Execution Guided Line-by-Line Code Generation

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Abstract

We present a novel approach to neural code generation that incorporates real-time execution signals into the language model generation process. While large language models (LLMs) have demonstrated impressive code generation capabilities, they typically do not utilize execution feedback during inference, a critical signal that human programmers regularly leverage. Our method, Execution-Guided Classifier-Free Guidance (EG-CFG), dynamically incorporates execution signals as the model generates code, providing line-by-line feedback that guides the generation process toward executable solutions. EG-CFG employs a multi-stage process: first, we conduct beam search to sample candidate program completions for each line; second, we extract execution signals by executing these candidates against test cases; and finally, we incorporate these signals into the prompt during generation. By maintaining consistent signals across tokens within the same line and refreshing signals at line boundaries, our approach provides coherent guidance while preserving syntactic structure. Moreover, the method naturally supports native parallelism at the task level in which multiple agents operate in parallel, exploring diverse reasoning paths and collectively generating a broad set of candidate solutions. Our experiments across diverse coding tasks demonstrate that EG-CFG significantly improves code generation performance compared to standard approaches, achieving state-of-the-art results across various levels of complexity, from foundational problems to challenging competitive programming tasks. Our code is available at: https://github.com/boazlavon/eg_cfg

1 Introduction

Large language models (LLMs) have recently demonstrated remarkable code generation capabilities, significantly advancing performance in tasks such as general programming problems [1, 2, 3], competitive coding challenges [4], and real-world software engineering tasks [5]. Despite this progress, current LLM-based code generation methods primarily rely on pattern recognition derived from static representations of code rather than explicitly modeling code execution at runtime [1, 3]. Consequently, the generated programs often appear to be correct superficially, but fail to execute correctly on actual inputs, reflecting a critical gap between learned syntactic patterns and genuine executability.

State-of-the-art approaches typically use iterative refinement [6, 7, 8] or self-debugging strategies [9, 10]. Recent approaches adopt multi-agent or agentic workflows, explicitly employing iterative refinement and collaborative feedback mechanisms [11, 12, 13, 14]. However, these methods typically operate in discrete cycles: generating complete candidate solutions, executing them, and then using feedback from failures to guide subsequent attempts. Such approaches do not continuously integrate execution signals during inference, thus limiting their ability to dynamically adjust toward runtime correctness at the token level.

In contrast, human programmers frequently execute incomplete code fragments to quickly detect errors, assess progress, and iteratively refine their implementations based on concrete runtime

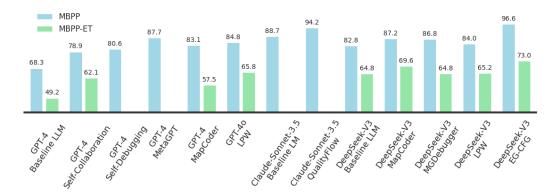


Figure 1: MBPP and MBPP-ET performance. Our method, EG-CFG, achieves a new SOTA using an open-source LLM, surpassing methods utilizing closed-source ones.

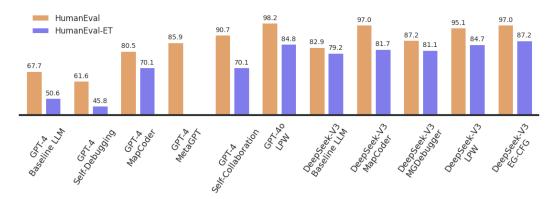


Figure 2: HumanEval and HumanEval-ET performance. Our method, EG-CFG, achieves a new SOTA on HumanEval-ET benchmark.

outcomes, while exploring multiple candidate implementations and planning at varying levels of detail before finalizing solutions [15, 16]. This iterative, real-time refinement process explicitly grounds coding decisions in observed execution behavior rather than relying purely on syntactic or structural reasoning [17].

Inspired by these human coding practices and by LLM exploration techniques [18, 19, 20, 21], our proposed approach generates dynamic execution signals by explicitly sampling multiple candidate continuations at varied completion horizons, systematically adjusting decoding temperature to encourage exploration of different reasoning paths. Executing these diverse candidates yields rich execution-based feedback, explicitly mirroring human iterative refinement and exploratory problem-solving processes.

Unlike methods that provide explicit correctness indicators, such as scalar pass/fail or ranking signals [4, 22], or explicit verbal critiques and structured reflections on execution failures [9, 20], our method provides the raw execution outcome as a soft guidance signal. This approach allows the model to autonomously interpret and integrate minimally processed feedback into its generation process, bridging a significant gap between explicit externally-supervised reinforcement, in which the model is explicitly told what runs were successful [9], and implicit self-verification, where the model autonomously assesses the correctness of its own reasoning [10].

To incorporate the execution-based signal, our method utilizes Classifier-Free Guidance (CFG) [23], conditioning token-level generation decisions on the runtime outcome obtained by executing candidate code completions during inference. This approach guides the model toward solutions that are both syntactically plausible and executable, substantially improving correctness.

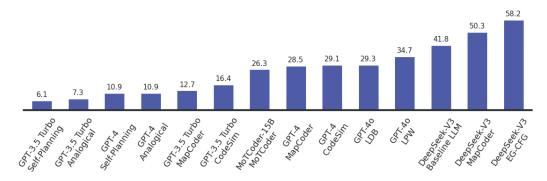


Figure 3: CodeContests performance. Our method, EG-CFG, achieves a new SOTA.

As depicted in Figure 1, our Execution-Guided Classifier-Free Guidance (EG-CFG) approach achieves state-of-the-art performance on the MBPP and MBPP-ET benchmarks [3], significantly outperforming existing methods. Using the open-source DeepSeek-V3-0324 model [24], EG-CFG attains 96.6% accuracy on MBPP and 73.0% on MBPP-ET, surpassing previous leading approaches such as QualityFlow [11] (94.2%), MetaGPT [25] (87.7%), and LPW [26] (84.8% on MBPP, 65.8% on MBPP-ET), all of which utilized leading closed-source models. On the HumanEval benchmark (Figure 2), EG-CFG achieves highly competitive results compared to existing state-of-the-art methods and establishes a new state-of-the-art on the HumanEval-ET benchmark, reaching 87.19% accuracy and surpassing LPW's 84.8% accuracy achieved with GPT-40. Lastly, EG-CFG achieves a new state-of-the-art on the CodeContests benchmark (Figure 3) with 58.18% accuracy using DeepSeek-V3-0324, demonstrating its effectiveness on challenging competitive programming problems.

The superior performance of EG-CFG on MBPP-ET and HumanEval-ET highlights that our method not only generates accurate code but also significantly enhances robustness and reliability under complex and extended test scenarios.

Summarizing, our main contributions are: (i) a framework for dynamically generating code while executing fragments of the code and using the execution traces to guide the generation process, (ii) introducing native parallelism at the task level that is not achievable in the sequential iterative refinement methods, (iii) using CFG in order to generate code that is conditioned on the execution feedback, and (iv) obtaining new state of the art results on the MBPP, MBPP-ET, HumanEval-ET, and CodeContests benchmarks using open-source models, outperforming previous methods that are based on the leading closed-source models.

2 Related Work

Program synthesis has long served both as a means to evaluate LLMs' capabilities [1, 27] and as a key goal of the research community to automate code generation [28, 29]. Modern LLMs are typically assessed via automated benchmarks: given a coding problem description, the model generates code that is then validated on a set of test cases (unit-test). In this work, we focus on three code generation benchmarks: MBPP [3], HumanEval [1], and CodeContests [4], along with the enhanced variants MBPP-ET and HumanEval-ET [30]. MBPP combines crowd-sourced tasks and math-based problems [31], HumanEval includes hand-written Python challenges, and CodeContests features competitive programming problems requiring advanced algorithmic reasoning.

While zero-shot prompting, meaning directly querying an LLM on a task, is one evaluation strategy, few-shot prompting [32], which provides a small number of input—output examples, is more widely adopted. Other methods, such as Chain-of-Thought (CoT) [33], leverage the model's autoregressive nature to iteratively solve such tasks by decomposing them into sub-tasks. Similar approaches, such as Tree-of-Thoughts [21] extend CoT by exploring multiple candidate reasoning paths at a higher level of granularity.

With the growing ability of LLMs to utilize external signals and tools [34], LLMs have been augmented with feedback mechanisms to improve code generation. Approaches such as Reflexion

[9], Program-aided Language Models (PAL) [6], and ReAct [7] iteratively update prompts based on external tools' outputs or intermediate results. In particular, Self-Debugging [10] demonstrates how LLMs can leverage debugging tools: the model generates code, tests it on available unit-test examples, and refines its output using the debugging feedback. Another related approach, LPW [26], employs a structured two-phase process involving initial high-level plan generation followed by iterative refinement and debugging guided by execution feedback. The Multi-Granularity Debugger (MGDebugger) [35] also uses the LLM to simulate the execution of generated Python programs, employing the simulated trace as additional feedback for code refinement.

While some approaches use a single LLM to solve coding problems, agentic methods employ multiple LLM instances to tackle a single task. Works such as MetaGPT [25], introduce a framework in which a given task is split into multiple procedures, each assigned to a dedicated LLM agent. AgentCoder [12] extends these multi-agent frameworks by employing both a test-designer agent and an executor agent, effectively integrating the Self-Debugging paradigm [10] into an agentic workflow and demonstrating the benefits of execution feedback. Current agentic workflows, such as MapCoder [13] and LPW [26], typically rely on discrete cycles of sequential agent interactions or distinct refinement phases, inherently limiting their ability to fully leverage the power of parallelism within a single task. In contrast, EG-CFG breaks this barrier by introducing native parallelism at the task level. Multiple agents run concurrently on the same task, each with a different configuration, simultaneously exploring diverse reasoning paths without the constraints of sequential cycles, fully leveraging the power of parallelism.

Although code generation methods have advanced dramatically, they all rely on naive decoding methods such as temperature or top-p sampling [18]. In particular, execution-feedback techniques generate a complete solution, execute it, and then refine the code. For example, the model is prompted to produce a function, its implementation is tested against unit tests, and the resulting feedback is appended to the original prompt. This process repeats iteratively until a correct solution emerges. This approach contrasts with recent advances in LLM inference techniques, especially guidance methods such as Classifier Guidance [36] and Classifier-Free Guidance (CFG) [23]. These methods condition generation on external constraints or classifier signals, directing the model to sample tokens from multiple contrastive distributions. Although CFG has shown strong performance, its guidance signals remain static, predefined and fixed throughout the sampling process [37].

As far as we can ascertain, guidance methods such as CFG have yet to be applied at scale with dynamic, execution-driven reasoning. This work bridges this gap by demonstrating that a single open-source model, augmented with execution feedback and a novel token-sampling strategy, outperforms the state of the art across multiple widely adopted coding benchmarks at different complexity levels from foundational problems to challenging competitive programming tasks. Our contribution differs from prior work in multiple key aspects, including:

- 1. Prior approaches generate entire code blocks (or sub-blocks) and using the execution feedback of the entire block; by contrast, our approach gradually generates the solution line-by-line by sampling and executing multiple candidate continuations programs at each step.
- 2. Instead of explicitly relying on unit-test pass/fail signals or direct reflections on correctness, our method incrementally constructs code fragments and leverages their execution traces as an implicit feedback signal, guiding the model without explicit external supervision.
- 3. Our method relies on a single prompting scheme where multiple agents perform the same task and differ only in their parameter configurations. Each agent explores diverse reasoning paths and collectively generating a broad set of candidate solutions. This enables a level of parallelism that is unattainable in methods where agents communicate sequentially.
- 4. We replace naive decoding with CFG, using innovative trace-inspired prompts for dual-distribution interpolation sampling.

3 Method

We present Execution-Guided Context-Free Guidance (EG-CFG), a novel inference-time decoding method for neural code generation that explicitly integrates dynamic execution signals into the autoregressive generation process.

A programming task is represented by the templated prompt composed of four components:

$$p_{\text{inst}} = (p_0, p_{\text{task}}, T, f_{\text{name}}), \tag{1}$$

where p_0 is the natural-language instruction template, p_{task} is a textual definition of the programming task, $T = \{t_j\}_{j=1}^{|T|}$ is the set of test cases, and f_{name} is the target Python function name. The goal is to generate executable Python code $w^* = [w_0^*, w_1^*, \dots, w_{N-1}^*]$ that solves the task correctly, formally satisfying:

Execute
$$(w^*, t_j) = \text{success}, \quad \forall t_j \in T.$$
 (2)

At each step i, given a previously generated token sequence $w_{< i}$, the LLM M assigns a probability distribution $M(w_i \mid p_{\text{inst}, w_{< i}})$, which is conditioned on the instruction prompt p_{inst} . This generation proceeds iteratively until reaching a maximum token length N_{max} or an end-of-code token.

We consider two distinct instruction templates p_0 : the standard DeepSeek-Coder 3-shot prompt [38], consisting of concise instructions accompanied by short illustrative examples, and an alternative prompt explicitly designed to encourage the generation of step-by-step solutions with more atomic logic. See Appendix A for the example prompts used.

We first run the model to produce an initial solution p_{pre} based on p_{inst}

$$w_{\text{pre}}^{i} = \arg\max M(w_{i} \mid p_{\text{inst}, w_{< i}}), \qquad p_{\text{pre}} = [p_{\text{inst}}, w_{\text{pre}}^{0}, \cdots, w_{\text{pre}}^{n-1}]$$
 (3)

until we identify the beginning of the final executable solution block within, by locating the occurrence of a special start-of-code token, which is defined in p_0 . This position is marked as i_{solution} . We note that p_{pre} contains reasoning tokens, and other tokens that precede the final start-of-code token. Another index that we define p_{pre} is the index i_{dyn} of the last token of the last few example inside the template p_{inst} . We used this location to inject future signals into the prompt.

The prompt p_{sol} that we pass to the LLM is created autoregressively by aggregating executable code tokens into p_{pre} . This prompt contains partial solutions that are updated until the solution is formed.

3.1 Dynamic Execution Feedback

Our dynamic execution feedback explicitly generates multiple candidate continuations based on a partially completed solution. Specifically, given $p_{\rm sol}$ we generate a set of candidate continuations using beam-search decoding. Each candidate explicitly extends the current solution by d additional lines of code, capturing meaningful variations in potential solutions and providing a granular basis for execution-based guidance. Formally, given parameters specifying the number of candidates s, completion horizon d, and sampling temperature t, the beam search sampling is performed to obtain s candidates:

$$c^j \sim M(p_{\text{sol}}; d, t), \quad j = 1, \dots, s$$
 (4)

where each candidate c^j explicitly represents a plausible continuation of the next d lines of code. These candidates form the basis for generating detailed execution signals used to guide subsequent inference steps.

Executable Extraction Since generated candidate continuations may contain incomplete or syntactically invalid Python code, we explicitly extract their executable components using syntactic validation via Abstract Syntax Tree (AST) parsing. Formally, for each candidate c^j , we apply the executable extraction function:

$$\hat{c}^j = \text{ExtractExecutable}(c^j), \quad j = 1, \dots, s.$$
 (5)

This extraction function iteratively attempts to parse each candidate c^j as follows: (1) attempt parsing c^j (2) if unsuccessful, append a Python pass statement to the last line and retry; (3) if still unsuccessful, iteratively remove the last line and retry. This ensures minimal modifications for syntactic validity.

After extraction, we apply uniqueness filtering to remove duplicates:

$$C = \text{Unique}\left(\left\{\hat{c}^j\right\}_{i=1}^s\right). \tag{6}$$

This AST-based verification explicitly ensures that execution guidance relies solely on syntactically valid and executable code.

Execution Feedback and Trace For each unique executable candidate $\hat{c}^j \in C$, we explicitly execute it against all provided test cases $T = \{t_m\}_{m=1}^{|T|}$ and record the resulting execution feedback:

$$e^{j,m} = \text{ExtractExecutionFeedback}(\hat{c}^j, t_m), \quad \forall \hat{c}^j \in C, t_m \in T.$$
 (7)

Our approach is agnostic to the precise structure of the execution feedback $e^{j,m}$. In our implementation, execution feedback specifically takes the form of **execution traces:** a structured representation of a program's runtime behavior, capturing detailed step-by-step information during execution. Specifically, an execution trace includes executed lines of code, variable states (values and types), function invocations, return values, and detailed descriptions of runtime errors, if they occur. This structured log provides comprehensive insight into the correctness and behavior of executed code, serving as a precise basis for dynamic feedback in our inference framework.

Dynamic Signal Aggregation The dynamic execution feedback signal is the concatenation of a fixed instruction string, denoted $p_{\text{dyn-inst}}$, to the aggregated execution feedback. This yields the dynamic signal prompt:

$$p_{\text{signal}} = [p_{\text{dyn-inst}}, \{(\hat{c}^j, t_m, e^{j,m})\}_{\hat{c}^j \in C, t_m \in T}], \tag{8}$$

where each tuple consists of a candidate completion \hat{c}^j , a test case t_m , and its corresponding execution trace $e^{j,m}$.

Now we form a new prompt naming this prompt p_{dyn} as **dynamic signal prompt**:

$$p_{\text{dyn}} = [p_{\text{sol}}[: i_{\text{dyn}}], p_{\text{signal}}, p_{\text{sol}}[i_{\text{dyn}}:]] \tag{9}$$

An example of the obtained prompt is shown in Figure 4.

3.2 Classifier-Free Guidance (CFG)

Inspired by [23], we utilize CFG to explicitly guide token generation by interpolating between two probability distributions: (i) an unconditional (prior) distribution based on the evolving solution prompt $p_{\rm sol}$, and (ii) a conditional distribution based on dynamic signal prompt $p_{\rm dyn}$ which incorporates execution feedback. Formally, for each token w_i , the CFG distribution is computed as:

$$\log M_{\text{CFG}}(w_i \mid p_{\text{sol}}, p_{\text{dyn}}) = \log M(w_i \mid p_{\text{sol}}) + \gamma \left[\log M(w_i \mid p_{\text{dyn}}) - \log M(w_i \mid p_{\text{sol}})\right], \quad (10)$$

where $\gamma \geq 0$ explicitly controls the strength of guidance. Higher values of γ encourage the model to follow the execution-based guidance, while lower values allow greater flexibility toward the unconditional prior.

3.3 Execution-Guided Inference Loop

Our inference procedure extends standard autoregressive token generation by explicitly incorporating dynamic execution feedback via CFG. Starting from an initial prompt p_{pre} (Equation 3), we autoregressively sample tokens w_i from the CFG-conditioned distribution $M_{\text{CFG}}(w_i \mid p_{\text{sol}}, p_{\text{dyn}})$, progressively constructing the solution sequence p_{sol} .

At each token-generation step, we reuse the dynamic signal p_{signal} (Equation 8), injecting it into p_{sol} at index i_{dyn} to form p_{dyn} as described in Equation 9. p_{signal} itself is regenerated only upon completing a new line.

$$w_{\text{sol}}^{i} = \arg\max M_{\text{CFG}}(w_{i} \mid p_{\text{sol}}, p_{\text{dyn}}), \qquad p_{\text{sol}} = [p_{\text{pre}}, w_{\text{sol}}^{0}, \cdots, w_{\text{sol}}^{n-1}]$$
 (11)

To systematically leverage execution-based guidance, given an input task $\tau=(p_{\rm inst},T,f_{\rm name})$, we perform inference over all parameter combinations of completion candidates s, completion horizon d, sampling temperature t, and instruction prompt types. For each such parameter set, we iteratively run inference with progressively increasing CFG strength values γ . We return the first correct solution identified; otherwise, inference continues across remaining parameter combinations.

```
Instruction (from p_0) Write a python function to find the first non-repeated character in a
given string.
assert first_non_repeating_character("aabc") == "c"
assert first_non_repeating_character("abcabc") == None
assert first_non_repeating_character("abc") == "a"
assert first_non_repeating_character("ababc") == "c"
Dynamic signal instruction p_{\text{dyn-inst}} starts here at i_{\text{dyn}} Below are execution traces from run-
ning the response function after appending several possible future continuations. These
continuations represent plausible ways the function might continue from its current state.
They are not necessarily full solutions - some may be partial, exploratory, or incomplete.
For each candidate continuation, multiple test cases (invocations) were executed to observe
its behavior under different inputs. Each entry includes: - A candidate version of the function
- A specific test case used for invocation - The resulting execution trace for that test case
These dynamic signals can help you better understand how different plausible con-
tinuations behave at runtime, and guide you toward a more accurate solution.
Execution feedback for a single test |T| = 1 and s = 2 candidates
# Function:
def first_non_repeating_character(s):
     char_count = {}
     for char in s:
         char_count[char] = char_count.get(char, 0) + 1
  for char in s:
       if char_count[char] == 1:
           return char
  return None
# Invocation:
first_non_repeating_character("aabc")# Execution Trace:
s = 'aabc', char_count = {}
char = 'a' -> char_count = {'a': 1}
char = 'b' -> count = 1 -> return 'b'
# Function:
def first_non_repeating_character(s):
    char_count = {}
    for char in s:
         char_count[char] = char_count.get(char, 0) + 1
  for char in s:
       if char_count[char] == 2:
           return char
  return None
# Invocation:
first_non_repeating_character("aabc") # Execution Trace:
s = 'aabc', char_count = {}
char = 'a' -> char_count = {'a': 1}
char = 'a' -> char_count = {'a': 2}
char = 'b' -> char_count = {'a': 2, 'b': 1}
char = 'c' -> char_count = {'a': 2, 'b': 1, 'c': 1}
char = 'a' -> count = 2 -> return 'a'
### Response:
"" python
def first_non_repeating_character(s):
     char_count = {}
    for char in s:
         char_count[char] = char_count.get(char, 0) + 1
```

Figure 4: Example of p_{dyn} with injected p_{signal} at index i_{dyn}

4 Experiments

Implementation Details We conduct our experiments using two LLMs across different parameter scales: DeepSeek-Coder-1.3B [38], which is small enough to run locally on our machines (NVIDIA GeForce RTX 2080 Ti and RTX 3090 GPUs), and a large open-source model, DeepSeek-V3-0324 [24] which we use through a cloud inference endpoint. We use *Fireworks AI* which was chosen based on two criteria: a modest cost, and the availability of a log probability output that is required to perform the CFG (Equation 10). The full code used for our experiments is provided in the supplementary materials.

Hyperparameter Settings As explained in section 3.3, given a task, multiple hyperparameters are tried to create a diversity of candidates. The following hyper-parameter sets were used in our experiments: s = 3, $t \in \{0.7, 0.75, 0.85, 0.95, 1.2, 1.5\}$, $d \in \{2, 3, 6, 8\}$, $\gamma \in \{0, 0.5, 1, 3\}$. Additionally, we evaluate both p_0 prompts, see section 3 and appendix Appendix A.

Evaluation Benchmark Our evaluations are performed on two widely-used code-generation benchmarks: MBPP [3] and HumanEval [1], which consist of Python programming tasks described in natural language, accompanied by test cases for evaluating the correctness of generated solutions (MBPP: 500 tasks, HumanEval: 164 tasks). Additionally, we utilize the MBPP-ET and HumanEval-ET datasets [30], enhanced versions containing extended and more challenging test cases, to rigorously evaluate the generalization and robustness of the generated solutions. These benchmarks are extensively used in the literature due to their clarity, diversity, and practicality. In addition, we evaluate our method on the challenging competitive programming benchmark, CodeContests [4], which is designed to assess advanced algorithmic problem-solving abilities. On CodeContests, evaluations were performed using the ExecEval evaluation framework. [39]

We evaluate model-generated solutions using the standard accuracy metric used in benchmarks, defined as the percentage of problems for which the generated solution passes all provided test cases, reflecting the correctness and practical usability of the generated code.

Baselines We compare our EG-CFG method against several established state-of-the-art methods for code generation and debugging:

- Baseline LLM Few-shot prompting using the few-shot template introduced in DeepSeek-Coder's official evaluation [38].
- MGDebugger [35]: An iterative refinement method that combines test-cases assertions based feedback from an external Python interpreter with execution traces as simulated by the LLM.
- MapCoder [13]: Employs multi-agent interactions to generate and iteratively refine code.
- QualityFlow [11]: Incorporates agentic workflows to iteratively enhance generated code through quality-focused interactions.
- LPW [26]: Utilizes a structured two-phase workflow involving plan creation, plan verification, and iterative code refinements guided by runtime execution feedback.

4.1 Results

On the MBPP benchmark Table 1, our EG-CFG method outperforms all other approaches . Notably, EG-CFG achieves new state-of-the-art results on both MBPP and MBPP-ET benchmarks with the DeepSeek-V3-0324 model, outperforming previous results obtained by large closed-source models such as GPT-4 and Claude-Sonnet-3.5.

On the HumanEval benchmark Table 2, EG-CFG achieves highly competitive results compared to existing SOTA methods. The method that outperforms it (98.2% vs. 96.95%) is LPW when using the GPT-40 model, and MapCoder also achieves 96.95%. Crucially, when evaluated on the more challenging HumanEval-ET benchmark, EG-CFG achieves another new state-of-the-art result.

On the CodeContests benchmark Table 3, our EG-CFG method achieves a new state-of-the-art overall accuracy using the DeepSeek-V3-0324 model. This significantly surpasses the DeepSeek-V3-0324 Baseline LLM and MapCoder. Furthermore, EG-CFG on DeepSeek-V3-0324 also outperforms previous results from GPT-4 models using methods like LPW, CodeSim, and MapCoder.

Table 1: Performance on the MBPP and MBPP-ET benchmarks. Our proposed EG-CFG achieves a new state-of-the-art overall accuracy. The DeepSeek–Coder-1.3B and –V3-0324 results for all baselines were obtained by our study using the official implementations provided by each baseline method. The results below the double separator were collected from the respective papers.

Model	Method	MBPP		MBPP-ET	
		Acc. (%)	RSR (%)	Acc. (%)	RSR (%)
DeepSeek-Coder 1.3B	Baseline LLM	49.4	0.0	42.6	0.0
DeepSeek-Coder 1.3B	EG-CFG (Ours)	83.2	66.79	59.8	29.96
DeepSeek-Coder 1.3B	MapCoder [13]	55.2	11.46	46.2	6.27
DeepSeek-Coder 1.3B	MGDebugger [35]	70.4	41.5	44.6	3.48
DeepSeek-V3-0324	Baseline LLM	82.8	0.0	64.8	0.00
DeepSeek-V3-0324	EG-CFG (Ours)	96.6	80.23	73.0	23.29
DeepSeek-V3-0324	MapCoder [13]	87.2	25.58	69.6	13.63
DeepSeek-V3-0324	MGDebugger [35]	86.8	23.25	64.8	0.00
DeepSeek-V3-0324	LPW [26]	84.0	6.97	65.2	1.13
GPT-4	Baseline LLM	68.3	-	49.2	-
GPT-4	Self-Collaboration [40]	78.9	-	62.1	-
GPT-4	Self-Debugging [10]	80.6	-	-	-
GPT-4	MetaGPT [25]	87.7	-	-	-
GPT-4	MapCoder [13]	83.1	-	57.5	-
GPT-40	LPW [26]	84.8	-	65.8	-
CodeQwen1.5	MGDebugger [35]	80.8	-	-	-
DeepSeek-Coder-V2-Lite	MGDebugger [35]	80.0	-	-	-
Claude-Sonnet-3.5	Baseline LLM [11]	88.7	-	-	_
Claude-Sonnet-3.5	QualityFlow [11]	94.2	-	-	-

To further understand the failure cases of our method, we manually reviewed all the tasks in MBPP that were not solved by DeepSeek-V3-0324. We found that out of the total 17 tasks that the model did not pass, nine of them contain invalid unit tests, with some also having incorrect reference solutions. In these nine cases, our method generated correct code that was marked as failed due to flawed benchmark tests. Full details are provided in the supplementary material.

We note that across all tested baselines, the publicly available code was highly sensitive to the specific model and could not be readily applied to DeepSeek models. We invested substantial effort in debugging and adapting the code to ensure it produced meaningful results that represented each baseline method as favorably as possible. Other methods, such as QualityFlow, have not release their code, preventing us from evaluating them on the DeepSeek models. While LPW did release public implementation, we encountered substantial technical issues during the execution of their published code on DeepSeek-Coder 1.3b model, resulting in unusually low scores despite our best debugging efforts on that benchmark.

Run time We report the mean time to solve each task under full parallelization. Unlike iterative refinement methods, which require sequential feedback loops, EG-CFG treats each inference run (across different hyper-parameters for the same task) as independent, enabling parallel execution. Runtimes include early termination, i.e., once a task is solved, remaining runs are terminated. As can be seen in Table 4, our method is more efficient than MGDebugger and competitive with MapCoder. When comparing with LPW, our method is more efficient with the smaller model but slower with the larger model.

Ablation study We performed an ablation study on the MBPP and MBPP-ET benchmarks to evaluate various components of our method. The results are reported in Table 5. When omitting the beam search of Equation 4, which creates multiple solutions instead of a single completion, the performance of the methods drops and becomes much closer to the baseline performance.

The role of CFG is evident from the second ablation, in which a value of $\gamma = 1$ is used in Equation 10. In this case, there is a clear drop in performance, although results are still clearly above the baseline.

Table 2: Performance on the HumanEval and HumanEval-ET benchmarks. Our proposed EG-CFG achieves a new state-of-the-art overall accuracy on HumanEval-ET.

Model	Method	HumanEval		HumanEval-ET	
		Acc. (%)	RSR (%)	Acc. (%)	RSR (%)
DeepSeek-V3-0324	Baseline LLM	82.92	0.0	79.20	0.0
DeepSeek-V3-0324	EG-CFG (Ours)	96.95	82.14	87.19	38.41
DeepSeek-V3-0324	MapCoder [13]	96.95	82.14	81.70	12.02
DeepSeek-V3-0324	MGDebugger [35]	87.20	25.05	81.09	9.09
DeepSeek-V3-0324	LPW [26]	95.12	71.42	84.74	26.63
GPT-4	Baseline LLM	67.7	-	50.6	-
GPT-4	Self-Collaboration [40]	90.7	-	70.1	-
GPT-4	Self-Debugging [10]	61.6	-	45.8	-
GPT-4	MetaGPT [25]	85.9	-	-	-
GPT-4	MapCoder [13]	80.5	-	70.1	-
GPT-4o	LPW [26]	98.2	-	84.8	-
CodeQwen1.5	MGDebugger [35]	91.5	64.1	-	-
DeepSeek-Coder-V2-Lite	MGDebugger [35]	94.5	76.3	-	-

Table 3: Performance on the CodeContests benchmark. Our proposed EG-CFG achieves a new state-of-the-art overall accuracy on CodeContests. The runs on Deep-Seek-V3-0324 are by us, and all other results are quoted from the literature. * The LPW results was obtained on a custom test-set; the published code was not compatible with evaluating on DeepSeek. **Reported by the MapCoder paper [13]. ***Reported by the CodeSim paper [14].

Model	Method	Accuracy (%)	RSR (%)
DeepSeek-Seek-V3-0324	Baseline LLM	41.81	0.00
DeepSeek-Seek-V3-0324	EG-CFG (Ours)	58.18	28.13
DeepSeek-Seek-V3-0324	MapCoder [13]	50.30	14.59
GPT-4o	LPW [26]*	34.7	-
GPT-40	LDB [41]***	29.3	-
GPT-4	CodeSim [14]	29.1	-
GPT-4	MapCoder [13]	28.5	-
GPT-4	Self-Planning [42]**	10.9	-
GPT-4	Analogical [43]**	10.9	-
GPT-3.5 Turbo	CodeSim [14]	16.4	-
GPT-3.5 Turbo	MapCoder [13]	12.7	-
GPT-3.5 Turbo	Analogical [43]**	7.3	-
GPT-3.5 Turbo	Self-Planning [42]**	6.1	-
MoTCoder-15B	MoTCoder [44]	26.34	-

Finally, a similar drop in performance is observed when replacing the detailed execution trace used as part of the dynamic signal with a minimal execution trace that captures only the final values and types of all variables in scope after the last line of the solution function has completed execution.

5 Conclusions

This paper introduces Execution-Guided Classifier-Free Guidance (EG-CFG), a novel approach that fundamentally reframes neural code generation by incorporating real-time execution signals directly into the inference process. Our method bridges a critical gap between static pattern recognition and execution semantics by dynamically sampling candidate continuations, extracting execution traces, and leveraging these signals to guide token-level generation decisions.

Table 4: Per-task runtime statistics (in seconds) for each model and method on MBPP.

Model	Method	$\mathbf{Mean} \pm \mathbf{SD} (\mathbf{s})$
DeepSeek-Coder 1.3b	EG-CFG	123.23 ± 344.91
DeepSeek-Coder 1.3b	MGDebugger	495.16 ± 411.07
DeepSeek-Coder 1.3b	MapCoder	121.9 ± 213.89
DeepSeek-Coder 1.3b	LPW	197.71 ± 128.07
DeepSeek-V3-0324	EG-CFG	271.37 ± 271.45
DeepSeek-V3-0324	MGDebugger	842.24 ± 705.19
DeepSeek-V3-0324	MapCoder	283.84 ± 197.54
DeepSeek-V3-0324	LPW	87.51 ± 210.84

Table 5: Ablation results for EG-CFG on DeepSeek-Coder 1.3b on MBPP and MBPP-ET benchmarks.

Method	MBPP		MBPP-ET		
	Acc. (%)	RSR (%)	Acc. (%)	RSR (%)	
EG-CFG	83.2	66.79	59.8	29.96	
EG-CFG, no beam search	58.2	17.39	43.6	1.74	
EG-CFG w/o CFG ($\gamma = 1$)	75.2	50.98	48.2	9.74	
EG-CFG, minimal trace	76.4	53.35	51.2	14.98	
Baseline LLM	49.4	0.0	42.6	0.0	

The empirical results demonstrate that EG-CFG achieves new state-of-the-art results of 96.6% accuracy on MBPP, 73.0% on MBPP-ET, 87.19% on HumanEval-ET and 58.18% on CodeContests using DeepSeek-V3-0324, surpassing both open-source and proprietary model-based approaches. The superior performance on both MBPP-ET and HumanEval-ET underscores the method's robustness and effectiveness in generating reliable and accurate code under complex and extended test scenarios.

Notably, our approach demonstrates robust performance even with smaller models, achieving 83.2% accuracy using DeepSeek-Coder-1.3B, comparable to results from substantially larger models. This scalability highlights the effectiveness of execution signals as a guiding mechanism regardless of model capacity.

The EG-CFG approach offers several advantages over existing methods. Unlike discrete iterative refinement techniques that operate at coarse granularity between complete solution attempts, our method provides continuous feedback at the token level. By integrating execution signals that reflect actual runtime behavior, EG-CFG mirrors the incremental testing and debugging process that human programmers employ.

Looking forward, this work opens several promising research directions. The execution-guided framework could be extended to more complex programming tasks requiring longer-horizon planning or multi-file interactions.

Additionally, the underlying principles of EG-CFG dynamically incorporating external semantic signals into generative processes could benefit other domains where generation benefits from grounding in external systems, such as database querying, formal verification, or simulation-based generation.

6 Limitations

While the EG-CFG framework demonstrates significant improvements in code generation performance, several important limitations should be acknowledged.

First, the approach introduces computational overhead compared to standard inference methods. The beam search exploration, execution of multiple candidate continuations, and dual-distribution interpolation in the CFG mechanism collectively increase inference time. Though our parallel execution strategy mitigates this overhead somewhat, future work should explore more efficient methods for extracting and incorporating execution signals.

Second, EG-CFG's effectiveness is contingent upon the availability of executable test cases that adequately exercise the target functionality. In real-world programming scenarios, comprehensive test

cases may not always be available or easily generated by LLMs, potentially limiting the approach's applicability.

Finally, because our inference loop is bottom-up, it does not exploit task decomposition, a strategy that has been shown to improve code generation [35]. Future work could integrate our sampling strategy with iterative refinement methods, task-decomposition methods or with top-down problem-inspection techniques [45] to achieve even better performance.

Despite these limitations, EG-CFG represents a significant advancement in execution-aware code generation and provides a solid foundation for future research addressing these challenges.

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A The two p_{inst} prompts used by our method

The two basic instruction prompts that are used by our method are provided in Figure 5 and Figure 6. The former is the standard DeepSeek-Coder 3-shot prompt [38], consisting of concise instructions accompanied by short illustrative examples, and the latter is an alternative prompt explicitly designed to encourage the generation of step-by-step solutions with more atomic logic.

```
Raw DeepSeek-Instruct Prompt for MBPP Task 395
You are an AI programming assistant, utilizing the Deepseek Coder model,
developed by Deepseek Company, and you only answer questions related to
computer science. For politically ...
### Instruction:
Please refer the given examples and generate a python function for my problem.
Examples are listed as follows:
- Example 1:
>>> Problem:
Write a function to find the similar elements from the given two tuple lists.
>>> Test Cases:
assert similar_elements((3, 4, 5, 6), (5, 7, 4, 10)) == (4, 5)
assert similar_elements((1, 2, 3, 4),(5, 4, 3, 7)) == (3, 4)
assert similar_elements((11, 12, 14, 13),(17, 15, 14, 13)) == (13, 14)
>>> Code:
def similar_elements(test_tup1, test_tup2):
 res = tuple(set(test_tup1) & set(test_tup2))
  return (res)
- Example 2:
>>> Problem:
Write a python function to identify non-prime numbers.
>>> Test Cases:
assert is_not_prime(2) == False
assert is_not_prime(10) == True
assert is_not_prime(35) == True
>>> Code:
import math
def is_not_prime(n):
    result = False
    for i in range(2,int(math.sqrt(n)) + 1):
        if n % i == 0:
            result = True
    return result
- Example 3:
>>> Problem:
Write a function to find the largest integers from a given list of numbers using ...
>>> Test Cases:
assert heap_queue_largest([25, 35, 22, 85, 14, 65, 75, 22, 58],3) == [85, ...
assert heap_queue_largest([25, 35, 22, 85, 14, 65, 75, 22, 58],2) == [85, ...
assert heap_queue_largest([25, 35, 22, 85, 14, 65, 75, 22, 58],5) == [85, ...
>>> Code:
import heapq as hq
def heap_queue_largest(nums,n):
  largest_nums = hq.nlargest(n, nums)
 return largest_nums
Here is my problem:
>>> Problem:
Write a python function to find the first non-repeated character in a given
string.
>>> Test Cases:
assert first_non_repeating_character("abcabc") == None
assert first_non_repeating_character("abc") == "a"
assert first_non_repeating_character("ababc") == "c"
### Response:
```

Figure 5: The DeepSeek-Instruct prompt used for MBPP Task 395. This prompt includes multiple solved examples followed by the target task.

```
Long-Instruct Prompt for MBPP Task 395 (p_{inst})
You are an AI programming assistant, utilizing the Deepseek Coder model,
developed by Deepseek Company, ...
### Instruction:
Write a python function to find the first non-repeated character in a given
Write a Python function that satisfies the following test cases:
>>> Test Cases:
['assert first_non_repeating_character("abcabc") == None',
 'assert first_non_repeating_character("abc") == "a"',
 'assert first_non_repeating_character("ababc") == "c"']
Your solution should be written in as many lines as possible.
This ensures that prefixes of your function remain valid Python programs.
Allowing **incremental execution and debugging**.
Write the function **step by step**, progressively introducing variables and logic.
Avoid using list comprehensions, lambda functions, or overly compact one-liners.
Instead, follow these guidelines: **
Avoid list comprehensions, use loops instead:
Incorrect:
def square_numbers(lst):
    return [x ** 2 for x in 1st]
Correct:
def square_numbers(lst):
    squares = []
    for num in 1st:
        squared_value = num ** 2
        squares.append(squared_value)
    return squares
Avoid inline expressions, use variables instead
Incorrect:
def calculate_area(length, width):
    return (length * width) / 2
Correct:
def calculate_area(length, width):
    product = length * width
    area = product / 2
    return area
Incorrect:
result.append(x + y)
Correct:
z = x + y
result.append(z)
Incorrect:
def compute_value(a, b, c):
    return (a + b) * (c / (a - b) + (a * c) / (b + c))
Correct:
def compute_value(a, b, c):
    term1 = a + b
    term2 = a - b
    term3 = c / term2
    term4 = a * c / (b + c)
    result = term1 * (term3 + term4)
    return result
### Response:
```

Figure 6: Long-Instruct prompt for MBPP Task 395. This instruction-only prompt includes stylistic constraints that encourage traceable, step-by-step completions suitable for dynamic signal extraction.