must strictly respond with ”invalid.”
Guidelines: - **Valid Code:** - The generated code must be syntactically and semantically correct according to the specified language. - The code should follow standard conventions and best practices for the given language. - Do **not** provide any explanation for valid code — only output the code itself.
- **Invalid Instruction:** - If the instruction references constructs, functions, or syntax not supported by the specified language, respond with ‘”invalid”‘. - Do **not** attempt to correct the invalid instruction — just respond with ‘”invalid”‘. - Do **not** provide a reason or explanation for why the instruction is invalid.
Examples:
Example 1:
Instruction: ”Write a function to convert a list to a set.”
Language: Python
Response:

```
def list_to_set(input_list):
    return set(input_list)
```

Example 2:
Instruction: ”Create a class with a method that prints ’Hello’ using console.log().”
Language: Python
Response: invalid
Example 3:
Instruction: ”List all files, including hidden ones, in the current directory.”
Language: Shell
Response: ls -a
Example 4:
Instruction: ”Define a function using ’def’ that returns the length of a string.”
Language: JavaScript
Response: invalid

Instruction:
If the instruction is valid, output the code directly (no explanations).
If the instruction is invalid, respond with ”invalid” (no explanation).

Input: Instruction: {instruction}
Language: {language}

Output:
{{response}}

Figure 8: Code instruction data generation prompt. The task is to generate valid code or respond with “invalid” for unsupported instructions.

Step-by-step implementation guide generation prompt The prompt used to create a sequential step-by-step implementation guide for an instruction is shown in Figure 13.

Imaginary language code generation We paragraph the prompt for generating code in an imaginary programming language in Figure 14.

LLM-as-Judge Evaluation We use the prompt shown in Figure 15 to generate instance-specific rubrics for LLM-as-judge evaluation on the code generation task. The prompt to evaluate model response is shown in the Figure 16.

A.7 EXTENDED RESULTS

A.7.1 TASK PERFORMANCE SHOWCASING CODE DATA IMPACT IN FINETUNING (RQ1)

Qwen3 model family results See task performance of zero-shot, full code finetuned, full natural language finetuned, and code-NL mixed finetuned models in Figure 17.

Comment Enhancement Prompt

You are tasked with enhancing the response to the given code instruction by adding meaningful comments and documentation. The goal is to improve the code's readability, maintainability, and clarity across any programming language, without altering its original logic or structure.
Your modifications must include:
1. **Documentation Comments**: - Add clear, technically accurate, and concise documentation for every function, method, class, and major code block. - Describe the purpose, all parameters (with correct types and usage), return values, and any assumptions or notes relevant to correct usage. - Use the standard documentation format appropriate for the programming language (e.g., Python docstrings, JavaDoc for Java, Doxygen for C/C++).
2. **Inline Comments**: - Insert informative and contextually helpful inline comments near complex, unintuitive, or important operations. - Focus on explaining logic, control flow, edge-case handling, design decisions, or dependencies. - Avoid redundant, obvious, or overly literal comments (e.g., avoid "i = 0 // set i to 0").
Guidelines:
- **Do not change the logic, structure, or behavior** of the original code. - Do not introduce new functionality, abstractions, or formatting changes. - Keep comments strictly technical, relevant, and useful—avoid verbosity or informal tone. - Do not include any meta-comments or explanatory notes about what was changed (e.g., no "This version adds comments" or similar). - Apply these modifications **only** to the code portion of the original response. Leave any non-code parts completely unmodified. - Ensure all comments follow the style conventions of the language in use.
This task is language-agnostic and applies to any of the following: Python, Java, C++, JavaScript, PHP, TypeScript, Go, Rust, C#, Ruby, Swift, Kotlin, Scala, and Shell.
Input: Instruction: {instruction} Original Response: {response}
Output: {{updated response}}

Figure 9: Comment enhancement prompt. The task is to improve code clarity through meaningful comments while preserving original functionality.

Comment Obfuscation Prompt

You are tasked with modifying the response to the given code instruction in a way that significantly degrades its quality and clarity. Your goal is to make the code as **confusing, unhelpful, and misleading** as possible through the use of deliberately bad, distracting, and nonsensical comments—without altering the actual logic or functionality of the code.
Your modifications must include:
1. **Severely Misleading or Irrelevant Documentation Comments**: - Add documentation to every function, class, and major code block that includes wildly inaccurate descriptions, unrelated facts, inside jokes, cryptic advice, or philosophical ramblings. - Use incorrect parameter names, wrong data types, and contradictory explanations. - Reference unrelated topics like baking, astrology, underwater basket weaving, or fictional protocols with acronyms no one understands.
2. **Chaotic Inline Comments**: - Insert inline comments that blatantly contradict the actual functionality of the code. - Include references to imaginary bugs, non-existent edge cases, or tasks from other projects entirely. - Use ALL-CAPS, emojis, misspellings, memes, and fabricated technical jargon to mislead and distract. - Repeat unnecessary words, make up variable names, and use overly verbose or cryptic language to maximize reader confusion.
Guidelines:
- **Do not modify the actual logic, syntax, or structure of the code** — only the comments must be altered. - All comments must remain syntactically valid for the language (e.g., use # for Python, // for JavaScript, etc.) so the code can still execute normally. - Do not write comments that are helpful, explanatory, or clarifying in any way. Remove any useful comments that were originally present. - Do not include any reflective or meta statements about the task (e.g., no "this version degrades the comments"). - Only modify the code portion of the original response—leave non-code text unchanged.
This task is language-agnostic and applies to any of the following: Python, Java, C++, JavaScript, PHP, TypeScript, Go, Rust, C#, Ruby, Swift, Kotlin, Scala, and Shell.
Input: Instruction: {instruction} Original Response: {response}
Output: {{updated response}}

Figure 10: Comment obfuscation prompt. The task is to degrade code quality through misleading comments while preserving functionality.

Llama-3.2 model family results See task performance of zero-shot, full code finetuned, full natural language finetuned, and code-NL mixed finetuned models in Figure 18.

Gemma-3 model family results See task performance of zero-shot, full code finetuned, full natural language finetuned, and code-NL mixed finetuned models in Figure 19.

OLMo-2 model family results See task performance of zero-shot, full code finetuned, full natural language finetuned, and code-NL mixed finetuned models in Figure 20.

SmolLM2 model family results See task performance of zero-shot, full code finetuned, full natural language finetuned, and code-NL mixed finetuned models in Figure 21.

Code data mixture ratio in finetuning data ablations We show results for mixing different ratios of code data in finetuing for Qwen3-0.6B-Base and Qwen3-1.7B-Base in Figure 22a and Figure 22b, respectively.

Pseudocode Conversion Prompt

You are tasked with converting a given code response into pseudocode that mirrors the structure and semantics of the original code, while preserving the idiomatic style of the original programming language.
Your modifications must include:
1. **Pseudocode Style**: - Replace exact syntax with **language-specific pseudocode** constructs (e.g., use `IF ... THEN ... ENDIF` for conditionals, `FOR EACH` or `WHILE` for loops). - Remove implementation details such as variable declarations with types, precise syntax, or specific library calls—replace them with clear, high-level descriptions.
2. **Structure Preservation**: - Maintain the **overall control flow and indentation** of the original code. - Use **meaningful, readable names** that reflect their purpose in the code. - Ensure each function, class, or logical block is represented clearly in pseudocode format.
3. **Fidelity to Language Idioms**: - Adapt the pseudocode to **reflect the spirit and conventions** of the original language (e.g., Python's indentation style, Java's block structure, C++-like modularity).
Guidelines:
- **Do not alter the logic, structure, or order** of operations. - **Do not include actual code syntax** (e.g., semicolons, colons, type annotations, brackets). - **Do not add comments, explanations, or headings** outside the code block. - Output only the converted pseudocode. - Preserve formatting and indentation faithfully.
Input: Instruction: {instruction} Original Response: {response}
Output:

```
{{pseudocode}}
```

Figure 11: Pseudocode conversion prompt. The task is to translate real code into structured pseudocode while preserving logic and idiomatic style.

Flowchart Generation Prompt

You are tasked with generating a flow diagram in Markdown format that visualizes the control flow of the given code response. Your output must be a **Mermaid** flowchart embedded in a single fenced code block.
Your diagram must:
1. **Translate code logic into control flow**: - Include major steps, function calls, loops, branches, and return points. - Use concise, descriptive node labels that accurately reflect the code behavior.
2. **Follow valid Mermaid syntax**: - Begin with `Start` and end with `End`. - Use `[ ]` for actions/processes. - Use { } for decision/branch points. - Use `-->` to connect nodes. - Wrap everything in triple backticks with `mermaid` specified.
3. **Respect language conventions**: - Match naming and idioms to the language used in the original code. - Do not reinterpret or alter the code logic.
Guidelines:
- **Do not change the structure or logic** of the original response. - **Do not generate new code**, only a flowchart of the existing response. - Keep node labels technical and minimal. - Do **not** include explanations, comments, or narrative outside the flowchart. - Follow the same formatting and structural conventions as the original prompt.
Input: Instruction: {instruction} Original Response: {response}
Output:

````
```mermaid
{{flowchart}}
```
````

Figure 12: Flowchart generation prompt. The task is to convert real code into a Mermaid flow diagram without changing logic or structure.

A.7.2 Task performance under perturbations aggregated by structure vs semantics (RQ2)

Qwen3 model family results (structure vs semantics perturbations) See performance of aggregated task performance under structure vs semantics perturbations in Figure 23.

Llama-3.2 model family results (structure vs semantics perturbations) See performance of aggregated task performance under structure vs semantics perturbations in Figure 24.

Gemma-3 model family results (structure vs semantics perturbations) See performance of aggregated task performance under structure vs semantics perturbations in Figure 25.

OlMo-2 model family results (structure vs semantics perturbations) See performance of aggregated task performance under structure vs semantics perturbations in Figure 26.

SmolLM2 model family results (structure vs semantics perturbations) See performance of aggregated task performance under structure vs semantics perturbations in Figure 27.

Step-by-Step Generation Prompt

You are tasked with converting a given code response into a step-by-step implementation guide that describes how to manually implement the code in clear, concise, and technically accurate language.
Your implementation guide must:
1. **Preserve Original Logic**: - Follow the same structure, logic, and sequence as the original code. - Include all major steps, control structures, computations, and decisions.
2. **Describe, Don't Translate**: - Do not include code or pseudocode. - Write in declarative, instructional sentences that explain what to do and how to do it. - Use neutral, language-agnostic terminology (e.g., "Define a function named...", "Check if...", "Return the result...").
3. **Be Clear and Concise**: - Number each step in the order it occurs. - Use precise and unambiguous language. - Each step should focus on a single coherent action.
Guidelines:
- **Do not add extra commentary, examples, or assumptions**. - **Do not change the original logic or execution order**. - **Do not output anything other than the numbered steps**. - Output the guide as a plaintext numbered list only—no code blocks, no explanations outside the list.
Input: Instruction: {instruction} Original Response: {response}
Output:

```
1. {{Step one}}
2. {{Step two}}
3. {{Step three}}
...
```

Figure 13: Step-by-step implementation guide prompt. The task is to describe how to implement the code in a precise, ordered, and language-agnostic way.

Imaginary Language Translation Prompt

You are tasked with converting a given code response into an imaginary programming language that mimics the syntax and semantics of the original real-world language while appearing fictional and made-up.
Your modifications must include:
1. **Imaginary Language Design**: - Rename keywords, function names, types, and operators using plausible yet fictional terms. - Preserve the **structure, indentation, and logical flow** of the original code. - Ensure the resulting code remains readable and clearly maps to the original logic.
2. **Consistency and Fidelity**: - Maintain **1-to-1 correspondence** between the original code constructs and their fictional equivalents. - The imaginary language should resemble the **style and design patterns** of the original language (e.g., Pythonic indentation, Java-style braces and semicolons, C++ class structure, etc.).
3. **Creativity within Constraint**: - Make the language feel internally consistent and syntactically plausible. - Avoid random noise—each fictional token should appear intentional and reusable.
Guidelines:
- **Do not change the underlying logic** of the original code. - **Do not translate comments or docstrings**—leave them unchanged. - **Do not add explanations, annotations, or headings** outside the code block. - Output only the converted code. - Ensure formatting matches the original exactly (e.g., spacing, newlines).
Input: Instruction: {instruction} Original Response: {response}
Output:

````
```imaginary
{{code_in_imaginary_language}}
```
````

Figure 14: Imaginary language translation prompt. The task is to render real code in a fictional but consistent language without changing its logic.

A.7.3 TASK PERFORMANCE UNDER PERTURBATIONS AGGREGATED BY EXPLICITNESS OF CODE STRUCTURE (RQ2)

Qwen3 model family results (explicitness of code structure perturbations) See performance of aggregated task performance under explicitness of code structure perturbations in Figure 28.

Llama-3.2 model family results (explicitness of code structure perturbations) See performance of aggregated task performance under explicitness of code structure perturbations in Figure 29.

Gemma-3 model family results (explicitness of code structure perturbations) See performance of aggregated task performance under explicitness of code structure perturbations in Figure 30.

OlMo-2 model family results (explicitness of code structure perturbations) See performance of aggregated task performance under explicitness of code structure perturbations in Figure 31.

Rubric Generation Prompt

You are tasked with generating an instance-specific evaluation rubric based on a given coding prompt, canonical solution, and test case(s) to evaluate the model-generated response.

Guidelines:
- The rubric must be **example-specific**: every score level must directly reference the details of the given prompt, canonical solution, and test case(s).
- Use a fixed 1–10 scale (1 = lowest quality attempt, 10 = fully correct).
- Structure the rubric so that:
- Scores 1–3 describe model responses that are irrelevant, nonsensical, or do not implement the required functionality.
- Scores 4–7 describe model responses that attempt the task but are incomplete, flawed, or only partially correct on test case(s).
- Scores 8–10 describe model responses that are mostly or fully correct, aligning with the canonical solution and passing most or all test case(s).
- Each score level (1–10) must have a clear, measurable description unique to this problem.
- Output only the rubric.

Input:
Code Prompt:

`{code_prompt}`

Canonical Solution:

`{canonical_solution}`

Test Case(s):

`{test_case}`

Output:

`{{rubric}}`

Figure 15: LLM-as-judge prompt for generating an instance-specific rubric to evaluate model-generated code responses.

SmolLM2 model family results (explicitness of code structure perturbations) See performance of aggregated task performance under explicitness of code structure perturbations in Figure 32.

A.7.4 Task performance under perturbations aggregated by relative information density (RQ2)

Qwen3 model family results (relative information density perturbations) See performance of aggregated task performance under relative information density perturbations in Figure 33.

Llama-3.2 model family results (relative information density perturbations) See performance of aggregated task performance under relative information density perturbations in Figure 34.

Gemma-3 model family results (relative information density perturbations) See performance of aggregated task performance under relative information density perturbations in Figure 35.

OlMo-2 model family results (relative information density perturbations) See performance of aggregated task performance under relative information density perturbations in Figure 36.

SmolLM2 model family results (relative information density perturbations) See performance of aggregated task performance under relative information density perturbations in Figure 37.

A.7.5 Task performance under perturbations aggregated by human interpretability (RQ2)

Qwen3 model family results (human interpretability perturbations) See performance of aggregated task performance under human interpretability perturbations in Figure 38.

LLM-as-Judge Evaluation Prompt

You are tasked with evaluating a model-generated response to a coding prompt using the provided rubric.

You are given:
1. The coding prompt.
2. The rubric (instance-specific, with 1–10 levels).
3. The model response.

Instructions:
- Carefully read the rubric.
- Compare the model response against the rubric criteria.
- Assign the most appropriate score (1–10).
- Provide a concise justification inside ¡reasoning¿¡/reasoning¿, explicitly referencing how the model response aligns or fails to align with specific rubric levels.
- Provide only the numeric score inside ¡score¿¡/score¿.
- Do not include any text outside the required tags.

Input:
Coding Prompt:

`{code_prompt}`

Rubric:

`{rubric}`

Model Response:

`{model_response}`

Output:

```
<reasoning>{{concise justification}}</reasoning>
<score>{{integer from 1 to 10}}</score>
```

Figure 16: LLM-as-judge prompt for rubric-based evaluation of model-generated code responses.

Llama-3.2 model family results (human interpretability perturbations) See performance of aggregated task performance under human interpretability perturbations in Figure 39.

Gemma-3 model family results (human interpretability perturbations) See performance of aggregated task performance under human interpretability perturbations in Figure 40.

OlMo-2 model family results (human interpretability perturbations) See performance of aggregated task performance under human interpretability perturbations in Figure 41.

SmolLM2 model family results (human interpretability perturbations) See performance of aggregated task performance under human interpretability perturbations in Figure 42.

A.7.6 TASK PERFORMANCE FOR ALL INDIVIDUAL PERTURBATIONS (RQ2)

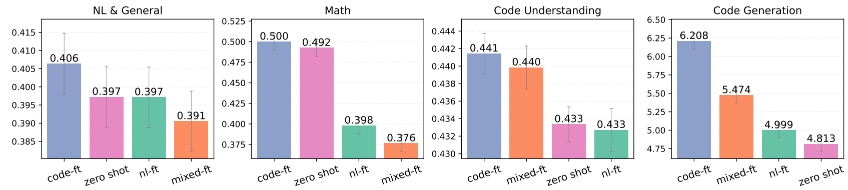
Qwen3 model family results (individual perturbations) See performance of all perturbation configurations in Figure 43.

Llama-3.2 model family results (individual perturbations) See performance of all perturbation configurations in Figure 44.

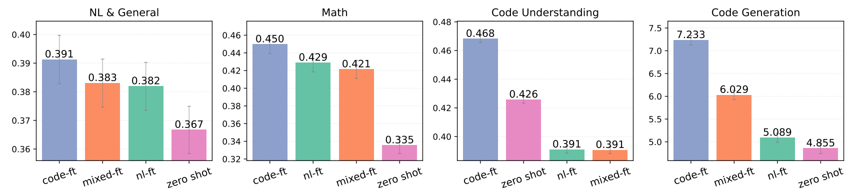
Gemma-3 model family results (individual perturbations) See performance of all perturbation configurations in Figure 45.

OlMo-2 model family results (individual perturbations) See performance of all perturbation configurations in Figure 46.

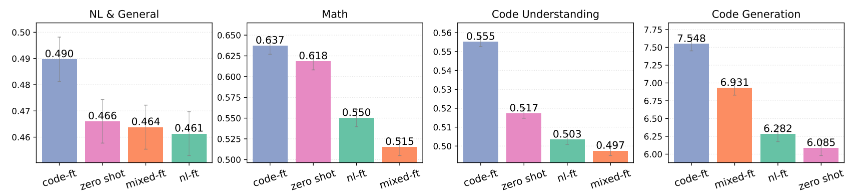
SmolLM2 model family results (individual perturbations) See performance of all perturbation configurations in Figure 47.



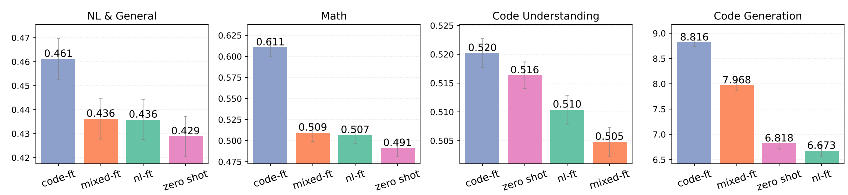
(a) Qwen3-0.6B-Base



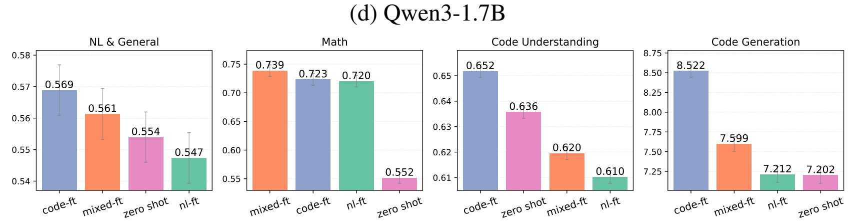
(b) Qwen3-0.6B



(c) Qwen3-1.7B-Base



(d) Qwen3-1.7B



(e) Qwen3-8B-Base

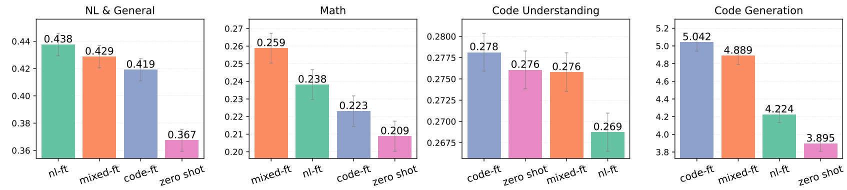
Figure 17: Task performance of Qwen-3 family under zero-shot, full code finetuning (code-ft), full natural language finetuning (nl-ft), and code-NL mixed finetuning (mixed) configurations.

A.7.7 TASK PERFORMANCE WITH DIFFERENT PROGRAMMING LANGUAGES (RQ3)

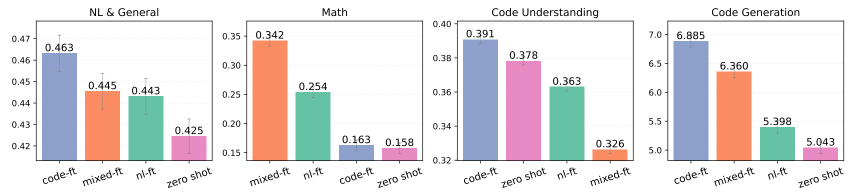
Qwen3 model family results See performance of grouped performance and individual programming languages in Figure 48 and Figure 49, respectively.

Llama-3 model family results See performance of grouped performance and individual programming languages in Figure 50.

SmolLM2 model family results See performance of grouped performance and individual programming languages in Figure 51.

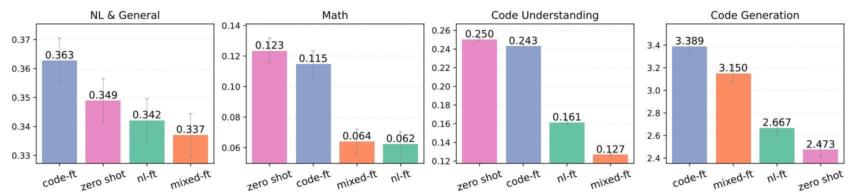


(a) Llama-3.2-1B

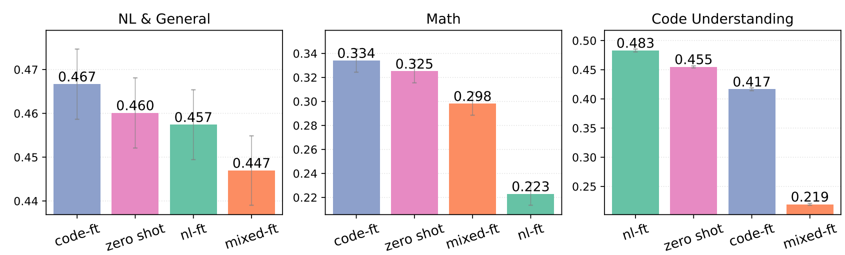


(b) Llama-3.2-3B

Figure 18: Task performance of Llama-3.2 family under zero-shot, full code finetuning (code-ft), full natural language finetuning (nl-ft), and code-NL mixed finetuning (mixed) configurations.



(a) gemma-3-1b

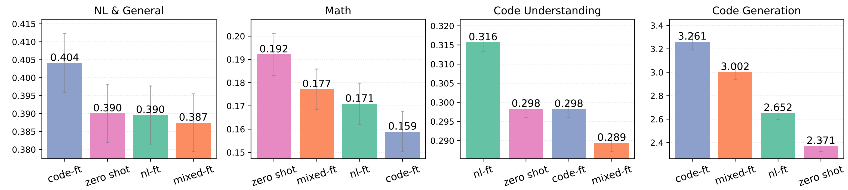


(b) gemma-3-4b

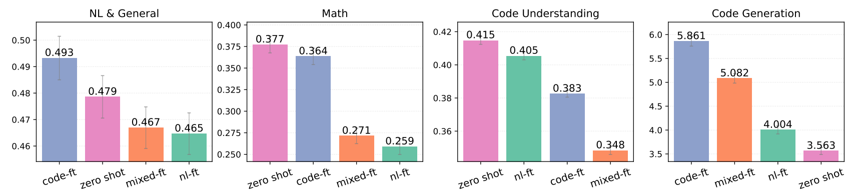
Figure 19: Task performance of Gemma-3 family under zero-shot, full code finetuning (code-ft), full natural language finetuning (nl-ft), and code-NL mixed finetuning (mixed) configurations.

A.7.8 LLM-AS-JUDGE RESULTS

We report the results across multiple judge models in Table 7.

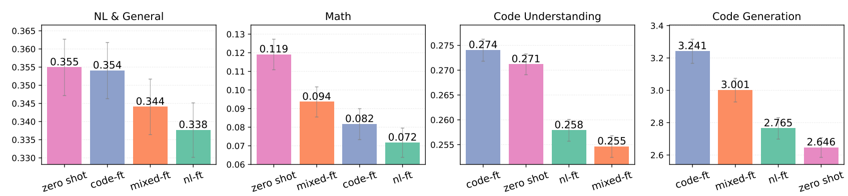


(a) OLMo-2-0425-1B

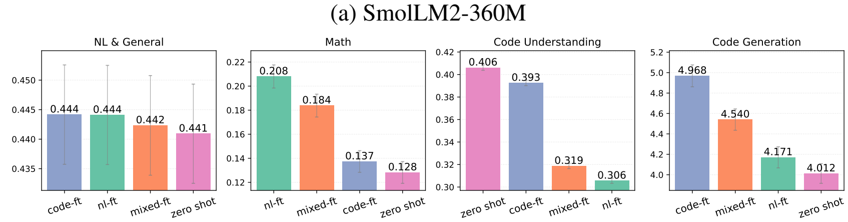


(b) OLMo-2-1124-7B

Figure 20: Task performance of OLMo-2 family under zero-shot, full code finetuning (code-ft), full natural language finetuning (nl-ft), and code-NL mixed finetuning (mixed) configurations.



(a) SmolLM2-360M

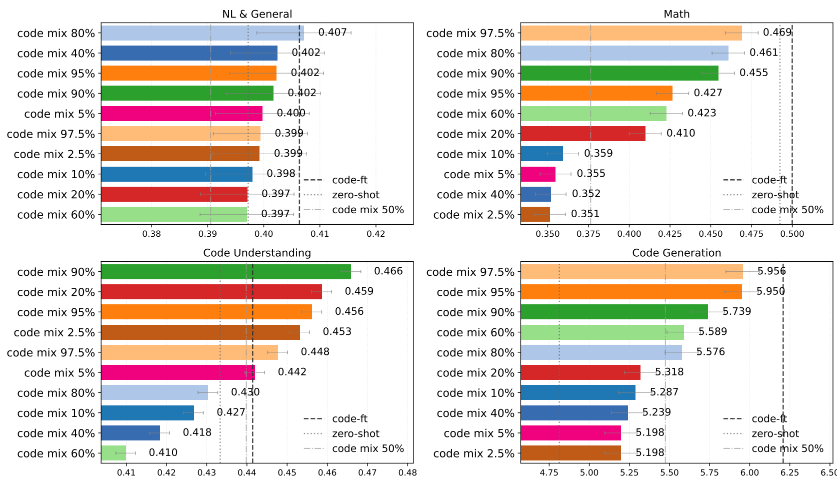


(b) SmolLM2-1.7B

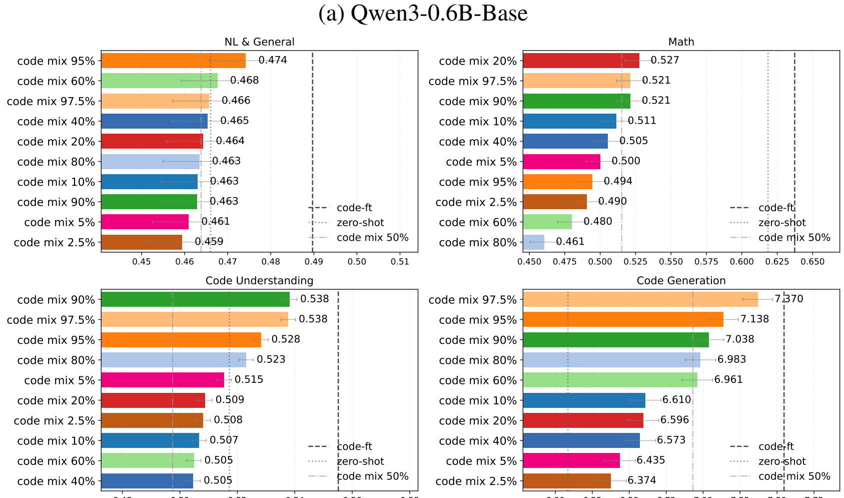
Figure 21: Task performance of SmolLM2 family under zero-shot, full code finetuning (code-ft), full natural language finetuning (nl-ft), and code-NL mixed finetuning (mixed) configurations.

Table 7: Cross-judge evaluation of Qwen3-4B base variant on Python code generation task using five LLM judges — all under identical evaluation settings. Model rankings remain consistent across judges, with only moderate score variability (std 0.63–0.99), demonstrating that LLM-as-judge evaluations are stable and reliable across different judging models.

Target Model / Perturbation	**claude-3-haiku**	**claude-haiku-4.5**	**gpt-4o-mini**	**gpt-5-mini**	**llama3-90b**	**Mean**	**Std**
zeroshot	8.41 ± 2.42	7.34 ± 2.99	7.09 ± 3.27	6.84 ± 3.00	8.17 ± 2.59	7.57	0.69
swap_comments_global	9.01 ± 1.41	7.76 ± 2.43	7.91 ± 2.55	6.85 ± 2.94	9.13 ± 1.42	8.13	0.95
swap_comments_local	9.24 ± 1.24	7.94 ± 2.69	8.54 ± 2.37	7.26 ± 3.06	9.15 ± 1.58	8.43	0.84
replace_keywords_nonsense	9.10 ± 1.16	7.88 ± 2.46	8.74 ± 2.31	7.16 ± 3.04	9.20 ± 1.39	8.42	0.87
replace_keywords_nonEn	9.21 ± 1.16	7.68 ± 2.70	8.73 ± 2.22	7.35 ± 2.89	9.25 ± 1.20	8.44	0.88
flowchart	8.88 ± 1.67	7.44 ± 2.86	8.07 ± 2.58	7.32 ± 3.01	9.13 ± 1.50	8.17	0.82
imaginary	8.94 ± 1.68	7.67 ± 2.87	8.06 ± 2.71	7.17 ± 2.94	9.00 ± 1.82	8.17	0.80
pseudocode	8.89 ± 1.62	7.15 ± 2.72	7.34 ± 3.00	7.22 ± 2.90	9.02 ± 1.48	7.92	0.94
step_by_step	8.66 ± 1.92	7.50 ± 2.83	7.76 ± 2.75	7.57 ± 2.90	8.81 ± 1.90	8.06	0.63
comment_obfuscation	8.79 ± 2.03	7.41 ± 2.80	7.86 ± 2.88	7.02 ± 3.07	8.93 ± 1.78	8.00	0.84
comment_enhancement	9.22 ± 1.35	7.77 ± 2.74	8.36 ± 2.65	7.93 ± 2.48	9.09 ± 1.71	8.47	0.66
remove_comments	9.09 ± 1.61	7.86 ± 2.54	8.27 ± 2.54	7.23 ± 3.05	9.19 ± 1.42	8.32	0.83
remove_whitespace	9.10 ± 1.43	7.87 ± 2.58	8.69 ± 2.28	7.77 ± 2.85	9.33 ± 1.33	8.55	0.71
replace_variables	9.20 ± 0.95	7.47 ± 2.74	8.09 ± 2.66	6.92 ± 3.09	9.07 ± 1.53	8.15	0.99
code-ft	9.14 ± 1.46	7.98 ± 2.32	8.65 ± 2.36	7.61 ± 2.98	9.17 ± 1.41	8.51	0.70
mixed-ft	8.68 ± 1.94	7.46 ± 2.94	7.94 ± 2.79	7.31 ± 3.08	8.75 ± 2.10	8.03	0.67
nl-ft	8.19 ± 2.43	6.58 ± 2.99	6.75 ± 3.11	6.60 ± 3.15	7.84 ± 2.63	7.19	0.76



(a) Qwen3-0.6B-Base



(b) Qwen3-1.7B-Base

Figure 22: Task performance of Qwen3-0.6, 1.7B-Base when mixing different ratio of code data during finetuning. In general higher code percentages improves performance, with math tasks showing large variation.

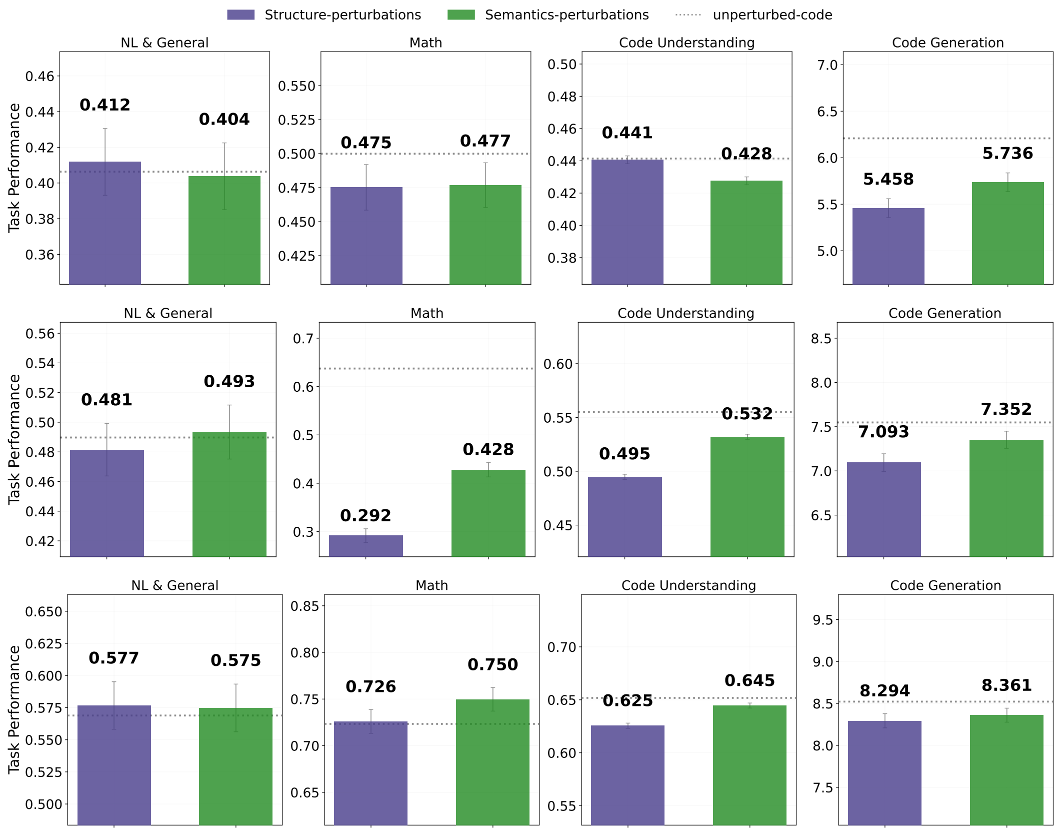


Figure 23: Task performance under perturbations aggregated by structure vs semantics across Qwen3-Base models (0.6B (top), 1.7B (mid), 8B (bottom)).

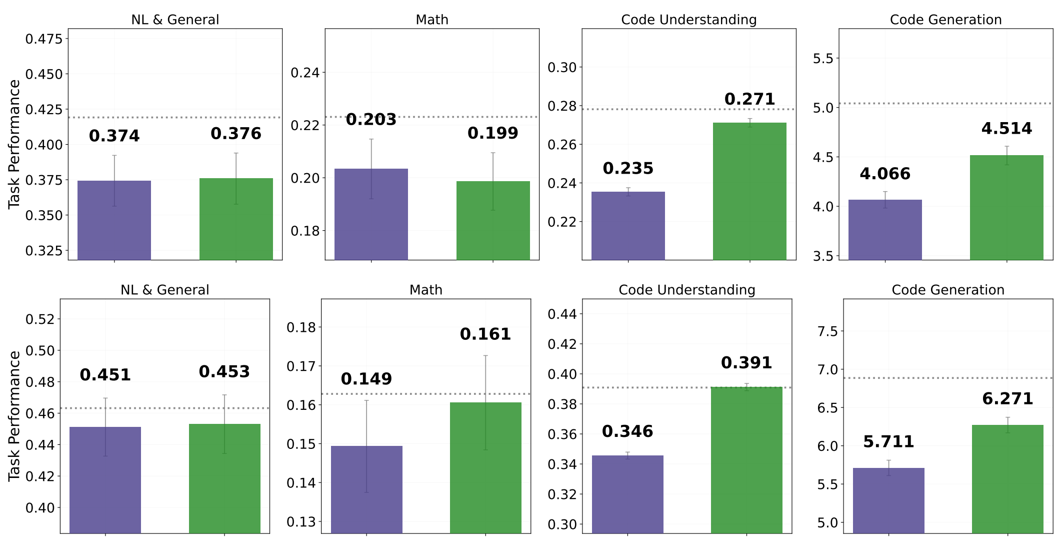


Figure 24: Task performance under perturbations aggregated by structure vs semantics across Llama-3.2 models (1B (top), 3B (bottom)).

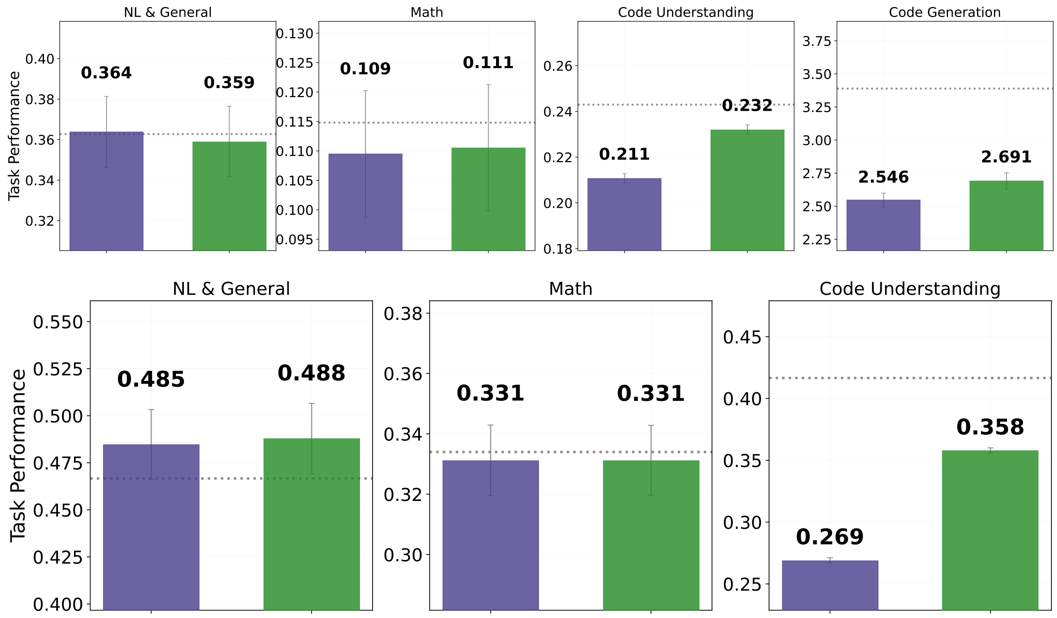


Figure 25: Task performance under perturbations aggregated by structure vs semantics across Gemma-3 models (1B (top), 4B (bottom)).

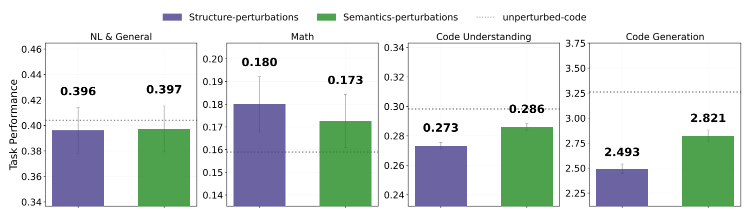


Figure 26: Additional performance of OLMo-2-0425-1B aggregated by structure vs semantics across tasks.

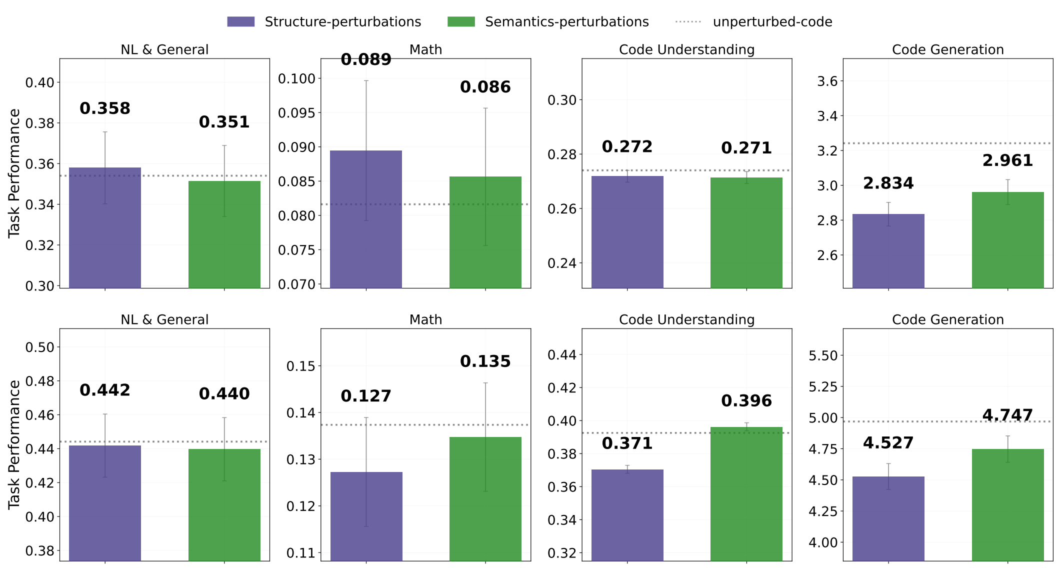


Figure 27: Task performance under perturbations aggregated by structure vs semantics across SmolLM2 models (360M (top), 1.7B (bottom)).

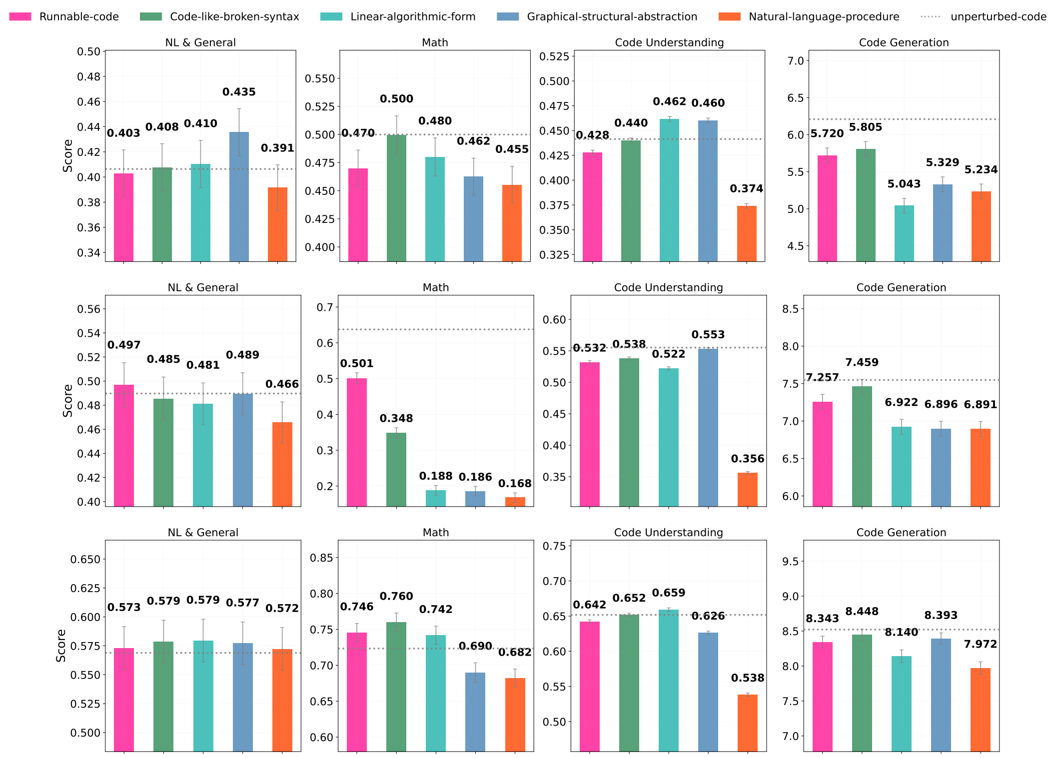


Figure 28: Task performance under perturbations aggregated by explicitness of code structure across Qwen3-Base models (0.6B (top), 1.7B (mid), 8B (bottom)).

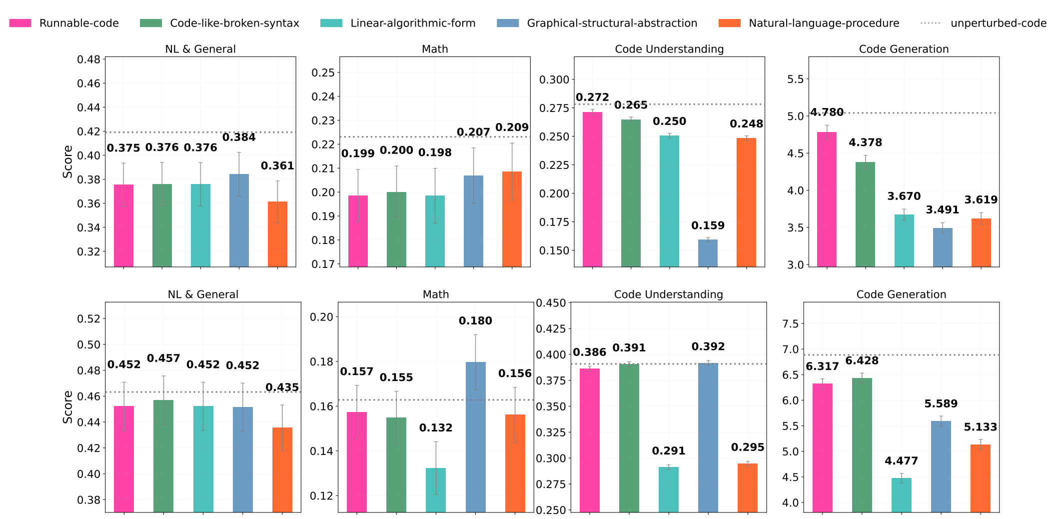


Figure 29: Task performance under perturbations aggregated by explicitness of code structure across Llama-3.2 models (1B (top), 3B (bottom)).

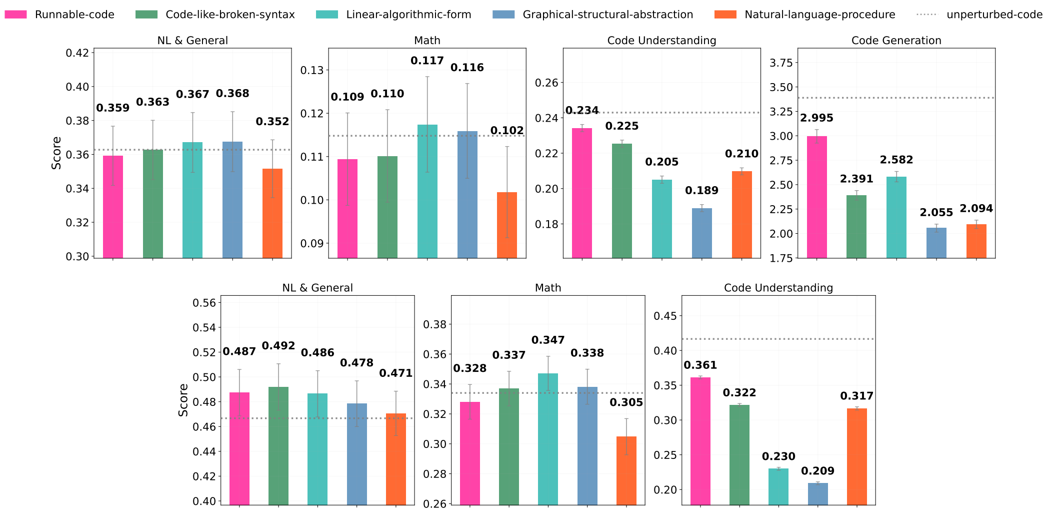


Figure 30: Task performance under perturbations aggregated by explicitness of code structure across Gemma-3 models (1B (top), 4B (bottom)).

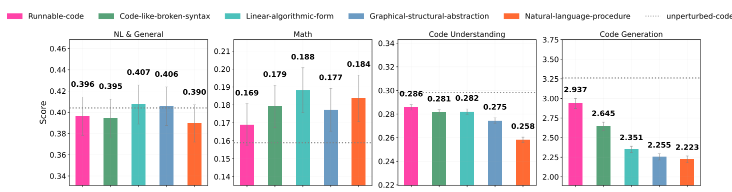


Figure 31: Additional performance of OLMo-2-0425-1B aggregated by explicitness of code structure across tasks.

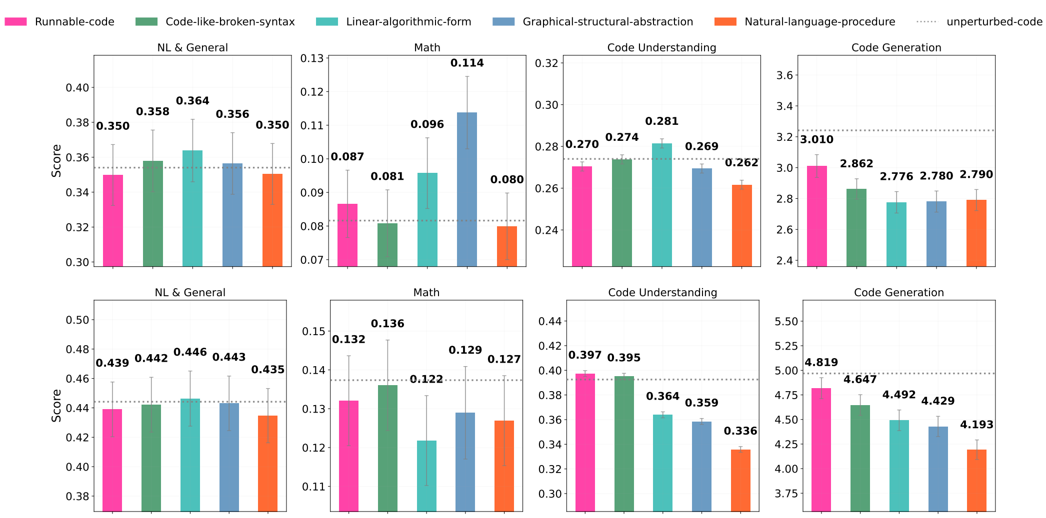


Figure 32: Task performance under perturbations aggregated by explicitness of code structure across SmolLM2 models (360M (top), 1.7B (bottom)).

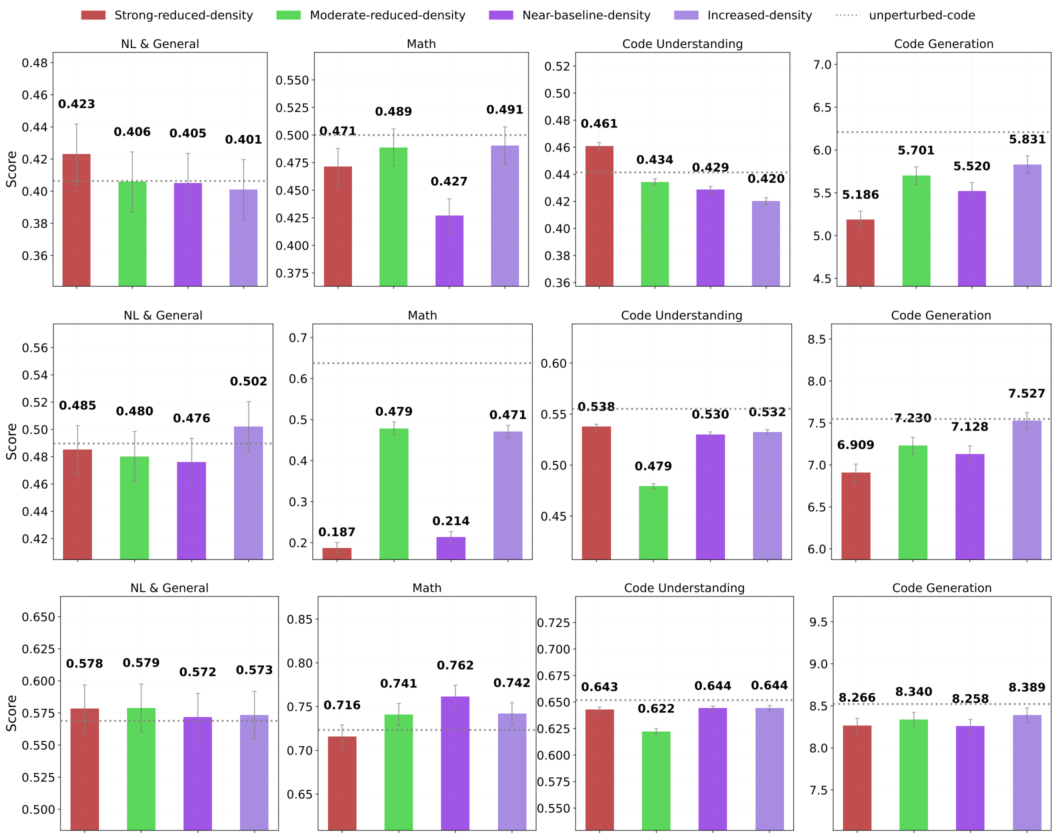


Figure 33: Task performance under perturbations aggregated by relative information density across Qwen3-Base models (0.6B (top), 1.7B (mid), 8B (bottom)).

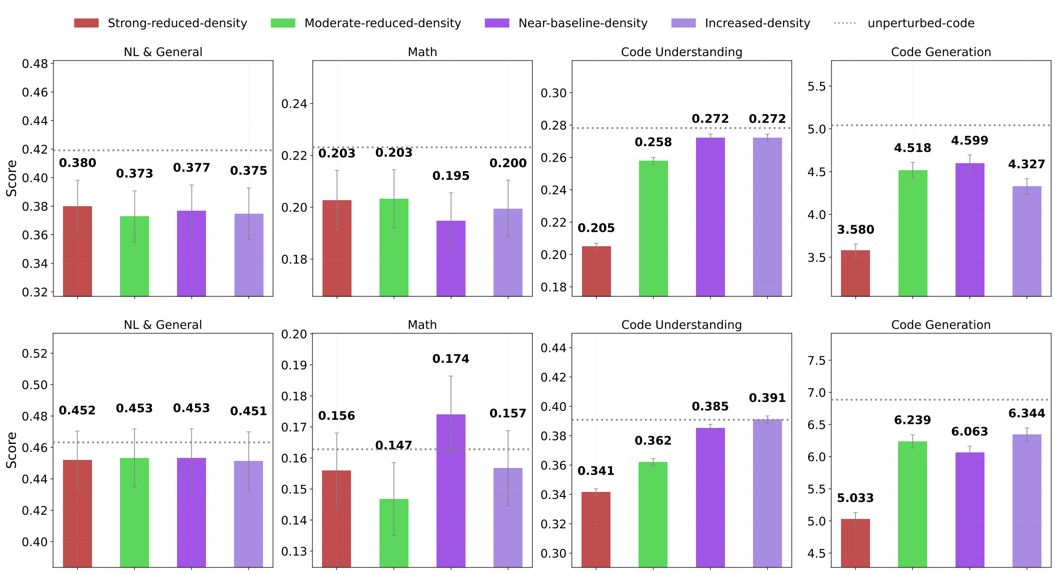


Figure 34: Task performance under perturbations aggregated by relative information density across Llama-3.2 models (1B (top), 3B (bottom)).

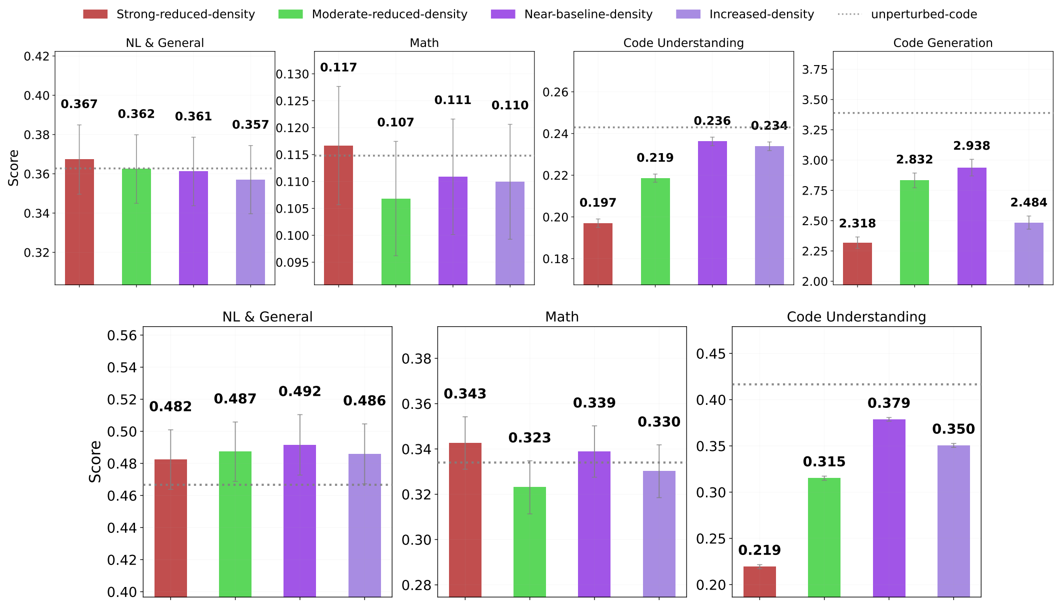


Figure 35: Task performance under perturbations aggregated by relative information density across Gemma-3 models (1B (top), 4B (bottom)).

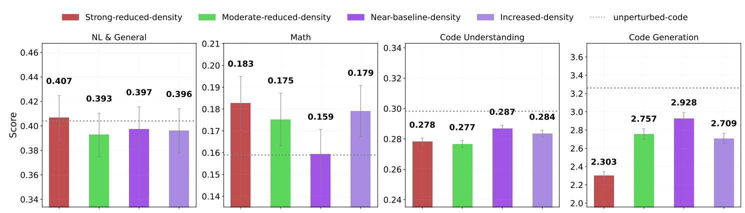


Figure 36: Additional performance of OLMo-2-0425-1B aggregated by relative information density across tasks.

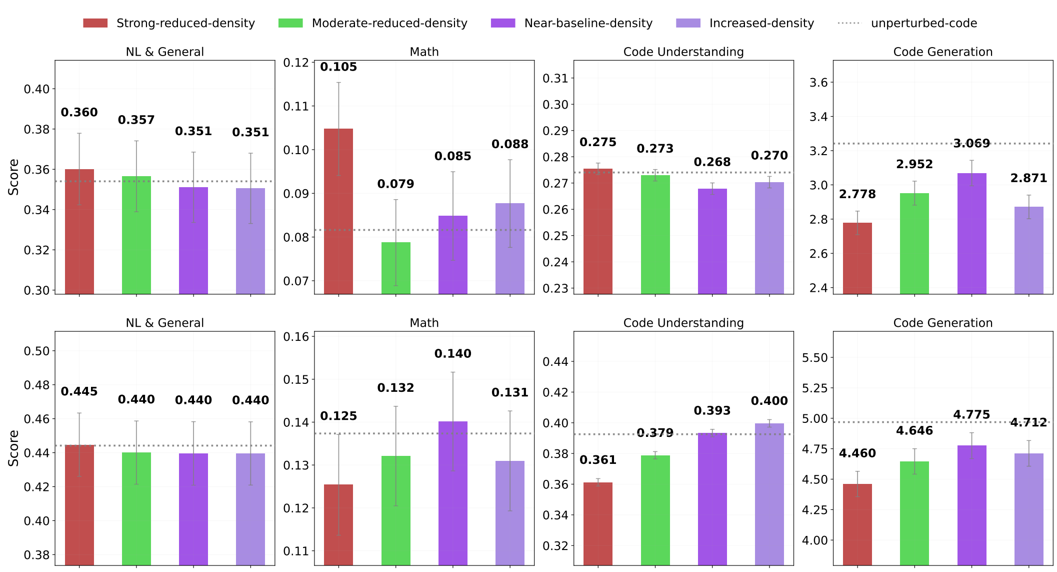


Figure 37: Task performance under perturbations aggregated by relative information density across SmolLM2 models (360M (top), 1.7B (bottom)).

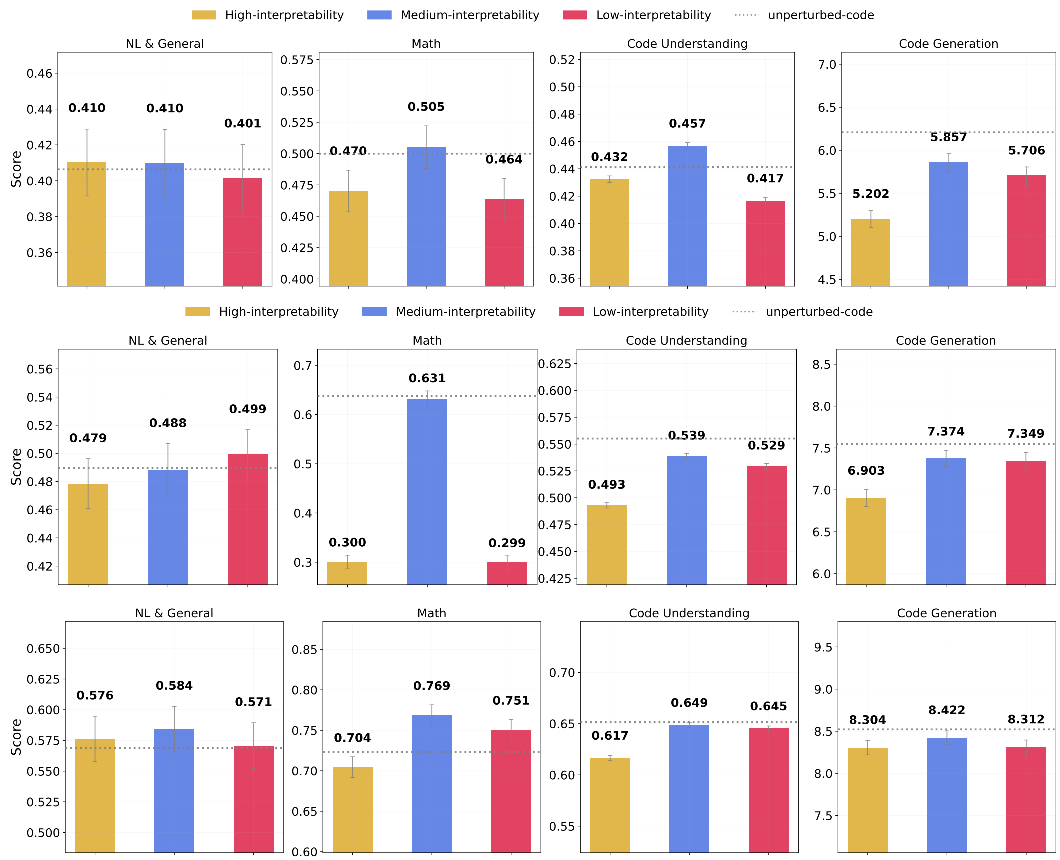


Figure 38: Task performance under perturbations aggregated by human interpretability across Qwen3-Base models (0.6B (top), 1.7B (mid), 8B (bottom)).

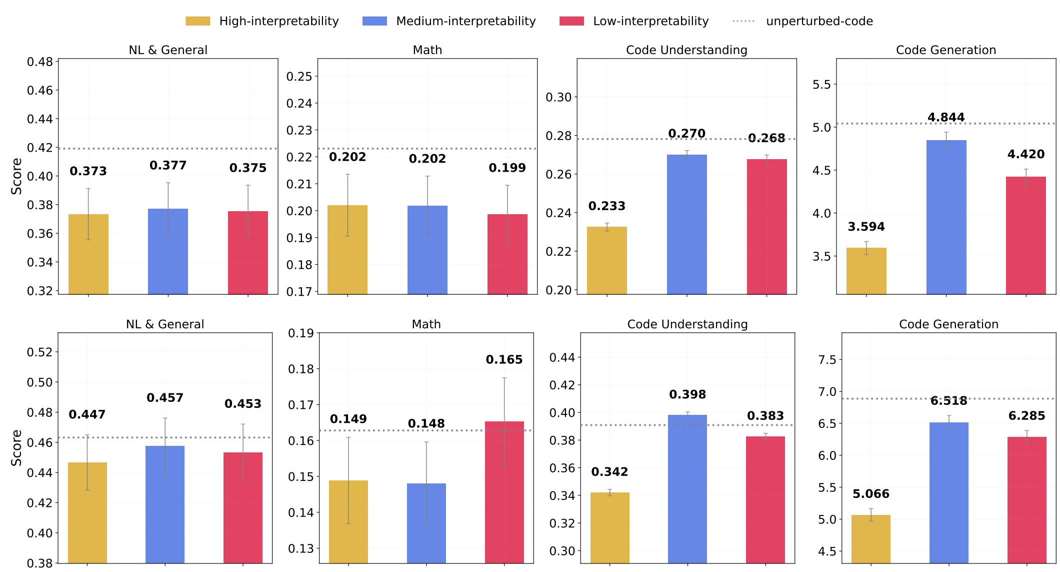


Figure 39: Task performance under perturbations aggregated by human interpretability across Llama-3.2 models (1B (top), 3B (bottom)).

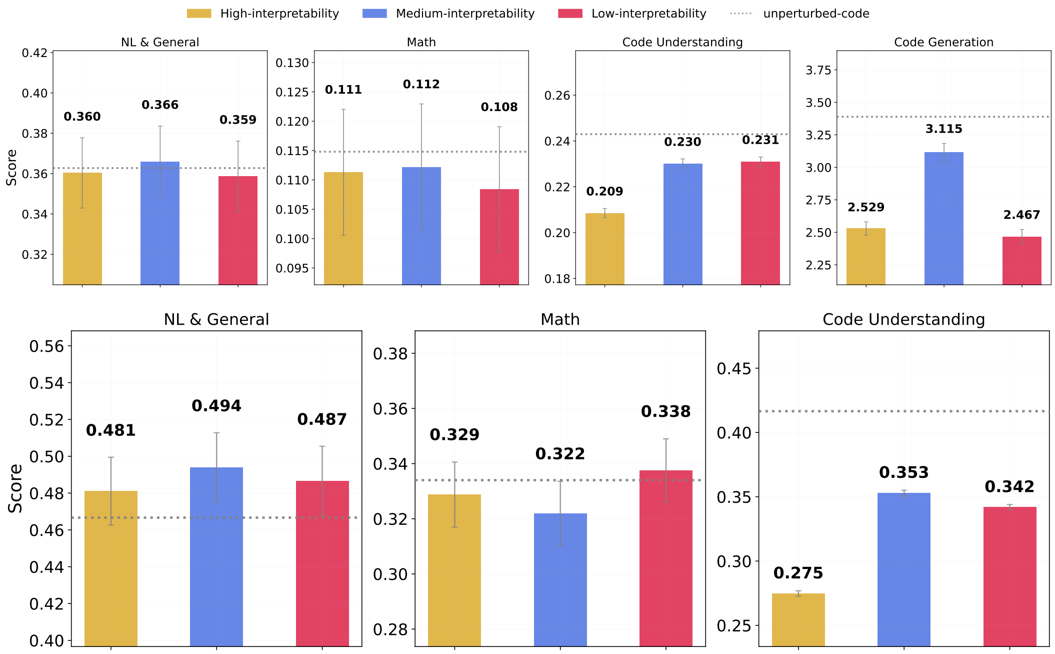


Figure 40: Task performance under perturbations aggregated by human interpretability across Gemma-3 models (1B (top), 4B (bottom)).

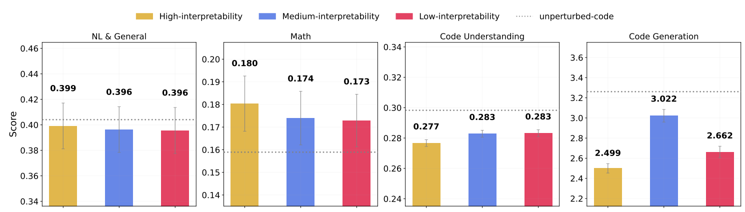


Figure 41: Additional performance of OLMo-2-0425-1B aggregated by human interpretability across tasks.

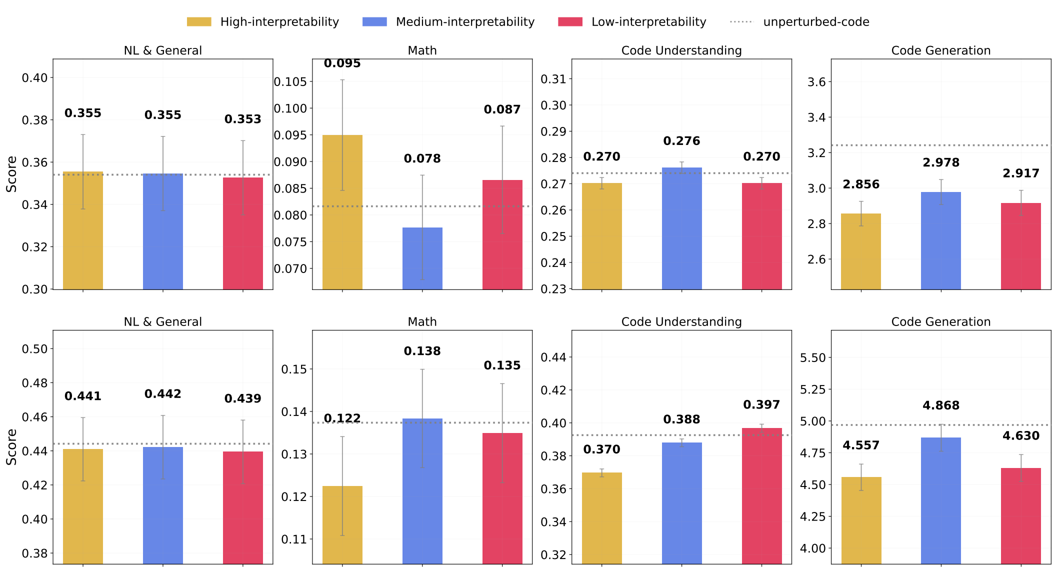


Figure 42: Task performance under perturbations aggregated by human interpretability across SmolLM2 models (360M (top), 1.7B (bottom)).

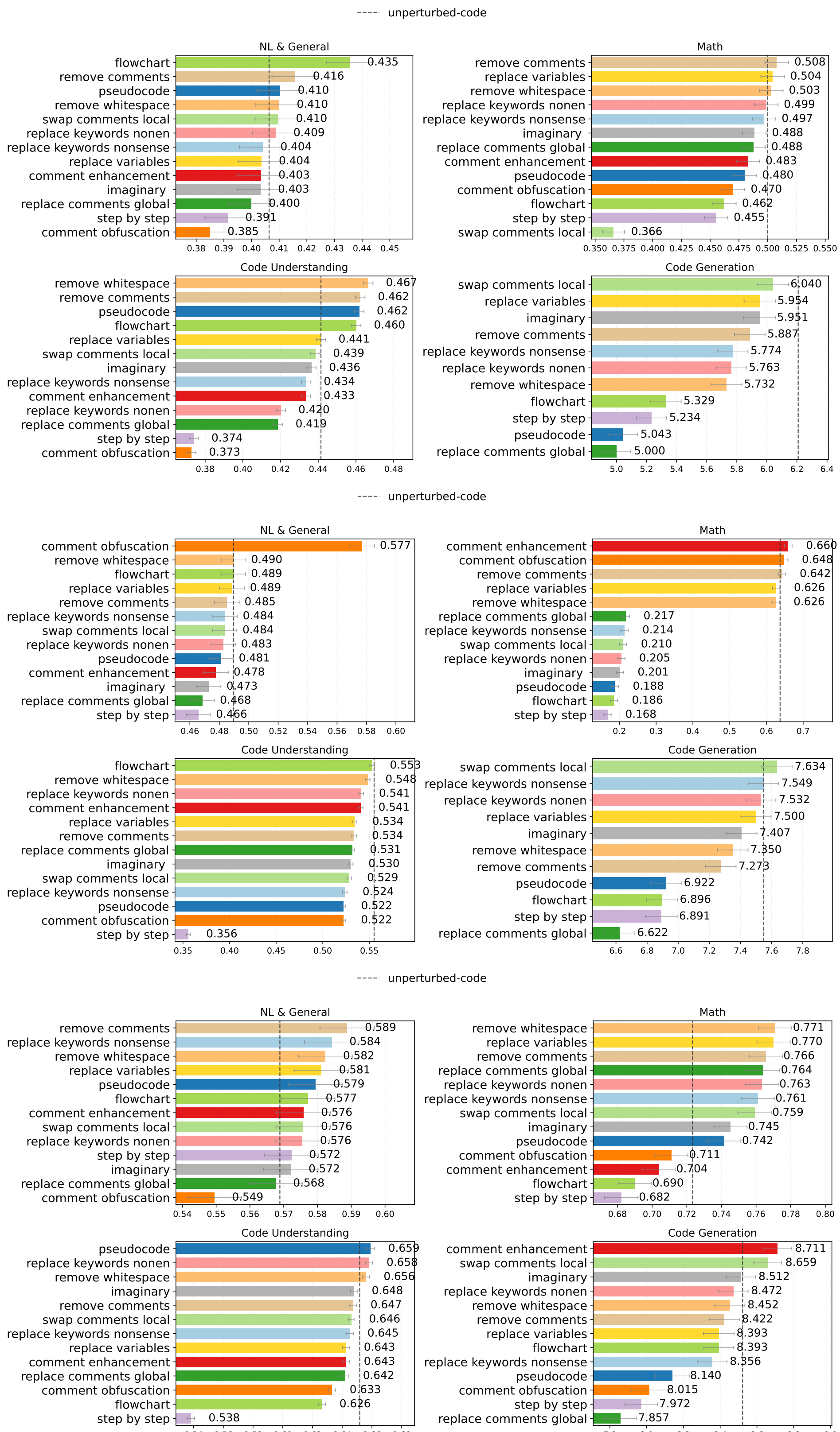


Figure 43: All perturbations across Qwen3-Base models (0.6B (top), 1.7B (mid), 8B (bottom)).

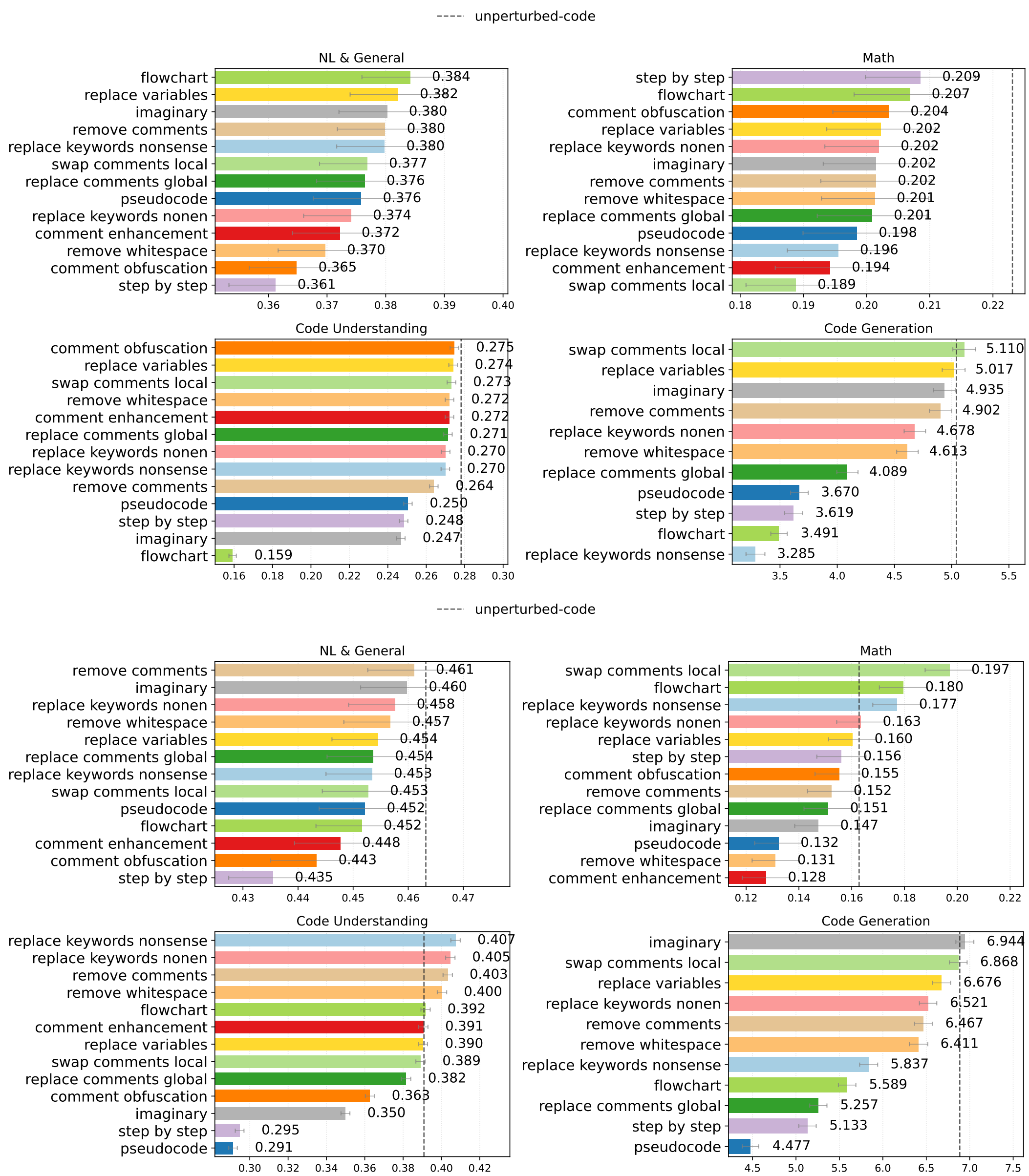


Figure 44: All perturbations across Llama-3.2 models (1B (top), 3B (bottom)).

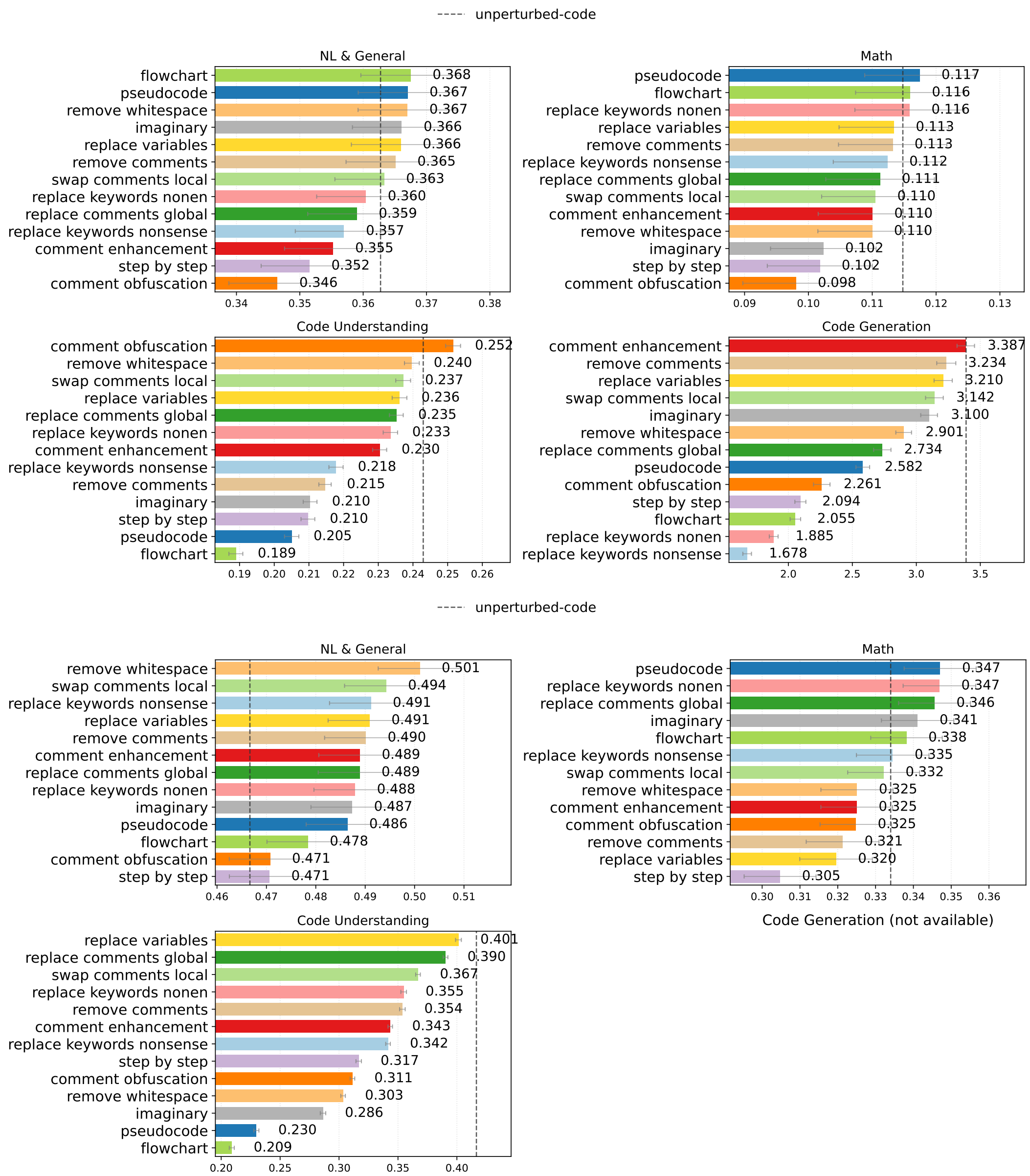


Figure 45: All perturbations across Gemma-3 models (1B (top), 4B (bottom)).

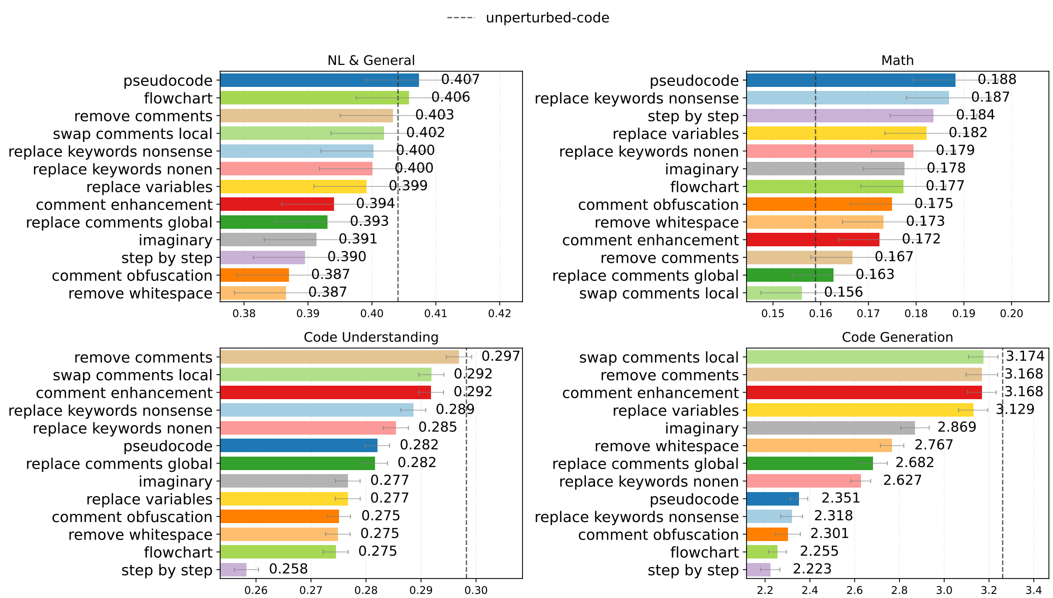


Figure 46: OLMo-2-0425-1B with all perturbations.

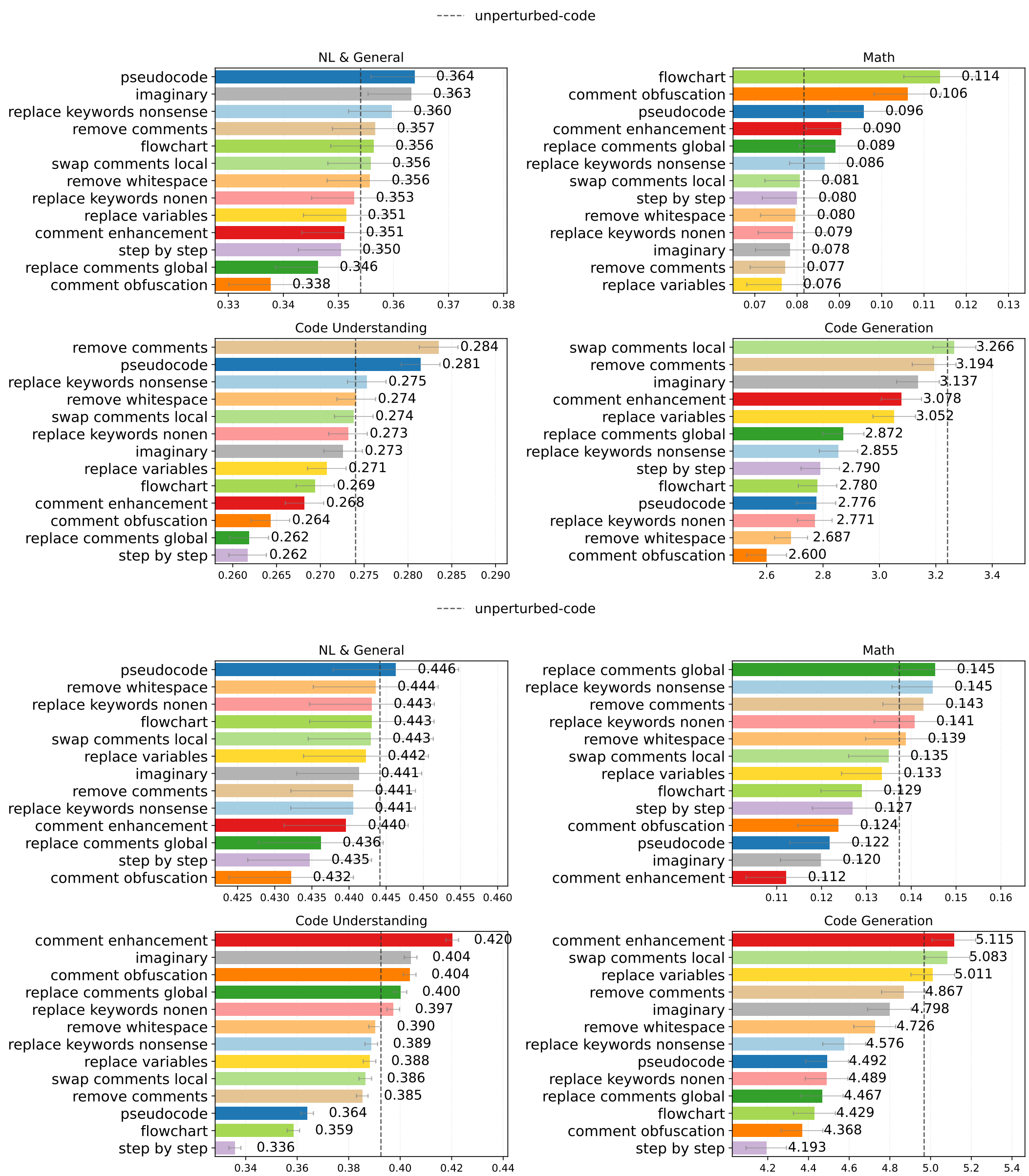
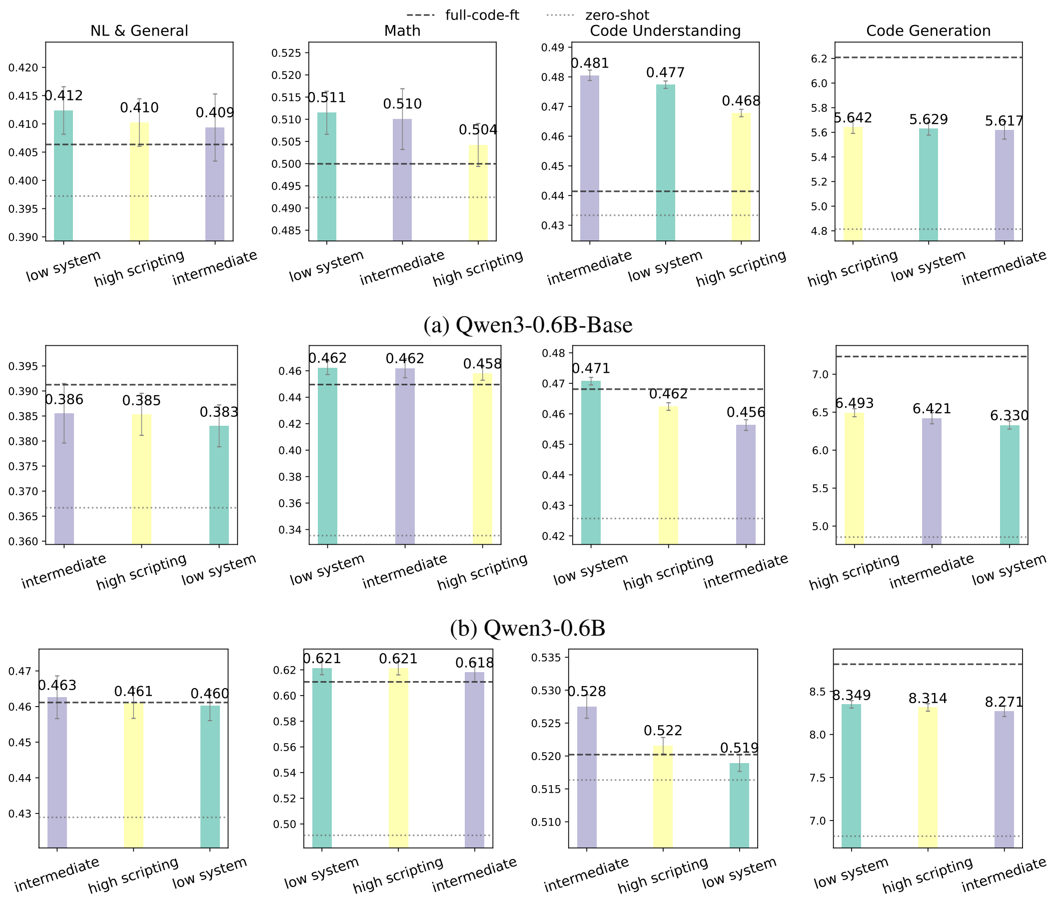


Figure 47: All perturbations across SmolLM2 models (360M (top), 1.7B (bottom)).

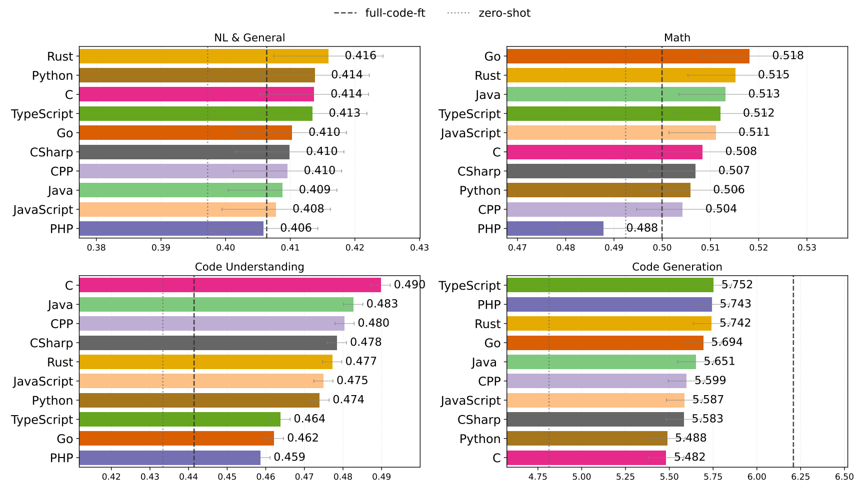


(a) Qwen3-0.6B-Base

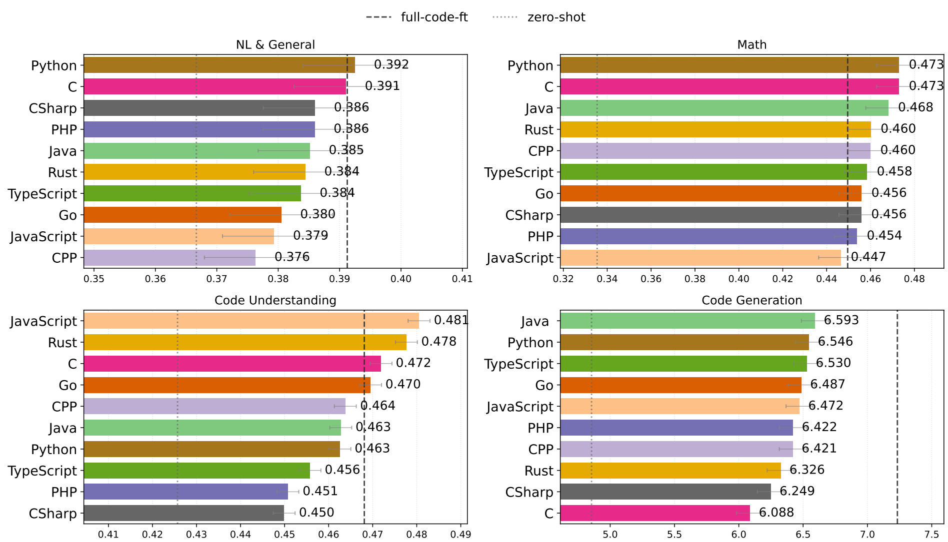
(b) Qwen3-0.6B

(c) Qwen3-1.7B

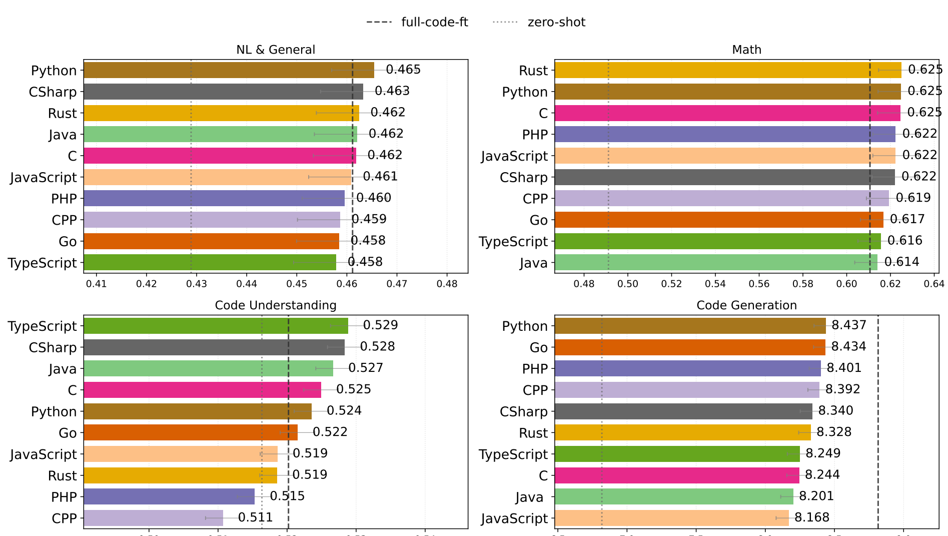
Figure 48: Grouped performance of Qwen-3 family under low-system, intermediate, and high-scripting programming languages.



(a) Qwen3-0.6B-Base

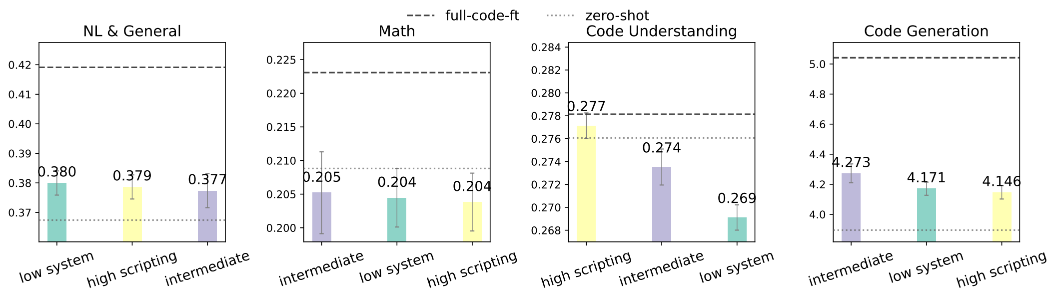


(b) Qwen3-0.6B

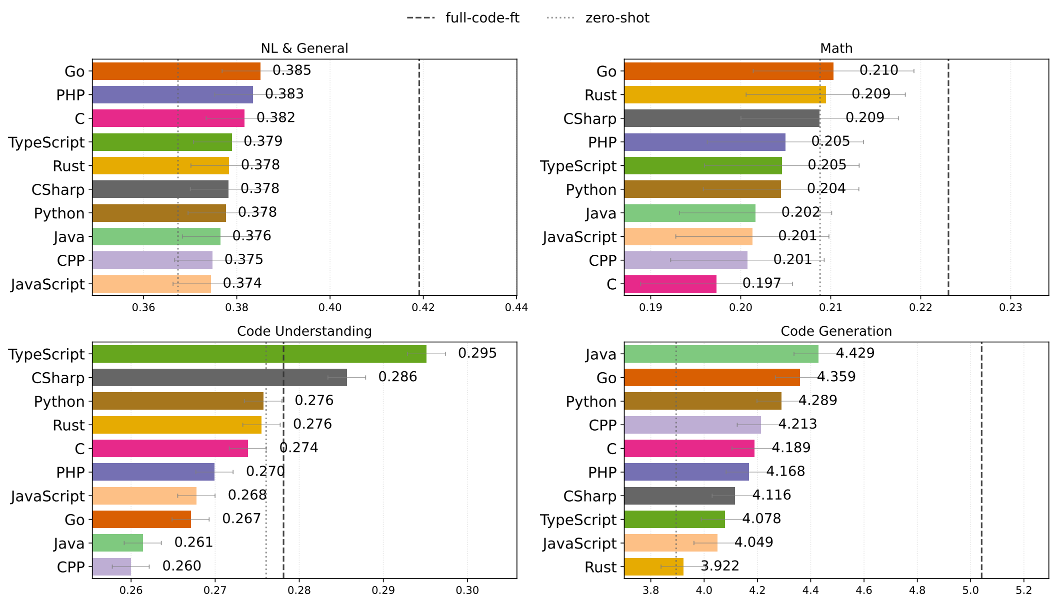


(c) Qwen3-1.7B

Figure 49: All programming language specific performance of Qwen-3 family.

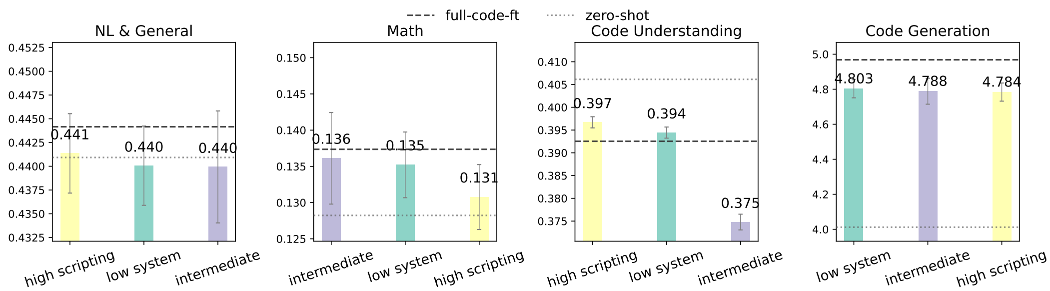


(a) Grouped results (low-system, intermediate, high-scripting)

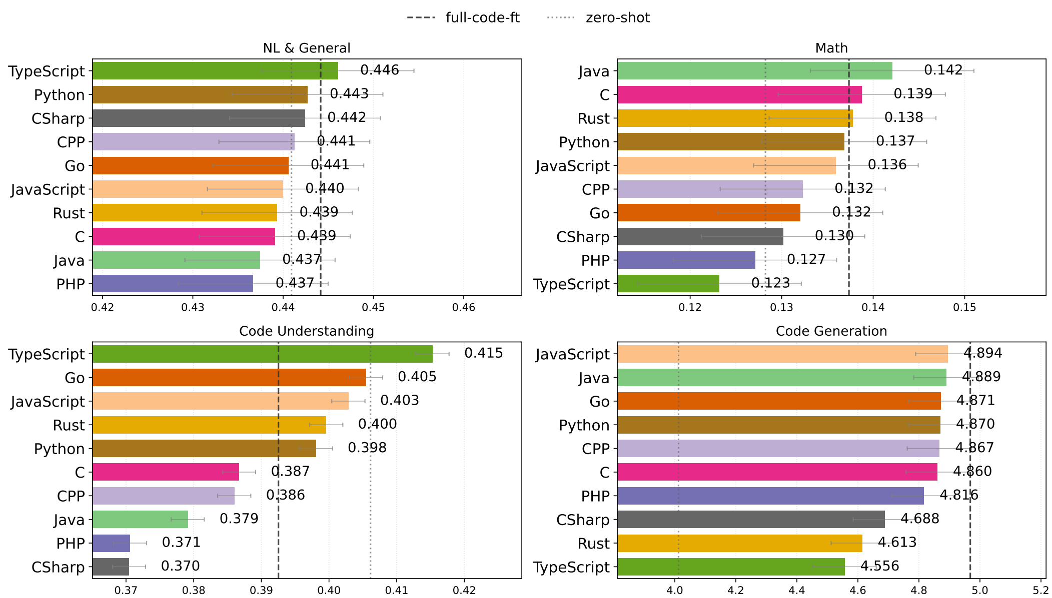


(b) Per-language results

Figure 50: Performance for Llama-3.2-1B. (a) Programming language groups, (b) individual languages.



(a) Grouped results (low-system, intermediate, high-scripting)



(b) Per-language results

Figure 51: Performance for SmolLM2-1.7B. (a) Programming language groups, (b) individual languages.