Code Generation with AlphaCodium: From Prompt Engineering to Flow Engineering

(paper presentation)

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Contents

Overview

- The paper addresses the challenge of enhancing code generation by LLMs, which struggle with syntax accuracy and handling problem-specific details.
- Code generation differs from typical natural language tasks due to the need for exact syntax, handling edge cases, and following detailed specifications.
- Techniques successful in natural language generation may not work well for code generation.

Overview (Cont)

- The authors propose AlphaCodium, a test-based, multistage, code-focused iterative method for improving code generation by large language models.
- AlphaCodium was evaluated on the CodeContests dataset, which includes competitive programming problems from platforms like Codeforces.
- The approach significantly improves performance; for instance, GPT-4's pass@5 accuracy rose from 19% (with a single prompt) to 44% using AlphaCodium.
- The insights and practices from AlphaCodium are considered broadly useful for general code generation tasks.

Dataset

- CodeContests is a challenging dataset introduced by DeepMind, sourced from competitive programming platforms like Codeforces.
- It includes 10K code problems for training, and separate validation (107 problems) and test sets (165 problems) for evaluation.
- This work focuses on applying a code-oriented flow to existing LLMs (e.g., GPT, DeepSeek) rather than training a new model, using only the validation and test sets.
- Each problem provides a description and public tests; the model must generate code that passes a hidden private test set.

Dataset

- Key strengths of CodeContests:
  - It includes ≈200 private tests per problem to ensure robustness and prevent false positives.
  - The problem descriptions are intentionally long and nuanced, requiring attention to small but critical details.
  - This setup better reflects real-world coding scenarios, which often involve complex and detail-rich tasks.
  - In contrast, simpler datasets like HumanEval contain shorter, more straightforward problems.
- Effective problem understanding, supported by techniques like self-reflection, improves clarity and increases the likelihood of generating correct solutions.

Dataset

Problem Description

Mr. Chanek's city can be represented as a plane. He wants to build a housing complex in the city. There are some telephone poles on the plane, which is represented by a grid a of size (n + 1) × (m + 1). There is a telephone pole at (x, y) if a_{x, y} = 1.For each point (x, y), define S(x, y) as the square of the Euclidean distance between the nearest pole and (x, y). Formally, the square of the Euclidean distance between two points (x_1, y_1) and (x_2, y_2) is (x_2 - x_1)^2 + (y_2 - y_1)^2. To optimize the building plan, the project supervisor asks you the sum of all S(x, y) for each 0 ≤ x ≤ n and 0 ≤ y ≤ m. Help him by finding the value of ∑_{x=0}^{n} {∑_{y=0}^{m} {S(x, y)}}.
...

Public Tests

Input:
2 2
101
000
000
Output:
18
...

Private Tests

Input:
5 4
10010
00000
01000
00001
00100
00010
Output:
36
...

(a) A typical CodeContests problem.

Self-reflection on the problem

- The problem is about a city represented as a plane with a grid of size (n + 1) x (m + 1) where some points have telephone poles.

- The task is to calculate the sum of the squares of the Euclidean distances from each point in the grid to its nearest telephone pole.

- The grid is represented by a matrix where 1 indicates the presence of a telephone pole and 0 indicates its absence.

- The input consists of the size of the grid (n, m) and the grid itself.

- The output is a single integer, the sum of the squares of the Euclidean distances from each point to its nearest telephone pole.

(b) An AI-generated self-reflection on the problem.

Figure 2: **Problem description and reflection** - an example of a typical CodeContests problem, with AI-generated self-reflection on the problem. While the original description is lengthy and complicated, proper self-reflection makes the problem clearer and more coherent, leading to improved code solutions.

AlphaCodium proposed flow

- Common prompt engineering techniques (e.g., single prompts, chain-of-thought) do not yield significant improvements for code generation tasks like CodeContests.
- LLMs often fail to fully comprehend the problem, producing incorrect or overfitted code that passes public tests but fails on unseen ones.
- Natural language generation flows are suboptimal for code generation tasks.
- Code generation tasks offer a unique advantage: the ability to run and test code iteratively.
- AlphaCodium introduces a dedicated, iterative flow optimized for code generation and testing.

AlphaCodium proposed flow

- The approach consists of two major phases:
  - Pre-processing phase:
    - Reflect on the problem in natural language.
    - Perform public tests reasoning.
    - Generate and rank 2-3 natural language solution strategies.
    - Enrich public tests by generating 6-8 additional diverse AI-generated tests.
  - Code iterations phase:
    - Generate an initial code solution based on the selected strategy.
    - Run the code on both public and AI tests, iterating and fixing errors.
    - Iterate further to fix code based on test failures and error messages.

AlphaCodium proposed flow

- Detailed stages of the flow:
  - Problem reflection: summarize the problem's goal, inputs, outputs, constraints, and rules in bullet points.
  - Public tests reasoning: explain why each input yields the corresponding output.
  - Generate possible solutions: write 2-3 natural language strategies.
  - Rank solutions: select the best based on correctness, simplicity, and robustness.
  - Generate AI tests: create additional tests covering edge cases and large inputs.

AlphaCodium proposed flow

Detailed stages of the flow (continued):

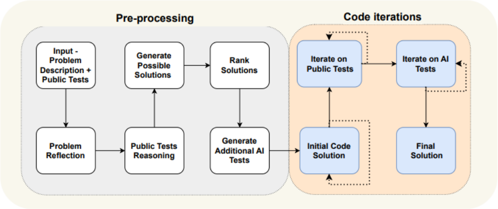
- Initial code solution:
  - Choose a solution, generate corresponding code.
  - Run code on selected tests, repeat until successful or try-limit reached.
  - Use the best-passing or closest-output code as a base.
- Iterate on public tests: run and fix code iteratively using feedback from public tests.
- Iterate on AI-generated tests: repeat the run-fix process using AI tests and test anchors.

AlphaCodium proposed flow

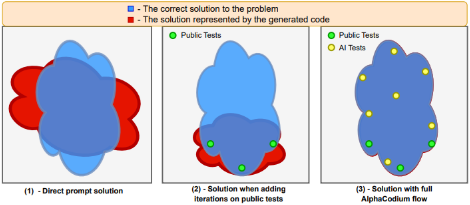
Additional insights:

- The flow supports knowledge accumulation, progressing from easy to hard tasks.
- Pre-processing outputs help the more difficult code generation stages.
- Generating test cases is easier for LLMs than writing complete solutions.
- Additional AI tests improve generalization by targeting underrepresented scenarios.
- Some stages can be combined in a single LLM call using structured prompts.

AlphaCodium proposed flow (continued)



(a) The proposed AlphaCodium flow.



(b) Illustrating the improvement from AlphaCodium.

Figure 1: **Illustration of AlphaCodium flow contribution** - with direct prompt, the model struggles to solve code problems. Iterating on public tests stabilizes and improves the solution but leaves "blind spots" because the public tests are not comprehensive. The full AlphaCodium flow, which includes a pre-processing phase as well as iterations on public and AI-generated tests, allows the solution to be further improved, leading to increased solve ratio.

Code Oriented design concepts

- *YAML structured output:* The use of YAML format, equivalent to a Pydantic class, provides a structured, code-like way to present complex tasks.
  - Simplifies prompt engineering by reducing ambiguity.
  - Facilitates multi-stage, logical thinking processes.
  - Preferred over JSON for code generation tasks due to better readability and structure.
- *Semantic reasoning via bullet points analysis:* Encouraging models to reason using bullet points improves understanding and output quality.
  - Bullet points help divide reasoning into semantic sections (e.g., description, rules, input, output).
  - Leads to clearer and more structured problem analysis.

Code Oriented design concepts

- *Modular code generation:* LLMs perform better when asked to generate code in modular sub-functions.
  - Reduces logical errors and bugs.
  - Enhances the effectiveness of iterative fixing by localizing errors.
- *Soft decisions with double validation:* To address hallucinations and errors in complex tasks, AlphaCodium uses a double validation step.
  - The model is asked to re-generate and correct its own output instead of being queried with binary (yes/no) correctness questions.
  - Encourages deeper reasoning and self-correction.

Code Oriented design concepts

- *Postpone decisions and leave room for exploration:* Avoid asking the model direct questions about complex problems too early.
  - Adopt a gradual process:
    - Start with self-reflection and reasoning about public tests.
    - Proceed to generate AI tests and explore possible solutions.
    - Only then generate the code and perform run-fix iterations.
  - Instead of selecting a single solution, rank multiple and explore iterations from top-ranked options.
  - This reduces the risk of hallucinations and premature commitments.

Code Oriented design concepts

- *Test anchors:* Designed to address the uncertainty of whether a failed test is due to incorrect code or an incorrect test.
    - Begin with public tests (known correct) to form initial anchor tests.
    - Iterate through AI-generated tests, adding passing ones to the anchor list.
    - For failing tests, assume the code is incorrect, but ensure that the fix still passes all anchor tests.
    - This process protects against overfitting to faulty AI-generated tests.
    - An additional optimization involves sorting AI-generated tests from easy to hard to build the anchor base early.

Code Oriented design concepts

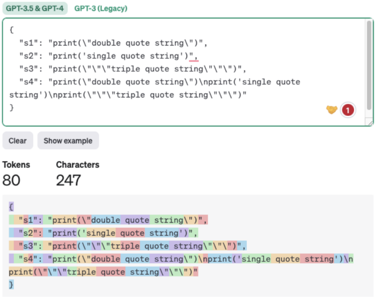
```
...
Your goal is to present possible solutions to the problem.
Make sure that each solution fully addresses the problem goals, rules, and
constraints.


The output must be a YAML object equivalent to type $PossibleSolutions, according to
the following Pydantic definitions:

class Solution(BaseModel):
   name: str = Field(description="The name of the solution")
   content: str = Field(description="A description of the solution")
   why_it_works: str = Field(description="Why this solution is correct. Be specific\
   and detailed regarding the problem rules and goals")
   complexity: str = Field(description="The complexity of the solution")

class PossibleSolutions(BaseModel):
   possible_solutions: List[Solution] = Field(max_items=3, description="A list of\
   possible solutions to the problem. Make sure each solution fully addresses the\
   problem rules and goals, and has a reasonable runtime - less than three seconds\
   on a modern computer, given the problem constraints for large inputs.")
```

Figure 3: **Example for a prompt with structured output** (*generate possible solutions* stage)

Why YAML?

- YAML is superior to JSON for code generation tasks:
  - Code often contains single quotes, double quotes, and special characters that cause problems in JSON format
  - JSON output must be surrounded by double quotes, requiring complex escaping
  - YAML with block scalar only requires proper indentation to be valid
- Additional benefits of YAML:
  - No need for curly brackets, quotations, or escape characters
  - Results in fewer tokens compared to JSON
  - Reduces cost and inference time
  - Improves quality by allowing the model to focus on essential content rather than syntax

Why YAML?



(a) Token counting with JSON output

(b) Token counting with YAML output

Figure 4: Comparison of the same output, once in JSON format, and once in YAML format. Taken from OpenAI playground.

Evaluating Solutions

- When testing a solution against input, the comparison yields a pass/fail result
- AlphaCodium also estimates the distance between generated and expected outputs:
  - For numeric outputs: Calculate L2 distance
  - For arrays of numbers: Sum of L2 distances between corresponding cells
  - For arrays of strings: Count the number of non-identical cells
- This methodology provides a more nuanced assessment of how close an incorrect solution is to being correct
- Helps prioritize which solutions to refine during iterative improvement

The pass@k Metric

- pass@k is a standard evaluation measure for code generation tasks
- Measures the probability that at least one of k generated solutions is correct
- Formula: $\text{pass@k} = 1 - \frac{\binom{n-c}{k}}{\binom{n}{k}}$ where:
  - n = total number of samples generated per problem
  - c = number of correct solutions among them
  - k = number of samples drawn (e.g., 5 for pass@5)
- In practice for pass@5:
  - Generate 5 solutions for each problem
  - Count as success if at least one solution is correct
  - Average across all problems for overall pass@5 score
- Higher pass@k indicates better model performance

Experiments

- Single direct prompt using the pass@k metric:
  - AlphaCodium significantly outperforms the direct prompt approach across both validation and test sets.
  - For example, GPT-4's pass@5 score on the validation set improves from 19% to 44%, a 2.3x improvement.
  - The improvement is consistent for both open-source (DeepSeek) and closed-source (GPT) models.
- Comparison with prior works:
  - AlphaCodium outperforms CodeChain when using the same model (GPT-3.5) and metric (pass@5).
  - AlphaCode employs a brute-force-like approach: fine-tuning an unknown model, generating up to 100K code solutions, clustering them, and submitting the top K clusters.

Experiments

- Comparison with prior works (continued):
  - Despite AlphaCode's large-scale generation strategy, AlphaCodium achieves better top results using significantly fewer resources.
  - Neither AlphaCode nor CodeChain released reproducible open-source code or evaluation scripts, while AlphaCodium provides a full reproducible solution to support consistent future comparisons.
  - Evaluation subtleties, such as handling multiple correct solutions or timeouts, are addressed in AlphaCodium's released framework.

Experiments

- Computational efficiency:
  - AlphaCodium requires around 15–20 LLM calls per solution; thus, a pass@5 submission uses approximately 100 LLM calls.
  - AlphaCode's pass@10@100K setup involves generating 100K solutions and selecting 10, leading to an estimated 1 million LLM calls.
  - AlphaCodium achieves superior performance with four orders of magnitude fewer LLM calls.
  - AlphaCode2, using a fine-tuned Gemini-Pro model, claims over 10,000$\times$ greater sample efficiency than AlphaCode.
  - Both AlphaCode2 and AlphaCodium achieve similar efficiency improvements over AlphaCode, but AlphaCodium relies solely on general-purpose models without extra training or fine-tuning.

Experiments

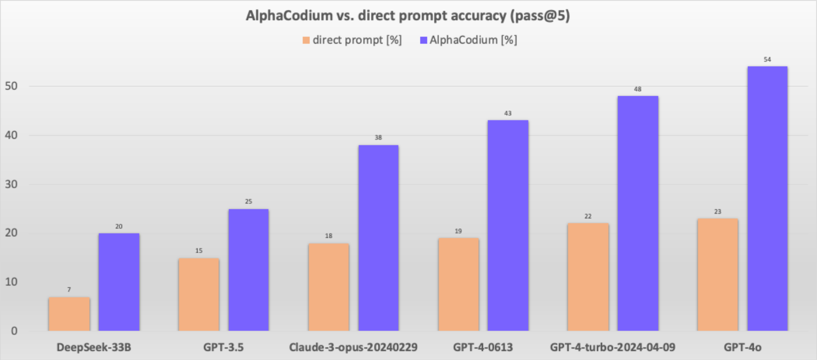
model	set	method	score (pass@5)
DeepSeek -33B [3]	validation	Direct	7%
		AlphaCodium	**20%**
	test	Direct prompt	12%
		AlphaCodium	**24%**
GPT-3.5	validation	Direct prompt	15%
		AlphaCodium	**25%**
	test	Direct prompt	8%
		AlphaCodium	**17%**
GPT-4	validation	Direct prompt	19%
		AlphaCodium	**44%**
	test	Direct prompt	12%
		AlphaCodium	**29%**

Table 1: **Comparison of AlphaCodium flow results to direct prompt on various models.**

model	set	method	score
GPT-3.5	validation	AlphaCodium (pass@5)	**25%**
		CodeChain (pass@5)	17%
	test	AlphaCodium (pass@5)	**17%**
		CodeChain (pass@5)	14%
GPT-4	validation	AlphaCodium (pass@5)	**44%**
AlphaCode		AlphaCode (pass@10@1K)	17%
		AlphaCode (pass@10@100K)	24%
GPT-4	test	AlphaCodium (pass@5)	**29%**
AlphaCode		AlphaCode (pass@10@1K)	16%
		AlphaCode (pass@10@100K)	28%

Table 2: **Comparison of AlphaCodium to other works from the literature.**

Experiments



Future Work

- The evaluation of each model-method pair is done over the wholde dataset, CodeForces has a great scoring system that assigns a difficulty ELO rating to each problem, calculating pass@k score based on rating bounds could give better insights into what works better for which difficulty of problem.
- Try the same experiment with Claude-3.7-sonnet which has shown better competency in solving software engineering problems.
- As it stands, AlphaCodium is completely automated and does not involve any human intervention. Involving human mathematical intuition to generate better test cases can lead to better results.

Conclusion

- The paper presents AlphaCodium, a code-oriented iterative flow that improves code generation by running and fixing generated code against input-output tests.
- The flow is divided into two main phases:
  - Pre-processing phase: natural language reasoning about the problem.
  - Code iterations phase: iteratively refining code using public and AI-generated tests.
- AlphaCodium incorporates several effective design practices:
  - Structured output in YAML format.
  - Modular code generation.
  - Semantic reasoning using bullet point analysis.
  - Soft decisions validated by double checks.
  - Encouragement of solution exploration.
  - Use of test anchors to guide iterations.

Conclusion

- The approach was evaluated on the CodeContests dataset, a challenging benchmark for code generation.
- AlphaCodium consistently improves performance across both closed-source and open-source models.
- It outperforms prior works while using a significantly smaller computational budget.

References

- Ridnik, Tal, Dedy Kredo, and Itamar Friedman. "Code generation with AlphaCodium: From prompt engineering to flow engineering." *arXiv preprint arXiv:2401.08500* (2024).

Thank you!

Questions?