Reasoning-Guided Evolutionary Prompt Optimization for Improved Financial Problem Solving

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Abstract

Prompt quality remains a primary bottleneck for deploying Large Language Models (LLMs) in high-stakes domains such as finance. Prior automated prompt optimization work has relied on ad-hoc heuristics or on LLM evaluators that lack explicit, stepwise reasoning, limiting the quality of discovered prompts. We introduce a Genetic Algorithm (GA) framework that uses *thinking models* (OpenAI's GPT-omni and GPT-5 variants) both to generate candidate prompts (initialization, crossover, mutation) and to evaluate their outputs, so evolution is guided by models that perform structured, multi-step inference. We evaluate this approach on a challenging Financial Math Reasoning benchmark, comparing GPT-5, GPT-5-mini, GPT5-nano, and GPT-o4-mini against non-thinking baselines, GPT-4.1, GPT-4.1-mini, GPT-4.1-nano, and GPT-4o. Fitness computation was standardized using GPT-5-nano as output evaluator, creating a consistent test bed for comparisons. Our results show that reasoning-enabled optimization consistently produces stronger prompts than non-thinking optimization and manually engineered prompts. More specifically, we show in this study that GA-evolved prompts exceeded manual prompts in 7 out of 8 model versions and yielded an average around 11% higher fitness over non-thinking baseline. These findings demonstrate that combining evolutionary search with reasoning-capable LLMs substantially improves automated prompt engineering for financial reasoning tasks.

1 Introduction

LLMs have rapidly become foundational in natural language processing, powering applications across domains such as healthcare, law, and finance [1, 17]. Despite their capabilities, performance remains strongly dependent on high-quality input prompts. Manual prompt engineering is labor-intensive, vendor-specific, and often infeasible for teams without domain expertise [10].

To address this challenge, recent studies have explored automated prompt optimization. Gradient-guided methods such as AutoPrompt [15], reinforcement learning approaches like RLPrompt [4], and evolutionary strategies such as EvoPrompting [2] have all shown measurable success. Previously reported work has demonstrated that GAs can autonomously evolve prompts by replacing traditional operators with LLM-driven meta-prompts [11]. Later extensions introduced self-evaluating pipelines where LLMs also judge outputs for fitness, reducing reliance on human labels [12].

However, a critical limitation in prior GA frameworks lies in the *type* of models used as evaluators and evolutionary operators. Non-thinking models such as GPT-4.1 can generate prompts and evaluate answers but often lack the reasoning depth to judge correctness on nuanced tasks like financial mathematics. This introduces noise into optimization and constrains achievable fitness.

In this work, we introduce thinking models, reasoning-capable LLMs such as GPT-5, as both the *engine* and the *judge* of GA-based prompt optimization. Thinking models generate more structured and

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semantically consistent offspring during initialization, crossover and mutation, while simultaneously serving as higher-quality evaluators of candidate prompt outputs. Our experiments on a Financial Math Reasoning dataset show that this dual use of reasoning-capable LLMs improves average fitness by 11% compared to non-thinking GPT-4.x baselines, establishing a new benchmark for automated prompt engineering in finance.

2 Related Literature

Prompt optimization: Manual prompt design remains a limiting factor for scaling LLMs across industries [10]. Automated methods span gradient-based optimization [15], reinforcement learning [4, 19], and meta-prompting frameworks [8, 18]. While effective, these approaches often require human supervision or handcrafted reward functions.

Evolutionary computation: GAs are well-suited for non-linear, large search spaces [7, 5]. Integration with LLMs is increasingly studied: Meyerson et al. [13] demonstrated crossover guided by language models, while Chen et al. [2] applied evolutionary search to neural architectures. Guo et al. [6] and Hsieh et al. [9] confirmed the effectiveness of GA-driven prompt optimization. Prior works established GA frameworks with either string-matching fitness [11] or non-thinking LLM judges [12].

Algorithm I: LLM-based GA for Prompt Optimization

0: **input**→ population size, generations, mutation prob., *LLM name*, *data*
1: Initialize population with *system*, *init. meta-prompts*, and data
2: Evaluate fitness using *fitness* and *system fitness prompts*
3: While generations not reached:
4: Selection via trio tournament
5: Pair crossover using *crossover meta-prompt*
6: Conditional mutation using *mutation meta-prompt*
7: Re-evaluate fitness
8: Increment generation count
9: End While loop
10: **output**← prompt with highest fitness

(a)

Role	Prompt
system	You are an AI that helps people solve problems. Avoid comments outside the proposed prompt as the user will use your answer to integrate with another downstream system.
initial.	Create a [LLM_MODEL] prompt that solves the problem exemplified by the following examples: [SAMPLE_QUESTION_1][SAMPLE_ANSWER_1] [SAMPLE_QUESTION_1][SAMPLE_ANSWER_2] ...
crossover	Given the following drafts for two prompts that aim to solve the same particular problem, create a better prompt using only ideas from them. [PROMPT_A] [PROMPT_B]
mutation	Given the following draft for a prompt that aims to solve a particular problem, create a better prompt using ideas from it. [PROMPT_A]
system fitness	You are an AI that validates automated answers against ground truth. You only answer 'yes' or 'no' with no extra comments, notes, or explanations as the user will use your answer to integrate with another downstream system.
fitness	My ground truth is [TRUTH]. Does the automated output [ANSWER] linguistically, symbolically, conceptually, or fundamentally match my ground truth?

(b)

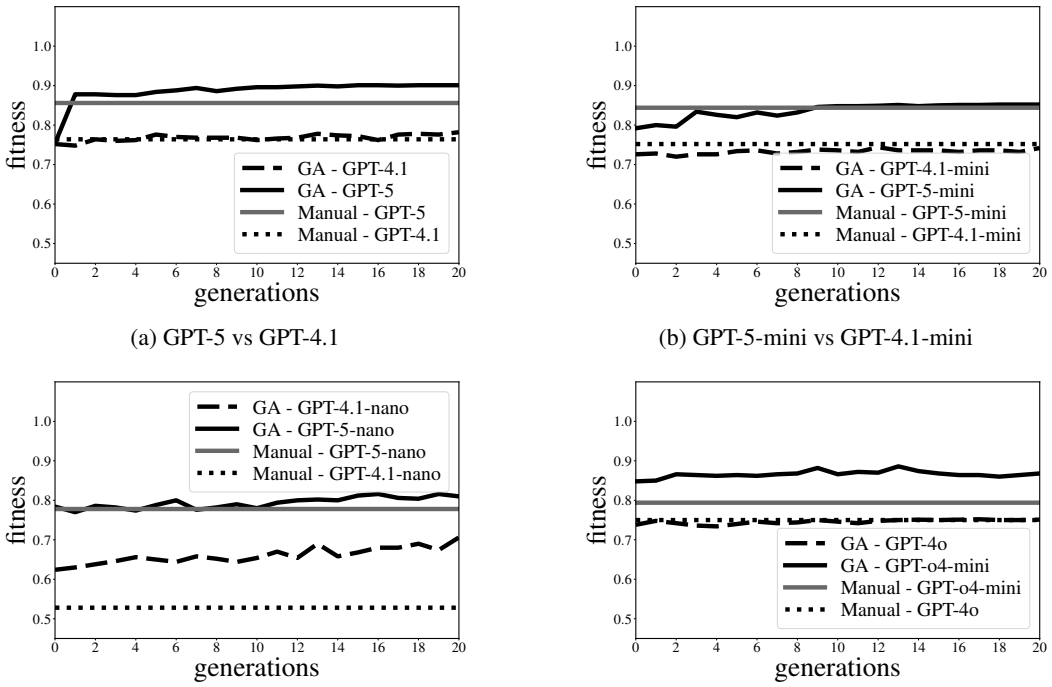
Table 1: The GA and meta-prompt designed used in [12]. (a) Algorithmic steps. (b) Meta-prompts guiding initialization, crossover, mutation, and fitness evaluation.

Thinking models: Recent reasoning-capable LLMs (e.g., GPT-5) provide explicit stepwise inference and structured decision-making [14]. Prior research has shown that chain-of-thought prompting can improve reasoning in non-thinking models [16], but our work is the first to systematically compare thinking vs. non-thinking models within GA-driven prompt optimization, using them simultaneously as evolutionary operators and fitness evaluators.

3 Proposed Method

We extend prior GA-based prompt optimization [11, 12] by using reasoning-enabled ("thinking") models to drive *both* candidate generation and fitness evaluation, so evolution can create and reward prompts that elicit multi-step reasoning.

GA with Thinking Models: GA implementation is outlined in Table. 1a where each individual is a candidate prompt. In short: (i) initialization uses thinking models with in-context examples; (ii) crossover/mutation operate via meta-prompts (Table. 1b) with reasoning models guiding semantic coherence; (iii) selection uses reasoning-grounded fitness so the GA rewards task-relevant, multi-step



(a) GPT-5 vs GPT-4.1

(b) GPT-5-mini vs GPT-4.1-mini

(c) GPT-5-nano vs GPT-4.1-nano

(d) GPT-o4-mini vs GPT-4o

Figure 1: Comparison of GA best fitness across generations. All models were optimized and judged with GPT-5-nano as the fitness function.

behaviors. This dual role makes generation and evaluation mutually informed while keeping the description compact.

Fitness Function: Fitness is measured as the average accuracy over a 500-sample evaluation set. All outputs are judged by GPT-5-nano using concise binary (yes/no) meta-prompts, providing a consistent baseline across models. While this standardization ensures fair comparison, it also introduces the limitation that fitness scores may reflect biases or variability in the judge model itself.

Dataset: We use the Financial Math Reasoning dataset [3] ($\sim$1,500+ pairs), the same benchmark used in our prior works to preserve comparability. Notably, in our earlier studies this has been the only dataset where LLM-based optimization underperformed manual prompting, largely because tasks require preprocessing intermediate results before the final computation. In this work, we address that gap by supplying the GA with reasoning-enabled models better suited for step-by-step problem solving.

Models Compared: We evaluate OpenAI's thinking models GPT-5, GPT-5-mini, GPT-5-nano, and GPT-o4-mini, against some of their non-thinking models GPT-4.1, GPT-4.1-mini, GPT-4.1-nano, and GPT-4o.

Experimental Setup: GA parameters mirror prior work with population size of 20, 20 evolving generations, and trio-tournament selection. While we also track average population fitness across runs, for simplicity we report only best-of-generation results in the tables and figures. Textual comments on averages are added when relevant. Results are contrasted between pairs of thinking and non-thinking models, as well as against manual prompting. While GA runs are initialized with problem-agnostic meta-prompts, the manual prompts serve as a human-engineered benchmark, allowing us to test whether autonomous evolution can match or surpass expert-designed prompts.

4 Results and Discussion

Among eight LLM variants evaluated on the Financial Math Reasoning dataset, GA evolution yielded best-performing prompts that surpassed manual prompts in 7 cases, with an average best improvement of $+4.3\%$. Average population gains, however, were modest ($+0.9\%$). This indicates that the GA

Table 2: Financial Math results: manual prompts vs. GA-evolved prompts. Here, "Manual" represents the results achieved by manually engineered prompts, "GA Best" represents the fitness by the best prompt evolved by the evolutionary algorithm, and "Diff-Best" represents the difference between GA Best and Manual. Fitness of all individuals was judged by GPT-5-nano.

Model	Manual	GA Best	Diff-Best
GPT-4.1	0.764	**0.782**	0.018
GPT-4.1-mini	**0.752**	0.742	-0.010
GPT-4.1-nano	0.528	**0.706**	0.178
GPT-4o	0.750	**0.751**	0.001
GPT-5	0.856	**0.901**	0.045
GPT-5-mini	0.844	**0.852**	0.008
GPT-5-nano	0.778	**0.810**	0.032
GPT-o4-mini	0.794	**0.868**	0.074
Overall Average	0.7583	**0.8015**	0.0433
Non-thinking Average	0.6985	**0.7453**	0.0468
Thinking Average	0.8180	**0.8578**	0.0398

reliably finds high-quality individuals while population-level quality remains model-dependent. When comparing thinking and non-thinking models, the former began at a substantially higher manual baseline (average manual fitness ≈ 0.818 vs. 0.699 for non-thinking models), so absolute improvements for thinking models are smaller even when evolution finds better prompts. We also observe that the smaller variants derived the largest relative gains (e.g., GPT-4.1-nano: $+0.178$), suggesting the GA is particularly useful when base-model prompting is weak.

While prior work demonstrated that GA-based prompting can surpass manual baselines in general NLP settings [11, 12], performance on the Financial Math Reasoning benchmark remained inconsistent. The present study closes this gap by showing consistent gains in 7 out of 8 model variants when reasoning-capable LLMs are used as both operators and evaluators. The GA increases the fitness of the best individuals more consistently than it does for the population average. This implies the method is effective at exploring promising prompt heuristics but that additional mechanisms (e.g., diversity maintenance, elitism tuning, or adaptive mutation) are likely required to shift the entire population distribution.

We employed GPT-5-nano as a judge in fitness evaluation to keep measurement consistent. However, LLM judges can misjudge equality and introduce bias and variance in fitness estimates [12]. Also, for Financial Math Reasoning, manual prompts that explicitly elicit Chain-of-Thought (CoT) can outperform automated candidates in some strong models [11, 16]. Therefore, future automated searches should consider including CoT-style meta-operators or explicitly expose CoT as a target behavior.

Table 2 reports fitness on the Financial Math Reasoning dataset for non-thinking models (GPT-4.1 family, GPT-4o) and thinking models (GPT-5 family, GPT-o4-mini). For each model, we compare manual prompting with the best GA-evolved individual. Diff-Best measures the gain (or loss) relative to manual prompting.

5 Conclusion

This study showed that integrating reasoning-enabled LLMs (GPT-5s and omni) into GA-based prompt optimization leads to more reliable evolution and evaluation of prompts for financial reasoning. Unlike earlier work that used string-matching fitness [11] or non-thinking evaluators [12], this study demonstrates that "thinking models" reduce noise in fitness and generate semantically coherent offspring, yielding consistent gains: GA prompts outperform manual prompts in 7 out of 8 cases, and results in fitness averages around 11% higher than GPT-4.1 and GPT-4o baselines.

These results highlight the practical role of evolutionary prompting: it can substantially boost weaker models while still improving stronger ones. Future work will focus on diversity-preserving operators, richer fitness objectives, and explicit chain-of-thought meta-prompts [16] to further automate and generalize prompt optimization in finance and beyond.

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