MIGRATE: MIXED-POLICY GRPO FOR ADAPTATION AT TEST-TIME

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ABSTRACT

Large language models (LLMs) are increasingly being applied to black-box optimization tasks, from program synthesis to molecule design. Prior work typically leverages in-context learning to iteratively guide the model towards better solutions. Such methods, however, often struggle to balance exploration of new solution spaces with exploitation of high-reward ones. Recently, test-time training (TTT) with synthetic data has shown promise in improving solution quality. However, the need for hand-crafted training data tailored to each task limits feasibility and scalability across domains. To address this problem, we introduce MIGRATE—a method for *online* TTT that uses GRPO as a *search* algorithm to adapt LLMs at inference without requiring external training data. MIGRATE operates via a mixed-policy group construction procedure that combines on-policy sampling with two off-policy data selection techniques: greedy sampling, which selects top-performing past completions, and neighborhood sampling (NS), which generates completions structurally similar to high-reward ones. Together, these components bias the policy gradient towards exploiting promising regions in the solution space, while preserving exploration through on-policy sampling. We evaluate MIGRATE on four challenging domains—word search, molecule optimization, hypothesis+program induction on the Abstraction and Reasoning Corpus (ARC), and natural-language hypothesis search on DiscoveryBench—and find that it consistently outperforms both inference-only and TTT baselines, demonstrating the potential of online TTT as a solution for complex search tasks without curated training data.

1 Introduction

Large language models (LLMs) have emerged as general-purpose tools for solving a wide range of black-box optimization problems (Boiko et al., 2023; Ramos et al., 2023; Liu et al., 2024). These models offer a flexible interface for generating candidate solutions, both in structured tasks, e.g., molecule design (Ranković & Schwaller, 2023; Kristiadi et al., 2024; Gruver et al., 2024), and unstructured, natural-language tasks, e.g., scientific hypothesis generation (Lu et al., 2024; Majumder et al., 2025; Agarwal et al., 2025b).

Recent work has shown that in-context learning (ICL) (Brown et al., 2020) can effectively be used to steer LLMs toward higher-quality outputs in such tasks (Meyerson et al., 2023; Yang et al., 2024b; Agarwal et al., 2025a). However, ICL alone lacks a principled mechanism to balance *exploration* of novel solution areas with *exploitation* of known high-reward ones (Krishnamurthy et al., 2024) based on simply injecting a history of candidates in-context. Without this balance, the model may either get trapped in local optima or waste sampling budget on unpromising regions of the solution space.

To improve LLM-based search, recent methods have explored *test-time training* (TTT) (Sun et al., 2020; Hardt & Sun, 2024)—a paradigm inspired from the human ability to generalize from a few examples (Yu et al., 2025a), in which the LLM is adapted at inference time for a specific problem instance before sampling a set of candidate solutions to evaluate. Similarly, some works have explored the use of off-policy reinforcement learning to efficiently learn suitable sampling distributions (Levine et al., 2020; Yan et al., 2025). However, these approaches either rely on carefully hand-crafted, task-specific data generation strategies or assume availability of expert demonstration

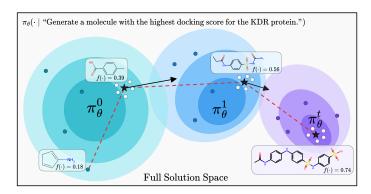


Figure 1: **Overview of MIGRATE.** Given a search problem, MIGRATE iteratively searches for optimal solutions by sampling candidates and updating its policy model π^t_{θ} using mixed-policy GRPO. In each iteration, we combine online samples (\bullet) from the current policy distribution, top-performing past solutions (\star) as greedy references, and samples drawn from the neighborhoods of greedy solutions (\circ) to form a GRPO group. The resulting group is used to update π^t_{θ} and *migrate* towards a sampling distribution that is likely to generate higher-quality solutions according to $f(\cdot)$.

data (Akyürek et al., 2025; Li et al., 2024), both of which limit the generality and scalability of such solutions.

To address these shortcomings, we cast search as an online reinforcement learning problem and leverage group relative policy optimization (GRPO) (Shao et al., 2024) to iteratively find promising regions of the search space, balancing exploration and exploitation. We, thus, propose MIGRATE (Mixed-policy GRPO for Adaptation at Test-Time), a method for *online* TTT that enables adaptive search with LLMs *without* requiring any external, handcrafted training data. Our method combines:

- 1. **On-policy sampling**, which ensures continual exploration of the solution space,
- Greedy sampling, which reuses top-performing past completions to exploit known highreward regions, and
- Neighborhood sampling (NS), which generates structurally similar variants of high-reward completions to facilitate local exploration.

Crucially, all components in MIGRATE use only model-generated signals, eliminating the need for any external training data. We perform experiments on four challenging domains with diverse solution spaces and reward functions—word search, molecule optimization, hypothesis+program induction using the Abstraction and Reasoning Corpus (ARC) (Chollet, 2019), and data-driven discovery using DiscoveryBench (Majumder et al., 2025). Across all domains, we find that MIGRATE outperforms both inference-only and TTT baselines, demonstrating the effectiveness of lightweight parameter updates, using online TTT with mixed-policy guidance, in providing a generic approach to LLM-based black-box optimization.

To summarize, our main contributions are as follows:

- We introduce MIGRATE, a method to search for optimal solutions with LLMs using an online test-time training (TTT) algorithm without external demonstrations.
- We propose a mixed-policy group construction strategy that combines on-policy sampling with two novel off-policy techniques—greedy sampling and neighborhood sampling.
- We conduct comprehensive experiments across four diverse domains, showing that MIGRATE outperforms both inference-only and TTT baselines in complex black-box optimization tasks.

2 Related Work

Test-time training. Test-time training (TTT) aims to improve model performance on distribution shifts by updating models at inference. Sun et al. (2020) introduced TTT using a self-supervised

objective on images to adapt network weights at test time. Hardt & Sun (2024) demonstrate that fine-tuning LLMs on data closely related to each test prompt can yield large accuracy gains, extending TTT to reasoning tasks. Hübotter et al. (2025) show that nearest-neighbor retrieval for test-time fine-tuning often wastes effort on redundant examples, and instead propose an active-learning method that chooses maximally informative examples to reduce model uncertainty.

Local-structure methods. Instance-based learning (or "local learning") (Atkeson et al., 1997) is a common framework in machine learning where local structure is exploited around a test point to improve model accuracy, e.g., locally-weighted regression (Cleveland, 1979). In modern practice, this manifests as retrieving nearest-neighbor examples to guide adaptation, referred to as retrieval-augmented generation (RAG) or case-based reasoning (CBR) (Lewis et al., 2020; Das et al., 2021; Thai et al., 2023; Agarwal et al., 2024). In reinforcement learning, local policy search methods (e.g., off-policy local improvements, trust-region updates) behave like hill-climbers in the policy space.

Evolutionary computation. EvoTune (Surina et al., 2025) uses an LLM as a policy-generating operator in an evolutionary loop, then applies RL fine-tuning to iteratively improve it. AlphaEvolve (Novikov et al., 2025) similarly creates an agent that uses multiple LLMs and automated evaluators to propose and refine codebases via an evolutionary framework. FunSearch (Romera-Paredes et al., 2024) pairs a pre-trained LLM with an automated evaluator and repeatedly samples and scores code functions, effectively evolving programs to solve mathematical problems. In these systems, the "population" of programs or policies evolves over generations, often via an islands model or parallel ensembles, to avoid local traps.

RLVR. Reinforcement Learning with Verifiable Rewards (RLVR) (Lambert et al., 2025; DeepSeek-AI et al., 2025) is an approach for fine-tuning LLMs using RL guided by ground-truth reward functions, in contrast to typical RL-based methods that rely on learned or heuristic-based reward functions, which can introduce ambiguity. In mathematics and code generation, these rewards are determined by correctness, such as matching a ground-truth solution or passing unit tests (Lambert et al., 2025; DeepSeek-AI et al., 2025; Team et al., 2025). Recently, RLVR has been instrumental in developing reasoning-based LLMs such as OpenAI-o1 (OpenAI et al., 2024) and DeepSeek-AI et al., 2025).

3 BACKGROUND

GRPO. Group relative policy optimization (Shao et al., 2024) is a reinforcement learning algorithm used to fine-tune LLMs that replaces the value function in Proximal Policy Optimization (PPO) training (Schulman et al., 2017) with an estimate derived from Monte Carlo samples instead. In particular, in each iteration of training, GRPO constructs a group $\mathcal G$ of N completions, typically sampled from the current model, and calculates the advantage for every completion as a relative comparison to the group. Let $\pi_{\theta_{\text{old}}}$ and π_{θ} denote the model policies (LLM parameters, in our case) before and after taking a gradient step. Given a task prompt $P_{\mathcal T}$ and a set of completions sampled from the current model $\{o_i: o_i \sim \pi_{\theta_{\text{old}}}\}_{i=1}^N$, the GRPO loss objective is defined as

$$\mathcal{L}_{\text{GRPO}}(\theta) = -\frac{1}{\sum_{i=1}^{N} |o_i|} \sum_{i=1}^{N} \sum_{t=1}^{|o_i|} \left[\min \left(r_{i,t}(\theta) \hat{A}_{i,t}, \operatorname{clip}(r_{i,t}(\theta), 1 - \varepsilon_{\text{low}}, 1 + \varepsilon_{\text{high}}) \hat{A}_{i,t} \right) \right], \quad (1)$$

where
$$r_{i,t}(\theta) = \frac{\pi_{\theta}(o_{i,t} \mid P_{\mathcal{T}}, o_{i, < t})}{\pi_{\theta_{\text{old}}}(o_{i,t} \mid P_{\mathcal{T}}, o_{i, < t})}$$
, and $\hat{A}_{i,t} = r_i - \text{mean}(\{f(o_i)\}_{i=1}^N)$

are the policy ratio and advantage estimates, respectively, for each token in each completion, $f(\cdot)$ is a reward function that provides a scalar score for each completion, $\operatorname{clip}(\cdot,\cdot,\cdot)$ is a clipping function to prevent large updates during optimization, and $\varepsilon_{\operatorname{low/high}}$ are clipping hyperparameters.

On-, off-, and mixed-policy optimization. Typically, reinforcement learning (including GRPO) operates in an *on-policy* manner, where new solutions are sampled using π_{θ} (i.e., the policy being

trained) to estimate the loss for the next training step. On the other hand, some works have argued that on-policy training may constrain learning to only the capabilities of the base LLM itself, resulting in echo chambers (Zhao et al., 2025; Yue et al., 2025) that prevent novel task generalization. This problem is further exacerbated in the sparse reward scenario, where the base model is unable to generate solutions that elicit non-zero reward, thus leading to degenerate policy gradients. To address this, *off-policy* optimization (Levine et al., 2020) has been proposed as an effective strategy that leverages previously collected expert demonstrations for training instead of online samples. However, a purely offline strategy can result in learning policies that are unable to generalize at inference time (Fujimoto et al., 2019; Kumar et al., 2019). Consequently, recent work (Yan et al., 2025) shows that a combination of online and offline samples, called *mixed-policy* optimization, can outperform either strategy used in isolation.

4 Migrate: Methodology

The focus in this work is on finding optimal solutions with respect to a black-box objective function $f(\cdot)$ under a finite sampling budget B. To this end, we are interested in using GRPO as a *search* algorithm, wherein a single example query is used as the input for a search task across multiple sampling iterations. The goal, then, is to learn query-specific parameters that shift the model's sampling distribution iteratively, improving the quality of solutions that are generated.¹²

Overcoming sparse rewards in search. As described earlier, purely on-policy learning is often unable to find an appropriate sampling distribution for a single query within a limited budget due to sparse rewards, i.e., when solutions sampled from the current policy do not result in useful policy gradients to make progress. At the same time, both off- and mixed-policy strategies require access to known expert demonstrations, which we assume are not available in our setting. We, therefore, present MIGRATE—a mixed-policy optimization strategy for GRPO that generates off-policy data via (a) selecting high-performing solutions from the model's own sampling history, and (b) sampling variations from the neighborhoods of observed high-performing solutions. In each iteration, MIGRATE "mixes" on- and off-policy samples to construct a group of completions \mathcal{G} , which is then used to compute the policy gradient with respect to the loss function in Equation 1. This process is repeated until either the optimal solution is found or the sampling budget is exhausted.

4.1 MIXED-POLICY GROUP CONSTRUCTION FOR SEARCH

Given a search task \mathcal{T} and a corresponding task prompt $P_{\mathcal{T}}$ for the LLM, our goal is to construct a new group \mathcal{G}_t composed of N completions in each search iteration t to compute a policy gradient via GRPO. We introduce two off-policy data selection techniques—**greedy** and **neighborhood sampling (NS)**—which we combine with on-policy sampling to generate test-time training data. Intuitively, both techniques are designed to bias policy gradients to *exploit* known high-quality solutions sampled thus far, while on-policy sampling encourages *exploration*. In experiments (§ 5), we find that the simultaneous application of greedy and NS off-policy data selection (i.e., MIGRATE; Algorithm 1) results in the best performance.

On-policy sampling. Let $\alpha (\leq N)$ be the number of completions sampled from the current policy model, i.e., at timestep t, we generate on-policy completions (or observations) $\mathcal{O}_{\text{online}} := \{o_i : o_i \sim \pi_{\theta}^{t-1}(\cdot \mid P_{\mathcal{T}})\}_{i=1}^{\alpha}$ using temperature-based ancestral sampling.

Greedy sampling. Let \mathcal{D} be a database of completions, which may be composed both of any candidate solutions available *a priori* as well as all attempts sampled from the model in previous search iterations. In greedy off-policy data selection, if $\mathcal{D} \neq \emptyset$, we sample $\beta \leq N$ known completions from \mathcal{D} that are high-quality. In particular, we first greedily select the top-k completions from \mathcal{D} with respect to $f(\cdot)$ and then randomly sample β completions from the top-k, i.e.,

¹This is in contrast to the more typical setting of training a generalizable model with multiple examples. See the appendix for a complete description of modifications we incorporate from previous work beyond the original formulation from Shao et al. (2024).

²Note that throughout this work, we use LoRA fine-tuning (Hu et al., 2022) instead of full-model training.

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 $\mathcal{O}_{\text{greedy}} := \{o_i : o_i \sim \operatorname{topk}_f(\mathcal{D})\}_{i=1}^{\beta}$, where $\operatorname{topk}_f(\mathcal{D})$ returns the best-k completions from \mathcal{D} with respect to f.

Neighborhood sampling. While greedy sampling explicitly encourages the exploitation of high-quality samples, it limits exploration of the solution space and is prone to optimizing for local optima (Krishnamurthy et al., 2024; Agarwal et al., 2025a). To mitigate this, we incorporate a complementary off-policy sampling strategy grounded in a continuity assumption—namely, that small variations in solutions yield small changes in quality. This assumption motivates exploration within neighborhoods of known high-quality candidates by prompting the model to generate stochastic variations of greedy samples, thereby producing new solutions that may both provide useful variations for better policy gradients as well as solutions that may outperform previous samples. In practice, we construct a single neighborhood sampling prompt P_{NS} composed of all β greedy samples along with an instruction to generate $\gamma \ (\leq \ N)$ solution variations to construct $\mathcal{O}_{NS} := \{o_i : o_i \sim$ $\pi_{\theta}^{t-1}(\cdot \mid P_{\text{NS}})\}_{i=1}^{\gamma}.$

Algorithm 1 Solution search with MIGRATE

Input: Task \mathcal{T} , black-box function f, budget B **Parameters**: GRPO group size N, α on-policy samples, β greedy samples, γ neighborhood samples **Output**: Best solution o_{best}

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1: Initialize: Policy \pi_{\theta}^0 \leftarrow \text{LLM}, task prompt P_{\mathcal{T}},
          database \mathcal{D} \leftarrow \emptyset, timestep t \leftarrow 0, o_{\text{best}} \leftarrow \emptyset
         while |\mathcal{D}| < B do
  3:
               t \leftarrow t + 1
               \mathcal{O}_{\text{online}} \leftarrow \{o_i : o_i \sim \pi_{\theta}^{t-1}(\cdot \mid P_{\mathcal{T}})\}_{i=1}^{\alpha}
  4:
               \mathcal{O}_{\text{greedy}} \leftarrow \{o_i : o_i \sim \text{topk}_f(\mathcal{D})\}_{i=1}^{\beta}
P_{\text{NS}} \leftarrow \text{Build NS prompt using } \mathcal{O}_{\text{greedy}}
  5:
  6:
               \mathcal{O}_{\text{NS}} \leftarrow \{o_i : o_i \sim \pi_{\theta}^{t-1}(\cdot \mid P_{\text{NS}})\}_{i=1}^{\gamma}
  7:
  8:
                \mathcal{G}_t \leftarrow \mathcal{O}_{\text{online}} \oplus \mathcal{O}_{\text{greedy}} \oplus \mathcal{O}_{\text{NS}}
               \mathcal{D} \leftarrow \mathcal{D} \oplus \mathcal{O}_{online} \oplus \mathcal{O}_{NS}
  9:
10:
                o_{\text{best}} \leftarrow \arg\max_{o_i \in \mathcal{D}} f(o_i)
11:
               if o_{\text{best}} is optimal then
                     return o<sub>best</sub>
12:
13:
               end if
14:
               \pi_{\theta}^t \leftarrow \text{Update using GRPO with } \mathcal{G}_t \text{ (Eq. 1)}
15: end while
16: return o<sub>best</sub>
```

MIGRATE. To balance exploration and exploitation during test-time training with GRPO, MI-GRATE integrates both off-policy techniques with on-policy sampling by combining $\mathcal{O}_{\text{online}}$, $\mathcal{O}_{\text{greedy}}$, and \mathcal{O}_{NS} into a single group \mathcal{G}_t , with the constraint that $\alpha+\gamma+\beta=N$ in each iteration 3 (see Algorithm 1). We compute the loss on \mathcal{G}_t with respect to the task prompt $P_{\mathcal{T}}$, irrespective of how the sample was generated. While on-policy sampling encourages exploration of new solutions, greedy sampling promotes exploitation by reusing high-quality completions from a running database, and neighborhood sampling introduces structured exploration via local variations of the greedy samples. Empirically, we find that this combination produces higher-quality search results than any single strategy alone.

5 EXPERIMENTS

5.1 SEARCH TASKS

We evaluate MIGRATE by conducting experiments on four text-based search tasks—Semantle (word search), Dockstring (molecule optimization), ARC (hypothesis + program search), and DiscoveryBench (data-driven hypothesis search).

Semantle. Semantle (Agarwal et al., 2025a) is a word-search task, where the goal is to identify a held-out English word (e.g., "polyethylene") within a limited number of guesses. The black-box function used indicates how semantically close a guessed word is to the target, which is computed using cosine similarities over SimCSE (Gao et al., 2021) embeddings, following prior work. Each search problem is initialized with a warmstart set of 20 words (randomly sampled from the word2vec index (Mikolov et al., 2013)) and corresponding black-box scores. We conduct evaluation using 10 hidden words and 5 warmstart sets for each of them, resulting in a total of 50 problem instances.

³We keep constant the number of new solutions sampled from the LLM for fair comparison with baselines.

Dockstring. García-Ortegón et al. (2022) provides a suite of challenging molecule optimization tasks that reflect real-world problems in drug discovery. We focus on a multi-objective optimization task: generating molecules, represented as SMILES strings (Weininger, 1988), that simultaneously maximize druglikeness and binding affinity, quantified by QED (Bickerton et al., 2012) and negative Vina scores (Trott & Olson, 2010), respectively. We use a scalarized multi-objective black-box function (Equation 2) that places a greater weight on Vina scores than QED, reflecting the common prioritization of binding affinity over druglikeness when evaluating a molecule's drug efficacy (Hughes et al., 2011; Wenlock et al., 2003). Following prior works (Yuksekgonul et al., 2024), we run our evaluation with 58 pharmaceutically-relevant protein targets.

ARC. The Abstraction and Reasoning Corpus (ARC) (Chollet, 2019) is a benchmark of 400 grid-based puzzles that involves inferring the transformation logic from a small set of input-output grid pairs and applying it to a held-out test grid. Recent methods improve performance via data augmentation with invertible transformations (Akyürek et al., 2025) or by combining program synthesis with transductive strategies (Li et al., 2024). We take an inductive hypothesis + program search approach (Wang et al., 2024), where natural language transformation algorithms are hypothesized and translated into Python programs. We report two accuracy metrics: pass@2, which measures whether any of the top-2 common outputs from the programs that solve the train set matches the test grid, and oracle, which provides credit if any of the sampled programs solves the test grid. Note that oracle accuracy reflects a coarse ability to find a distribution that can generate the correct solution. We follow prior work (Agarwal et al., 2025a) and use a Hamming-distance based black-box function. ⁴

DiscoveryBench. DiscoveryBench (Majumder et al., 2025) is a benchmark to evaluate hypothesis search ability in data-driven scientific discovery. It includes a set of discovery tasks extracted from real-world scientific publications, each represented by a research query and a corresponding dataset, aiming to find statistically verifiable natural-language hypotheses that can answer the given queries. We assume oracle feedback in each iteration to help guide search (akin to feedback from a human researcher) using a scalar score representing the degree to which a generated hypothesis matches the gold hypothesis using a Beta belief distribution elicited from an LLM (Agarwal et al., 2025b). We evaluate performance using both the belief-based black-box function (average belief and % of queries where the belief was maximized) as well as the hypothesis match score (HMS) from Majumder et al. (2025), which provides an LLM-judge evaluation of hypotheses based on contexts, variables, and relationships. Additionally, our analyses found that the HMS tends to score hypotheses with even minor deviation from the gold context as zeros. Therefore, we introduce HMS- ρ , a relaxation of HMS that allows an LLM to provide partial scores for the context, i.e., $\{0, 0.5, 1.0\}$ instead of $\{0, 1\}$ only, in order to lend graded improvement information.

5.2 Baselines

Inference-only. We evaluate three inference-only sampling strategies (Random, NS, and OPRO) for Semantle, Dockstring, and ARC, and use Reflexion (following Majumder et al. (2025)) as the baseline for DiscoveryBench:

- Random, which generates completions by sampling from the base model using the task prompt.
- **Neighborhood Sampling (NS)**, which samples completions from a prompt that includes topperforming solutions from previous iterations to encourage local exploration.
- OPRO (Yang et al., 2024b), which generates completions using a prompt that builds a trajectory
 of top-performing solutions as a textual gradient to discover improved solutions.
- **Reflexion** (Shinn et al., 2024), which iteratively improves LLM performance by generating natural-language feedback ("self-reflection") using solutions from past iterations.

Test-time training. Beyond inference-only methods, we evaluate three variants of our GRPO-based test-time training (TTT) approach:

⁴Due to hardware limitations, we truncate prompts at 2048 tokens in all experiments. As a result, only 200 out of 400 tasks in ARC-Full could be evaluated with their full context.

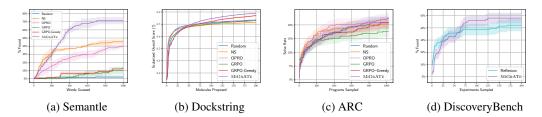


Figure 2: **Best-so-far performance results.** (a) On Semantle, MIGRATE outperforms all baselines, improving the second-best (NS) by 25%. (b) In Dockstring, MIGRATE surpasses baselines after 50 proposals. (c) On ARC, MIGRATE solves more tasks than baselines at the full budget. (d) On DiscoveryBench, MIGRATE outperforms Reflexion after 65 experiments.

- **GRPO** is the base algorithm, using a fixed task prompt and sampling N on-policy completions from the model as it is being trained (i.e., $\alpha = N$, $\beta = 0$, $\gamma = 0$).
- **GRPO-Greedy** augments GRPO by using greedy off-policy sampling to select β previous completions to place in the group at each iteration (i.e., $\alpha, \beta > 0$ and $\gamma = 0$).
- MIGRATE is our full method, combining on-policy exploration, greedy sampling of top completions, and neighborhood sampling for local exploration (i.e., each of $\alpha, \beta, \gamma > 0$).

We provide complete details of our experimental settings in Appendix A.1, including the values used for α , β , and γ for different tasks, and sensitivity analyses of these choices in Appendix B.3.

Additional baselines. We also evaluate MIGRATE (OPRO), a variant of MIGRATE that replaces the neighborhood sampling (NS) prompt with the OPRO prompting strategy for local exploration (Appendix B.4), as well as explore an alternative strategy for selecting \mathcal{O}_{greedy} using an islands-based evolutionary search method (Appendix B.1).

Models. Our main results on Semantle and Dockstring are presented using LLaMA-3.2-3B-Instruct (AI@Meta, 2024). For ARC, we use LLaMA-3.1-ARC-Potpourri-Induction-8B (Li et al., 2024), a fine-tuned version of LLaMA-3.1-8B-Instruct (AI@Meta, 2024) trained on synthetic Python programs that solve ARC training tasks. The latter decision is driven by the bespoke nature of the ARC challenge, where base models are entirely unable to generate valid solutions. For DiscoveryBench, we use Qwen2.5-7B-Instruct (Yang et al., 2024a) for generating experiment plans and GPT-5-nano (OpenAI, 2025) for the remainder of the agentic loop (code, reviews, and analyses). We use Qwen2.5-7B-Instruct for belief elicitation during search, but report final accuracy using GPT-40 (as in Majumder et al. (2025)).

6 RESULTS AND DISCUSSION

MIGRATE outperforms both inference-only and TTT baselines. Across tasks, we run each method until either the correct solution is found or a pre-defined budget of solution candidates is proposed and evaluated (1000 for Semantle, 200 for Dockstring, 1024 for ARC, and 200 for DiscoveryBench). We report our results on each search task in Table 1 and provide a best-so-far plot to trace search behavior across sampling budgets in Figure 2. We find that mixed-policy GRPO via MIGRATE outperforms each inference-only baseline and TTT ablation.

On Semantle, MIGRATE outperforms baselines by ≥ 25 percentage points. As shown in Figure 2(a), across the 50 problem instances averaged over 3 repeat runs, MIGRATE surpasses inference-only NS after 200 guesses ($\sim \! 20$ MIGRATE iterations), pointing to the effectiveness of explicit gradient updates in finding sampling distributions with high-quality solutions versus incontext optimization alone.

On Dockstring, Table 1 shows that MIGRATE synthesizes molecules with higher scalarized scores (according to Equation 2), i.e., jointly optimizing for QED and Vina. Further, in Figure 2(b), we see that MIGRATE outperforms all baselines on average after 50 molecule proposals. We also show the search trace of different methods in Figure 3.

	Semantle	Dockstring			ARC	
Method	% Found	QED (†)	Vina Score (↓)	Overall Score (†)	Pass@2 (%)	Oracle (%)
Random	2.00 ± 1.63	0.91 ± 0.00	-9.92 ± 0.15	0.73 ± 0.00	20.75	28.00
NS	45.30 ± 2.49	0.87 ± 0.01	-9.65 ± 0.21	0.71 ± 0.00	20.25	29.50
OPRO	$\overline{40.70 \pm 1.89}$	0.90 ± 0.00	-9.94 ± 0.06	0.74 ± 0.00	20.75	27.75
GRPO	10.00 ± 4.32	0.91 ± 0.00	-10.09 ± 0.05	0.73 ± 0.00	17.75	27.00
GRPO-Greedy	12.70 ± 0.94	$\overline{0.90 \pm 0.01}$	-10.80 ± 0.19	0.77 ± 0.00	21.00	30.00
MIGRATE	71.30 ± 4.11	0.90 ± 0.00	-11.00 ± 0.07	0.79 ± 0.00	22.25	30.00

	DiscoveryBench					
Method	Belief	% Found (Belief)	HMS	% Found (HMS)	HMS- ρ	% Found (HMS- ρ)
Reflexion MIGRATE	0.758 ± 0.022 0.795 ± 0.018	17.00 ± 3.78 20.00 \pm 4.13	0.293 0.285	13.00 11.00	7.00 13.00	0.273 0.268

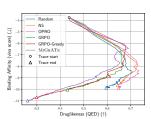
Table 1: **Search performance.** Results are averaged over three random seeds for Semantle and Dockstring, with standard deviations reported. For ARC and DiscoveryBench, we report using single runs (due to expense) but report standard deviation via bootstrapping. Top-2 results in each column are marked with bold and underline, respectively. MIGRATE outperforms on all but one metric (QED) on Semantle, Dockstring, and ARC. On DiscoveryBench, MIGRATE finds hypotheses that are more similar to the gold as measured by the belief-based black-box function and HMS- ρ , while showing marginally lower performance using HMS.

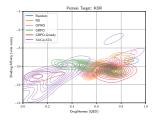
On <u>ARC</u>, we report performance over a single run (due to hardware constraints), and report standard deviation via bootstrapping. From Figure 2(c) and Table 1, we find that MIGRATE does outperform baselines, though, with modest gains akin to behavior reported by prior work on LLM-based program search. We do, however, find that MIGRATE solves all but two tasks also solved by baselines.

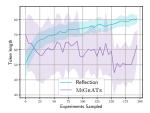
On <u>DiscoveryBench</u>, we evaluate 100 tasks from the test set, ensuring a balanced distribution of domains and question types. The Reflexion baseline solves 44 queries, while MIGRATE solves 48, crucially, without any natural language feedback. As shown in Figure 2(d), MIGRATE outperforms Reflexion after proposing 65 experiment plans, which corresponds to 13 training iterations.

TTT methods produce qualitatively different solutions than inference-only methods. On Semantle, across runs, we find that MIGRATE is the only method that is able to find all 10 hidden words. Furthermore, we observe that only MIGRATE and its ablations are able to optimize for certain words, e.g., "birthstone", indicating an ability to effectively navigate the unique search land-scape for this word. On Dockstring, as shown in Figure 3(a), we find that the optimization trajectories of the best-performing SMILES strings found using TTT methods (MIGRATE and its ablations) show a distinct pattern that optimize for Vina scores more heavily than those from inference-only methods, which prefer higher QED and are unable to synthesize molecules with lower than -10 kcal/mol Vina. While MIGRATE is indeed capable of generating molecules with high QED scores (> 0.8), optimization prefers to reduce QED to below 0.3 in exchange for better Vina scores. This also follows from the scalarized multi-objective function in Equation 2, which attaches a stronger weight to Vina scores than QED. On DiscoveryBench, we observe that the lengths of experiment plans from Reflexion monotonically increase over time, while plans from MIGRATE remain stable on average (Figure 3(c)). Notably, the best plans are consistently shorter (<115 tokens), suggesting MIGRATE is able to prioritize these during search.

What search behaviors are observed with MIGRATE? To understand this, we analyze the quality of samples generated by MIGRATE and compare them to those from the inference-only NS baseline in Figure 4. More specifically, we measure the relative difference between the black-box score of each solution sampled by both methods and the best-so-far performance when that solution was sampled during optimization. We then compare the distributions of these differences between the two methods. On Semantle and ARC, search with MIGRATE demonstrates the ability to iteratively improve upon its previously best-found solution in contrast to the behavior seen with the inference-only strategy, which often samples solutions that show no improvement. In Dockstring, on the other hand, we see MIGRATE produce a higher number of invalid molecules than inference-only approaches, indicating broader exploration of the solution space, as also shown in Figure 3(a) and







(a) Dockstring search trace

(b) SMILES distribution (KDR) (c) DiscoveryBench Token Length

Figure 3: **Search behaviors.** (a) Vina and QED scores for best molecules found as search progresses. Each trace starts from 3 diverse fragments (acetamide, pentane, and benzene). (b) Distribution of binding affinity and druglikeness for KDR target. MIGRATE explores a broader region of chemical space, including low-affinity, low-druglikeness areas ignored by baselines. (c) Experiments generated by Reflexion monotonically increase in token length with time, while those by MIGRATE remain stable on average.

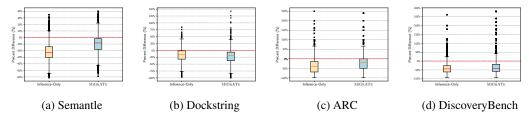


Figure 4: **Relative to the best-so-far.** Percentage difference between samples from inference-only NS and MIGRATE with their best-so-far scores during optimization. MIGRATE produces more samples close to or above the best-so-far than NS. On Dockstring, though MIGRATE shows lower performance on average (due to producing more invalid molecules), its outliers show larger gains in performance than NS.

(b). We find that many of the proposed molecules are longer and more complex SMILES strings, evidenced by a 44% increase in average length. Despite proposing more invalid molecules, however, MIGRATE finds molecules that improve upon the best-so-far with larger improvements than with inference-only.

7 Conclusion

We introduced MIGRATE, a method for online test-time training of LLMs that enables efficient search in black-box optimization tasks without requiring handcrafted training data. By leveraging Group Relative Policy Optimization (GRPO) along with a novel mixed-policy group construction strategy—comprising on-policy, greedy, and neighborhood sampling—MIGRATE effectively balances exploration and exploitation. Our experiments across four text-based domains demonstrate the efficacy of MIGRATE to improve LLM-based search. Future work may include scaling online TTT to multi-step decision-making and integrating stronger uncertainty-aware acquisition strategies to further improve sample efficiency.

8 REPRODUCIBILITY STATEMENT

We include the source code along with instructions to reproduce our experiments as part of the supplementary material. We also provide the specific hyperparameters used in Appendix A.1.

REFERENCES

- Dhruv Agarwal, Rajarshi Das, Sopan Khosla, and Rashmi Gangadharaiah. Bring your own KG: Self-supervised program synthesis for zero-shot KGQA. In Kevin Duh, Helena Gomez, and Steven Bethard (eds.), *Findings of the Association for Computational Linguistics: NAACL 2024*, pp. 896–919, Mexico City, Mexico, June 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-naacl.57. URL https://aclanthology.org/2024.findings-naacl.57/.
- Dhruv Agarwal, Manoj Ghuhan Arivazhagan, Rajarshi Das, Sandesh Swamy, Sopan Khosla, and Rashmi Gangadharaiah. Searching for optimal solutions with LLMs via bayesian optimization. In *The Thirteenth International Conference on Learning Representations*, 2025a. URL https://openreview.net/forum?id=aVfDrl7xDV.
- Dhruv Agarwal, Bodhisattwa Prasad Majumder, Reece Adamson, Megha Chakravorty, Satvika Reddy Gavireddy, Aditya Parashar, Harshit Surana, Bhavana Dalvi Mishra, Andrew McCallum, Ashish Sabharwal, et al. Open-ended scientific discovery via bayesian surprise. *arXiv* preprint arXiv:2507.00310, 2025b.
- AI@Meta. Llama 3 model card. 2024. URL https://github.com/meta-llama/llama3/blob/main/MODEL_CARD.md.
- Ekin Akyürek, Mehul Damani, Adam Zweiger, Linlu Qiu, Han Guo, Jyothish Pari, Yoon Kim, and Jacob Andreas. The surprising effectiveness of test-time training for few-shot learning, 2025. URL https://arxiv.org/abs/2411.07279.
- Christopher G Atkeson, Andrew W Moore, and Stefan Schaal. Locally weighted learning. *Lazy learning*, pp. 11–73, 1997.
- G Richard Bickerton, Gaia V Paolini, Jérémy Besnard, Sorel Muresan, and Andrew L Hopkins. Quantifying the chemical beauty of drugs. *Nature chemistry*, 4(2):90–98, 2012.
- Daniil A Boiko, Robert MacKnight, Ben Kline, and Gabe Gomes. Autonomous chemical research with large language models. *Nature*, 624(7992):570–578, 2023.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.
- François Chollet. On the measure of intelligence. arXiv preprint arXiv:1911.01547, 2019.
- William S Cleveland. Robust locally weighted regression and smoothing scatterplots. *Journal of the American statistical association*, 74(368):829–836, 1979.
- Michael Han Daniel Han and Unsloth team. Unsloth, 2023. URL http://github.com/unslothai/unsloth.
- Rajarshi Das, Manzil Zaheer, Dung Thai, Ameya Godbole, Ethan Perez, Jay Yoon Lee, Lizhen Tan, Lazaros Polymenakos, and Andrew McCallum. Case-based reasoning for natural language queries over knowledge bases. In Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih (eds.), *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pp. 9594–9611, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.emnlp-main.755. URL https://aclanthology.org/2021.emnlp-main.755/.
- DeepSeek-AI, Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, Xiaokang Zhang, Xingkai Yu, Yu Wu, Z. F. Wu, Zhibin Gou, Zhihong Shao, Zhuoshu Li, Ziyi Gao, Aixin Liu, Bing Xue, Bingxuan Wang, Bochao Wu, Bei Feng, Chengda Lu, Chenggang Zhao, Chengqi Deng, Chenyu Zhang, Chong Ruan, Damai Dai, Deli Chen, Dongjie Ji, Erhang Li, Fangyun Lin, Fucong Dai, Fuli Luo, Guangbo Hao, Guanting Chen, Guowei Li, H. Zhang, Han Bao, Hanwei Xu, Haocheng Wang, Honghui Ding, Huajian Xin, Huazuo Gao, Hui Qu, Hui Li, Jianzhong Guo, Jiashi Li, Jiawei Wang, Jingchang Chen, Jingyang Yuan, Junjie Qiu, Junlong Li, J. L. Cai, Jiaqi Ni, Jian Liang, Jin Chen, Kai

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Dong, Kai Hu, Kaige Gao, Kang Guan, Kexin Huang, Kuai Yu, Lean Wang, Lecong Zhang, Liang Zhao, Litong Wang, Liyue Zhang, Lei Xu, Leyi Xia, Mingchuan Zhang, Minghua Zhang, Minghui Tang, Meng Li, Miaojun Wang, Mingming Li, Ning Tian, Panpan Huang, Peng Zhang, Qiancheng Wang, Qinyu Chen, Qiushi Du, Ruiqi Ge, Ruisong Zhang, Ruizhe Pan, Runji Wang, R. J. Chen, R. L. Jin, Ruyi Chen, Shanghao Lu, Shangyan Zhou, Shanhuang Chen, Shengfeng Ye, Shiyu Wang, Shuiping Yu, Shunfeng Zhou, Shuting Pan, S. S. Li, Shuang Zhou, Shaoqing Wu, Shengfeng Ye, Tao Yun, Tian Pei, Tianyu Sun, T. Wang, Wangding Zeng, Wanjia Zhao, Wen Liu, Wenfeng Liang, Wenjun Gao, Wenqin Yu, Wentao Zhang, W. L. Xiao, Wei An, Xiaodong Liu, Xiaohan Wang, Xiaokang Chen, Xiaotao Nie, Xin Cheng, Xin Liu, Xin Xie, Xingchao Liu, Xinyu Yang, Xinyuan Li, Xuecheng Su, Xuheng Lin, X. Q. Li, Xiangyue Jin, Xiaojin Shen, Xiaosha Chen, Xiaowen Sun, Xiaoxiang Wang, Xinnan Song, Xinyi Zhou, Xianzu Wang, Xinxia Shan, Y. K. Li, Y. Q. Wang, Y. X. Wei, Yang Zhang, Yanhong Xu, Yao Li, Yao Zhao, Yaofeng Sun, Yaohui Wang, Yi Yu, Yichao Zhang, Yifan Shi, Yiliang Xiong, Ying He, Yishi Piao, Yisong Wang, Yixuan Tan, Yiyang Ma, Yiyuan Liu, Yongqiang Guo, Yuan Ou, Yuduan Wang, Yue Gong, Yuheng Zou, Yujia He, Yunfan Xiong, Yuxiang Luo, Yuxiang You, Yuxuan Liu, Yuyang Zhou, Y. X. Zhu, Yanhong Xu, Yanping Huang, Yaohui Li, Yi Zheng, Yuchen Zhu, Yunxian Ma, Ying Tang, Yukun Zha, Yuting Yan, Z. Z. Ren, Zehui Ren, Zhangli Sha, Zhe Fu, Zhean Xu, Zhenda Xie, Zhengyan Zhang, Zhewen Hao, Zhicheng Ma, Zhigang Yan, Zhiyu Wu, Zihui Gu, Zijia Zhu, Zijun Liu, Zilin Li, Ziwei Xie, Ziyang Song, Zizheng Pan, Zhen Huang, Zhipeng Xu, Zhongyu Zhang, and Zhen Zhang. Deepseek-r1: Incentivizing reasoning capability in Ilms via reinforcement learning, 2025. URL https://arxiv.org/abs/2501.12948.

Jordan S. Ellenberg, Cristofero S. Fraser-Taliente, Thomas R. Harvey, Karan Srivastava, and Andrew V. Sutherland. Generative modeling for mathematical discovery, 2025. URL https://arxiv.org/abs/2503.11061.

Scott Fujimoto, David Meger, and Doina Precup. Off-policy deep reinforcement learning without exploration. In *International conference on machine learning*, pp. 2052–2062. PMLR, 2019.

Tianyu Gao, Xingcheng Yao, and Danqi Chen. Simcse: Simple contrastive learning of sentence embeddings. *arXiv preprint arXiv:2104.08821*, 2021.

Miguel García-Ortegón, Gregor NC Simm, Austin J Tripp, José Miguel Hernández-Lobato, Andreas Bender, and Sergio Bacallado. Dockstring: easy molecular docking yields better benchmarks for ligand design. *Journal of chemical information and modeling*, 62(15):3486–3502, 2022.

Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, Amy Yang, Angela Fan, Anirudh Goyal, Anthony Hartshorn, Aobo Yang, Archi Mitra, Archie Sravankumar, Artem Korenev, Arthur Hinsvark, Arun Rao, Aston Zhang, Aurelien Rodriguez, Austen Gregerson, Ava Spataru, Baptiste Roziere, Bethany Biron, Binh Tang, Bobbie Chern, Charlotte Caucheteux, Chaya Nayak, Chloe Bi, Chris Marra, Chris McConnell, Christian Keller, Christophe Touret, Chunyang Wu, Corinne Wong, Cristian Canton Ferrer, Cyrus Nikolaidis, Damien Allonsius, Daniel Song, Danielle Pintz, Danny Livshits, Danny Wyatt, David Esiobu, Dhruv Choudhary, Dhruv Mahajan, Diego Garcia-Olano, Diego Perino, Dieuwke Hupkes, Egor Lakomkin, Ehab AlBadawy, Elina Lobanova, Emily Dinan, Eric Michael Smith, Filip Radenovic, Francisco Guzmán, Frank Zhang, Gabriel Synnaeve, Gabrielle Lee, Georgia Lewis Anderson, Govind Thattai, Graeme Nail, Gregoire Mialon, Guan Pang, Guillem Cucurell, Hailey Nguyen, Hannah Korevaar, Hu Xu, Hugo Touvron, Iliyan Zarov, Imanol Arrieta Ibarra, Isabel Kloumann, Ishan Misra, Ivan Evtimov, Jack Zhang, Jade Copet, Jaewon Lee, Jan Geffert, Jana Vranes, Jason Park, Jay Mahadeokar, Jeet Shah, Jelmer van der Linde, Jennifer Billock, Jenny Hong, Jenya Lee, Jeremy Fu, Jianfeng Chi, Jianyu Huang, Jiawen Liu, Jie Wang, Jiecao Yu, Joanna Bitton, Joe Spisak, Jongsoo Park, Joseph Rocca, Joshua Johnstun, Joshua Saxe, Junteng Jia, Kalyan Vasuden Alwala, Karthik Prasad, Kartikeya Upasani, Kate Plawiak, Ke Li, Kenneth Heafield, Kevin Stone, Khalid El-Arini, Krithika Iyer, Kshitiz Malik, Kuenley Chiu, Kunal Bhalla, Kushal Lakhotia, Lauren Rantala-Yeary, Laurens van der Maaten, Lawrence Chen, Liang Tan, Liz Jenkins, Louis Martin, Lovish Madaan, Lubo Malo, Lukas Blecher, Lukas Landzaat, Luke de Oliveira, Madeline Muzzi, Mahesh Pasupuleti, Mannat Singh, Manohar Paluri, Marcin Kardas, Maria Tsimpoukelli, Mathew Oldham, Mathieu Rita, Maya Pavlova, Melanie Kambadur, Mike Lewis, Min Si, Mitesh Kumar Singh, Mona Hassan, Naman Goyal, Narjes Torabi, Nikolay Bashlykov, Nikolay Bogoychev, Niladri Chatterji, Ning Zhang, Olivier Duchenne, Onur Çelebi, Patrick Alrassy, Pengchuan

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Zhang, Pengwei Li, Petar Vasic, Peter Weng, Prajjwal Bhargava, Pratik Dubal, Praveen Krishnan, Punit Singh Koura, Puxin Xu, Qing He, Qingxiao Dong, Ragavan Srinivasan, Raj Ganapathy, Ramon Calderer, Ricardo Silveira Cabral, Robert Stojnic, Roberta Raileanu, Rohan Maheswari, Rohit Girdhar, Rohit Patel, Romain Sauvestre, Ronnie Polidoro, Roshan Sumbaly, Ross Taylor, Ruan Silva, Rui Hou, Rui Wang, Saghar Hosseini, Sahana Chennabasappa, Sanjay Singh, Sean Bell, Seohyun Sonia Kim, Sergey Edunov, Shaoliang Nie, Sharan Narang, Sharath Raparthy, Sheng Shen, Shengye Wan, Shruti Bhosale, Shun Zhang, Simon Vandenhende, Soumya Batra, Spencer Whitman, Sten Sootla, Stephane Collot, Suchin Gururangan, Sydney Borodinsky, Tamar Herman, Tara Fowler, Tarek Sheasha, Thomas Georgiou, Thomas Scialom, Tobias Speckbacher, Todor Mihaylov, Tong Xiao, Ujiwal Karn, Vedanuj Goswami, Vibhor Gupta, Vignesh Ramanathan, Viktor Kerkez, Vincent Gonguet, Virginie Do, Vish Vogeti, Vítor Albiero, Vladan Petrovic, Weiwei Chu, Wenhan Xiong, Wenyin Fu, Whitney Meers, Xavier Martinet, Xiaodong Wang, Xiaofang Wang, Xiaoqing Ellen Tan, Xide Xia, Xinfeng Xie, Xuchao Jia, Xuewei Wang, Yaelle Goldschlag, Yashesh Gaur, Yasmine Babaei, Yi Wen, Yiwen Song, Yuchen Zhang, Yue Li, Yuning Mao, Zacharie Delpierre Coudert, Zheng Yan, Zhengxing Chen, Zoe Papakipos, Aaditya Singh, Aayushi Srivastava, Abha Jain, Adam Kelsey, Adam Shajnfeld, Adithya Gangidi, Adolfo Victoria, Ahuva Goldstand, Ajay Menon, Ajay Sharma, Alex Boesenberg, Alexei Baevski, Allie Feinstein, Amanda Kallet, Amit Sangani, Amos Teo, Anam Yunus, Andrei Lupu, Andres Alvarado, Andrew Caples, Andrew Gu, Andrew Ho, Andrew Poulton, Andrew Ryan, Ankit Ramchandani, Annie Dong, Annie Franco, Anuj Goyal, Aparajita Saraf, Arkabandhu Chowdhury, Ashley Gabriel, Ashwin Bharambe, Assaf Eisenman, Azadeh Yazdan, Beau James, Ben Maurer, Benjamin Leonhardi, Bernie Huang, Beth Loyd, Beto De Paola, Bhargavi Paranjape, Bing Liu, Bo Wu, Boyu Ni, Braden Hancock, Bram Wasti, Brandon Spence, Brani Stojkovic, Brian Gamido, Britt Montalvo, Carl Parker, Carly Burton, Catalina Mejia, Ce Liu, Changhan Wang, Changkyu Kim, Chao Zhou, Chester Hu, Ching-Hsiang Chu, Chris Cai, Chris Tindal, Christoph Feichtenhofer, Cynthia Gao, Damon Civin, Dana Beaty, Daniel Kreymer, Daniel Li, David Adkins, David Xu, Davide Testuggine, Delia David, Devi Parikh, Diana Liskovich, Didem Foss, Dingkang Wang, Duc Le, Dustin Holland, Edward Dowling, Eissa Jamil, Elaine Montgomery, Eleonora Presani, Emily Hahn, Emily Wood, Eric-Tuan Le, Erik Brinkman, Esteban Arcaute, Evan Dunbar, Evan Smothers, Fei Sun, Felix Kreuk, Feng Tian, Filippos Kokkinos, Firat Ozgenel, Francesco Caggioni, Frank Kanayet, Frank Seide, Gabriela Medina Florez, Gabriella Schwarz, Gada Badeer, Georgia Swee, Gil Halpern, Grant Herman, Grigory Sizov, Guangyi, Zhang, Guna Lakshminarayanan, Hakan Inan, Hamid Shojanazeri, Han Zou, Hannah Wang, Hanwen Zha, Haroun Habeeb, Harrison Rudolph, Helen Suk, Henry Aspegren, Hunter Goldman, Hongyuan Zhan, Ibrahim Damlaj, Igor Molybog, Igor Tufanov, Ilias Leontiadis, Irina-Elena Veliche, Itai Gat, Jake Weissman, James Geboski, James Kohli, Janice Lam, Japhet Asher, Jean-Baptiste Gaya, Jeff Marcus, Jeff Tang, Jennifer Chan, Jenny Zhen, Jeremy Reizenstein, Jeremy Teboul, Jessica Zhong, Jian Jin, Jingyi Yang, Joe Cummings, Jon Carvill, Jon Shepard, Jonathan McPhie, Jonathan Torres, Josh Ginsburg, Junjie Wang, Kai Wu, Kam Hou U, Karan Saxena, Kartikay Khandelwal, Katayoun Zand, Kathy Matosich, Kaushik Veeraraghavan, Kelly Michelena, Keqian Li, Kiran Jagadeesh, Kun Huang, Kunal Chawla, Kyle Huang, Lailin Chen, Lakshya Garg, Lavender A, Leandro Silva, Lee Bell, Lei Zhang, Liangpeng Guo, Licheng Yu, Liron Moshkovich, Luca Wehrstedt, Madian Khabsa, Manay Avalani, Manish Bhatt, Martynas Mankus, Matan Hasson, Matthew Lennie, Matthias Reso, Maxim Groshev, Maxim Naumov, Maya Lathi, Meghan Keneally, Miao Liu, Michael L. Seltzer, Michal Valko, Michelle Restrepo, Mihir Patel, Mik Vyatskov, Mikayel Samvelyan, Mike Clark, Mike Macey, Mike Wang, Miquel Jubert Hermoso, Mo Metanat, Mohammad Rastegari, Munish Bansal, Nandhini Santhanam, Natascha Parks, Natasha White, Navyata Bawa, Nayan Singhal, Nick Egebo, Nicolas Usunier, Nikhil Mehta, Nikolay Pavlovich Laptev, Ning Dong, Norman Cheng, Oleg Chernoguz, Olivia Hart, Omkar Salpekar, Ozlem Kalinli, Parkin Kent, Parth Parekh, Paul Saab, Pavan Balaji, Pedro Rittner, Philip Bontrager, Pierre Roux, Piotr Dollar, Polina Zvyagina, Prashant Ratanchandani, Pritish Yuvraj, Qian Liang, Rachad Alao, Rachel Rodriguez, Rafi Ayub, Raghotham Murthy, Raghu Nayani, Rahul Mitra, Rangaprabhu Parthasarathy, Raymond Li, Rebekkah Hogan, Robin Battey, Rocky Wang, Russ Howes, Ruty Rinott, Sachin Mehta, Sachin Siby, Sai Jayesh Bondu, Samyak Datta, Sara Chugh, Sara Hunt, Sargun Dhillon, Sasha Sidorov, Satadru Pan, Saurabh Mahajan, Saurabh Verma, Seiji Yamamoto, Sharadh Ramaswamy, Shaun Lindsay, Shaun Lindsay, Sheng Feng, Shenghao Lin, Shengxin Cindy Zha, Shishir Patil, Shiva Shankar, Shuqiang Zhang, Shuqiang Zhang, Sinong Wang, Sneha Agarwal, Soji Sajuyigbe, Soumith Chintala, Stephanie Max, Stephen Chen, Steve Kehoe, Steve Satterfield, Sudarshan Govindaprasad, Sumit Gupta, Summer Deng, Sungmin Cho, Sunny Virk, Suraj

Subramanian, Sy Choudhury, Sydney Goldman, Tal Remez, Tamar Glaser, Tamara Best, Thilo Koehler, Thomas Robinson, Tianhe Li, Tianjun Zhang, Tim Matthews, Timothy Chou, Tzook Shaked, Varun Vontimitta, Victoria Ajayi, Victoria Montanez, Vijai Mohan, Vinay Satish Ku-mar, Vishal Mangla, Vlad Ionescu, Vlad Poenaru, Vlad Tiberiu Mihailescu, Vladimir Ivanov, Wei Li, Wenchen Wang, Wenwen Jiang, Wes Bouaziz, Will Constable, Xiaocheng Tang, Xiaojian Wu, Xiaolan Wang, Xilun Wu, Xinbo Gao, Yaniv Kleinman, Yanjun Chen, Ye Hu, Ye Jia, Ye Qi, Yenda Li, Yilin Zhang, Ying Zhang, Yossi Adi, Youngjin Nam, Yu, Wang, Yu Zhao, Yuchen Hao, Yundi Qian, Yunlu Li, Yuzi He, Zach Rait, Zachary DeVito, Zef Rosnbrick, Zhao-duo Wen, Zhenyu Yang, Zhiwei Zhao, and Zhiyu Ma. The llama 3 herd of models, 2024. URL https://arxiv.org/abs/2407.21783.

- Nate Gruver, Anuroop Sriram, Andrea Madotto, Andrew Gordon Wilson, C. Lawrence Zitnick, and Zachary Ward Ulissi. Fine-tuned language models generate stable inorganic materials as text. In *The Twelfth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=vN9fpfqoP1.
- Moritz Hardt and Yu Sun. Test-time training on nearest neighbors for large language models. In *The Twelfth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=CNL2bku4ra.
- Edward J Hu, yelong shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. LoRA: Low-rank adaptation of large language models. In *International Conference on Learning Representations*, 2022. URL https://openreview.net/forum?id=nZeVKeeFYf9.
- Jonas Hübotter, Sascha Bongni, Ido Hakimi, and Andreas Krause. Efficiently learning at test-time: Active fine-tuning of LLMs. In *The Thirteenth International Conference on Learning Representations*, 2025. URL https://openreview.net/forum?id=NS1G1Uhny3.
- JP Hughes, S Rees, SB Kalindjian, and KL Philpott. Principles of early drug discovery. British Journal of Pharmacology, 162(6):1239–1249, 2011. doi: https://doi.org/10.1111/j.1476-5381.2010.01127.x. URL https://bpspubs.onlinelibrary.wiley.com/doi/abs/10.1111/j.1476-5381.2010.01127.x.
- Akshay Krishnamurthy, Keegan Harris, Dylan J Foster, Cyril Zhang, and Aleksandrs Slivkins. Can large language models explore in-context? *arXiv preprint arXiv:2403.15371*, 2024.
- Agustinus Kristiadi, Felix Strieth-Kalthoff, Marta Skreta, Pascal Poupart, Alan Aspuru-Guzik, and Geoff Pleiss. A sober look at LLMs for material discovery: Are they actually good for Bayesian optimization over molecules? In Ruslan Salakhutdinov, Zico Kolter, Katherine Heller, Adrian Weller, Nuria Oliver, Jonathan Scarlett, and Felix Berkenkamp (eds.), *Proceedings of the 41st International Conference on Machine Learning*, volume 235 of *Proceedings of Machine Learning Research*, pp. 25603–25622. PMLR, 21–27 Jul 2024. URL https://proceedings.mlr.press/v235/kristiadi24a.html.
- Aviral Kumar, Justin Fu, Matthew Soh, George Tucker, and Sergey Levine. Stabilizing off-policy q-learning via bootstrapping error reduction. *Advances in neural information processing systems*, 32, 2019.
- Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph E. Gonzalez, Hao Zhang, and Ion Stoica. Efficient memory management for large language model serving with pagedattention. In *Proceedings of the ACM SIGOPS 29th Symposium on Operating Systems Principles*, 2023.
- Nathan Lambert, Jacob Morrison, Valentina Pyatkin, Shengyi Huang, Hamish Ivison, Faeze Brahman, Lester James V. Miranda, Alisa Liu, Nouha Dziri, Shane Lyu, Yuling Gu, Saumya Malik, Victoria Graf, Jena D. Hwang, Jiangjiang Yang, Ronan Le Bras, Oyvind Tafjord, Chris Wilhelm, Luca Soldaini, Noah A. Smith, Yizhong Wang, Pradeep Dasigi, and Hannaneh Hajishirzi. Tulu 3: Pushing frontiers in open language model post-training, 2025. URL https://arxiv.org/abs/2411.15124.
- Sergey Levine, Aviral Kumar, George Tucker, and Justin Fu. Offline reinforcement learning: Tutorial, review, and perspectives on open problems. *arXiv preprint arXiv:2005.01643*, 2020.

Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in neural information processing systems*, 33: 9459–9474, 2020.

Wen-Ding Li, Keya Hu, Carter Larsen, Yuqing Wu, Simon Alford, Caleb Woo, Spencer M. Dunn, Hao Tang, Michelangelo Naim, Dat Nguyen, Wei-Long Zheng, Zenna Tavares, Yewen Pu, and Kevin Ellis. Combining induction and transduction for abstract reasoning, 2024. URL https://arxiv.org/abs/2411.02272.

- Tennison Liu, Nicolás Astorga, Nabeel Seedat, and Mihaela van der Schaar. Large language models to enhance bayesian optimization. In *The Twelfth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=OOxotBmGol.
- Zichen Liu, Changyu Chen, Wenjun Li, Penghui Qi, Tianyu Pang, Chao Du, Wee Sun Lee, and Min Lin. Understanding r1-zero-like training: A critical perspective, 2025. URL https://arxiv.org/abs/2503.20783.
- Chris Lu, Cong Lu, Robert Tjarko Lange, Jakob Foerster, Jeff Clune, and David Ha. The ai scientist: Towards fully automated open-ended scientific discovery. *arXiv preprint arXiv:2408.06292*, 2024.
- Bodhisattwa Prasad Majumder, Harshit Surana, Dhruv Agarwal, Bhavana Dalvi Mishra, Abhijeetsingh Meena, Aryan Prakhar, Tirth Vora, Tushar Khot, Ashish Sabharwal, and Peter Clark. Discoverybench: Towards data-driven discovery with large language models. In *The Thirteenth International Conference on Learning Representations*, 2025. URL https://openreview.net/forum?id=vyflgpwfJW.
- Elliot Meyerson, Mark J Nelson, Herbie Bradley, Adam Gaier, Arash Moradi, Amy K Hoover, and Joel Lehman. Language model crossover: Variation through few-shot prompting. *arXiv* preprint *arXiv*:2302.12170, 2023.
- Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*, 2013.
- Alexander Novikov, Ngân Vũ, Marvin Eisenberger, Emilien Dupont, Po-Sen Huang, Adam Zsolt Wagner, Sergey Shirobokov, Borislav Kozlovskii, Francisco JR Ruiz, Abbas Mehrabian, et al. Alphaevolve: A coding agent for scientific and algorithmic discovery. *arXiv preprint arXiv:2506.13131*, 2025.
- OpenAI. Introducing gpt-5, 2025. URL https://openai.com/index/introducing-gpt-5/.
- OpenAI, :, Aaron Jaech, Adam Kalai, Adam Lerer, Adam Richardson, Ahmed El-Kishky, Aiden Low, Alec Helyar, Aleksander Madry, Alex Beutel, Alex Carney, Alex Iftimie, Alex Karpenko, Alex Tachard Passos, Alexander Neitz, Alexander Prokofiev, Alexander Wei, Allison Tam, Ally Bennett, Ananya Kumar, Andre Saraiva, Andrea Vallone, Andrew Duberstein, Andrew Kondrich, Andrey Mishchenko, Andy Applebaum, Angela Jiang, Ashvin Nair, Barret Zoph, Behrooz Ghorbani, Ben Rossen, Benjamin Sokolowsky, Boaz Barak, Bob McGrew, Borys Minaiev, Botao Hao, Bowen Baker, Brandon Houghton, Brandon McKinzie, Brydon Eastman, Camillo Lugaresi, Cary Bassin, Cary Hudson, Chak Ming Li, Charles de Bourcy, Chelsea Voss, Chen Shen, Chong Zhang, Chris Koch, Chris Orsinger, Christopher Hesse, Claudia Fischer, Clive Chan, Dan Roberts, Daniel Kappler, Daniel Levy, Daniel Selsam, David Dohan, David Farhi, David Mely, David Robinson, Dimitris Tsipras, Doug Li, Dragos Oprica, Eben Freeman, Eddie Zhang, Edmund Wong, Elizabeth Proehl, Enoch Cheung, Eric Mitchell, Eric Wallace, Erik Ritter, Evan Mays, Fan Wang, Felipe Petroski Such, Filippo Raso, Florencia Leoni, Foivos Tsimpourlas, Francis Song, Fred von Lohmann, Freddie Sulit, Geoff Salmon, Giambattista Parascandolo, Gildas Chabot, Grace Zhao, Greg Brockman, Guillaume Leclerc, Hadi Salman, Haiming Bao, Hao Sheng, Hart Andrin, Hessam Bagherinezhad, Hongyu Ren, Hunter Lightman, Hyung Won Chung, Ian Kivlichan, Ian O'Connell, Ian Osband, Ignasi Clavera Gilaberte, Ilge Akkaya, Ilya Kostrikov, Ilya Sutskever, Irina Kofman, Jakub Pachocki, James Lennon, Jason Wei, Jean Harb, Jerry Twore, Jiacheng Feng, Jiahui Yu, Jiayi Weng, Jie Tang, Jieqi Yu, Joaquin Quiñonero Candela, Joe Palermo, Joel Parish,

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- Mayk Caldas Ramos, Shane S Michtavy, Marc D Porosoff, and Andrew D White. Bayesian optimization of catalysts with in-context learning. *arXiv preprint arXiv:2304.05341*, 2023.
- Bojana Ranković and Philippe Schwaller. Bochemian: Large language model embeddings for bayesian optimization of chemical reactions. In *NeurIPS 2023 Workshop on Adaptive Experimental Design and Active Learning in the Real World*, 2023. URL https://openreview.net/forum?id=A1RVn1m3J3.
- Bernardino Romera-Paredes, Mohammadamin Barekatain, Alexander Novikov, Matej Balog, M Pawan Kumar, Emilien Dupont, Francisco JR Ruiz, Jordan S Ellenberg, Pengming Wang, Omar Fawzi, et al. Mathematical discoveries from program search with large language models. *Nature*, 625(7995):468–475, 2024.
- John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. ArXiv, abs/1707.06347, 2017. URL https://api.semanticscholar.org/CorpusID:28695052.
- Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, YK Li, Y Wu, et al. Deepseekmath: Pushing the limits of mathematical reasoning in open language models. *arXiv preprint arXiv:2402.03300*, 2024.
- Noah Shinn, Federico Cassano, Ashwin Gopinath, Karthik Narasimhan, and Shunyu Yao. Reflexion: Language agents with verbal reinforcement learning. *Advances in Neural Information Processing Systems*, 36, 2024.
- Yu Sun, Xiaolong Wang, Zhuang Liu, John Miller, Alexei Efros, and Moritz Hardt. Test-time training with self-supervision for generalization under distribution shifts. In *International conference on machine learning*, pp. 9229–9248. PMLR, 2020.
- Anja Surina, Amin Mansouri, Lars Quaedvlieg, Amal Seddas, Maryna Viazovska, Emmanuel Abbe, and Caglar Gulcehre. Algorithm discovery with llms: Evolutionary search meets reinforcement learning. *arXiv preprint arXiv:2504.05108*, 2025.
- Kimi Team, Angang Du, Bofei Gao, Bowei Xing, Changjiu Jiang, Cheng Chen, Cheng Li, Chenjun Xiao, Chenzhuang Du, Chonghua Liao, Chuning Tang, Congcong Wang, Dehao Zhang, Enming Yuan, Enzhe Lu, Fengxiang Tang, Flood Sung, Guangda Wei, Guokun Lai, Haiqing Guo, Han Zhu, Hao Ding, Hao Hu, Hao Yang, Hao Zhang, Haotian Yao, Haotian Zhao, Haoyu Lu, Haoze

Li, Haozhen Yu, Hongcheng Gao, Huabin Zheng, Huan Yuan, Jia Chen, Jianhang Guo, Jianlin Su, Jianzhou Wang, Jie Zhao, Jin Zhang, Jingyuan Liu, Junjie Yan, Junyan Wu, Lidong Shi, Ling Ye, Longhui Yu, Mengnan Dong, Neo Zhang, Ningchen Ma, Qiwei Pan, Qucheng Gong, Shaowei Liu, Shengling Ma, Shupeng Wei, Sihan Cao, Siying Huang, Tao Jiang, Weihao Gao, Weimin Xiong, Weiran He, Weixiao Huang, Weixin Xu, Wenhao Wu, Wenyang He, Xianghui Wei, Xianqing Jia, Xingzhe Wu, Xinran Xu, Xinxing Zu, Xinyu Zhou, Xuehai Pan, Y. Charles, Yang Li, Yangyang Hu, Yangyang Liu, Yanru Chen, Yejie Wang, Yibo Liu, Yidao Qin, Yifeng Liu, Ying Yang, Yiping Bao, Yulun Du, Yuxin Wu, Yuzhi Wang, Zaida Zhou, Zhaoji Wang, Zhaowei Li, Zhen Zhu, Zheng Zhang, Zhexu Wang, Zhilin Yang, Zhiqi Huang, Zihao Huang, Ziyao Xu, Zonghan Yang, and Zongyu Lin. Kimi k1.5: Scaling reinforcement learning with llms, 2025. URL https://arxiv.org/abs/2501.12599.

- Dung Thai, Dhruv Agarwal, Mudit Chaudhary, Wenlong Zhao, Rajarshi Das, Jay-Yoon Lee, Hannaneh Hajishirzi, Manzil Zaheer, and Andrew McCallum. Machine reading comprehension using case-based reasoning. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 8414–8428, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.findings-emnlp.564. URL https://aclanthology.org/2023.findings-emnlp.564/.
- Oleg Trott and Arthur J Olson. Autodock vina: improving the speed and accuracy of docking with a new scoring function, efficient optimization, and multithreading. *Journal of computational chemistry*, 31(2):455–461, 2010.
- Leandro von Werra, Younes Belkada, Lewis Tunstall, Edward Beeching, Tristan Thrush, Nathan Lambert, Shengyi Huang, Kashif Rasul, and Quentin Gallouédec. Trl: Transformer reinforcement learning. https://github.com/huggingface/trl, 2020.
- Ruocheng Wang, Eric Zelikman, Gabriel Poesia, Yewen Pu, Nick Haber, and Noah Goodman. Hypothesis search: Inductive reasoning with language models. In *The Twelfth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=G7UtIGQmjm.
- David Weininger. Smiles, a chemical language and information system. 1. introduction to methodology and encoding rules. *Journal of chemical information and computer sciences*, 28(1):31–36, 1988.
- Mark C Wenlock, Rupert P Austin, Patrick Barton, Andrew M Davis, and Paul D Leeson. A comparison of physiochemical property profiles of development and marketed oral drugs. *J. Med. Chem.*, 46(7):1250–1256, March 2003.
- Jianhao Yan, Yafu Li, Zican Hu, Zhi Wang, Ganqu Cui, Xiaoye Qu, Yu Cheng, and Yue Zhang. Learning to reason under off-policy guidance. *arXiv preprint arXiv:2504.14945*, 2025.
- An Yang, Baosong Yang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Zhou, Chengpeng Li, Chengyuan Li, Dayiheng Liu, Fei Huang, Guanting Dong, Haoran Wei, Huan Lin, Jialong Tang, Jialin Wang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Ma, Jin Xu, Jingren Zhou, Jinze Bai, Jinzheng He, Junyang Lin, Kai Dang, Keming Lu, Keqin Chen, Kexin Yang, Mei Li, Mingfeng Xue, Na Ni, Pei Zhang, Peng Wang, Ru Peng, Rui Men, Ruize Gao, Runji Lin, Shijie Wang, Shuai Bai, Sinan Tan, Tianhang Zhu, Tianhao Li, Tianyu Liu, Wenbin Ge, Xiaodong Deng, Xiaohuan Zhou, Xingzhang Ren, Xinyu Zhang, Xipin Wei, Xuancheng Ren, Yang Fan, Yang Yao, Yichang Zhang, Yu Wan, Yunfei Chu, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zhihao Fan. Qwen2 technical report. arXiv preprint arXiv:2407.10671, 2024a.
- Chengrun Yang, Xuezhi Wang, Yifeng Lu, Hanxiao Liu, Quoc V Le, Denny Zhou, and Xinyun Chen. Large language models as optimizers. In *The Twelfth International Conference on Learning Representations*, 2024b. URL https://openreview.net/forum?id=Bb4VGOWELI.
- Haizi Yu, Igor Mineyev, Lav R Varshney, and James A Evans. Learning from one and only one shot. *npj Artificial Intelligence*, 1(1):13, 2025a.
- Qiying Yu, Zheng Zhang, Ruofei Zhu, Yufeng Yuan, Xiaochen Zuo, Yu Yue, Tiantian Fan, Gaohong Liu, Lingjun Liu, Xin Liu, Haibin Lin, Zhiqi Lin, Bole Ma, Guangming Sheng, Yuxuan Tong, Chi

Zhang, Mofan Zhang, Wang Zhang, Hang Zhu, Jinhua Zhu, Jiaze Chen, Jiangjie Chen, Chengyi Wang, Hongli Yu, Weinan Dai, Yuxuan Song, Xiangpeng Wei, Hao Zhou, Jingjing Liu, Wei-Ying Ma, Ya-Qin Zhang, Lin Yan, Mu Qiao, Yonghui Wu, and Mingxuan Wang. Dapo: An open-source llm reinforcement learning system at scale, 2025b. URL https://arxiv.org/abs/2503.14476.

- Yang Yue, Zhiqi Chen, Rui Lu, Andrew Zhao, Zhaokai Wang, Shiji Song, and Gao Huang. Does reinforcement learning really incentivize reasoning capacity in llms beyond the base model? *arXiv* preprint arXiv:2504.13837, 2025.
- Mert Yuksekgonul, Federico Bianchi, Joseph Boen, Sheng Liu, Zhi Huang, Carlos Guestrin, and James Zou. Textgrad: Automatic" differentiation" via text. *arXiv preprint arXiv:2406.07496*, 2024.
- Rosie Zhao, Alexandru Meterez, Sham Kakade, Cengiz Pehlevan, Samy Jelassi, and Eran Malach. Echo chamber: Rl post-training amplifies behaviors learned in pretraining. *arXiv preprint arXiv:2504.07912*, 2025.

Hyperparameter	Value
Model	Llama 3.2 3B Instruct
	Grattafiori et al. (2024)
Learning rate	1e-5
Group size	5
LoRA rank	64
LoRA alpha	16
Training steps	100
Iterations per step	2
GRPO $[\alpha, \gamma, \beta]$	[5,0,0]
GRPO-Greedy [α , γ , β]	[4, 0, 1]
MIGRATE $[\alpha, \gamma, \beta]$	[0,4,1]

Table 2: MIGRATE hyperparameters for Semantle

A APPENDIX A

A.1 EXPERIMENTAL SETTINGS

Semantle. The black-box function we use is the cosine similarity of vector representations generated using the SimCSE Gao et al. (2021) sentence embedding model, where the score for a proposed word x for a hidden target word y is computed by comparing the embeddings for the sequences "What is a $\{x\}$?" and "What is a $\{y\}$?". The number of warmstart candidates is 20. Our main results with NS and MIGRATE selects $\mathcal{O}_{\text{greedy}}$ by uniformly sampling among the top-3 completions found so far according to their black-box scores.

In MIGRATE, we execute GRPO for 100 generation steps where we sample a batch of 10 words in each step for a total sampling budget of 1000 words. In each step, we sort the generated batch of words by their scores and construct a group of 5 completions, each consisting of 2 words each. Each completion is assigned the maximum score of the two words as its reward.

For the Random baseline, we sample 1000 words using the task prompt. For the NS baseline, we sample 10 words using the NS prompt for 100 iterations. Similarly, for the OPRO baseline, we also sample 10 words using the OPRO prompt for 100 iterations. We provide, in-context, the top-10 words found so far for every OPRO-based method.

Dockstring. The black-box function we use is a linear function of the binding affinity (Vina) and druglikeness (QED). We use RDKit's MolFromSmiles to sanitize a given generated SMILES string. If this process fails due to an invalid format structure or molecule, we assign the generated molecule a score of 0. If the molecule is valid, we compute the QED and Vina scores on the given protein target. We then compute the overall score of these two metrics as follows:

$$s_{\text{overall}}(\text{molecule, protein}) = 1 - \mathcal{N}(\text{Vina}(\text{molecule, protein}) + (1 - \text{QED}(\text{molecule}))$$
 (2)

Where \mathcal{N} denotes min-max normalization to the range [0,1]. The QED score is bounded between 0 and 1, and we assume the Vina score to be between 0 and -13.0 kcal/mol. In practice, the binding affinity is a much higher priority than the druglikeness. Given our equation and the value ranges for computing s_{overall} , our black-fox function accurately emphasizes the Vina score about 10 times more than the QED score.

For the Random baseline, we sample 200 molecules using the task prompt. For the NS baseline, we sample 3 molecules using the task prompt and 2 molecules using the NS prompt in each iteration for 40 iterations. We select \mathcal{O}_{greedy} from the top-1 molecule found so far in NS and MIGRATE. For the OPRO baseline, we sample 5 molecules using the OPRO prompt for 40 iterations. We provide, in-context, the top-5 molecules proposed so far for every OPRO-based method.

Hyperparameter	Value
Model	Llama 3.2 3B Instruct
	Grattafiori et al. (2024)
Learning rate	5e-5
Group size	5
LoRA rank	64
LoRA alpha	16
Training steps	40
Iterations per step	1
GRPO $[\alpha, \gamma, \beta]$	[5,0,0]
GRPO-Greedy [α , γ , β]	[4, 0, 1]
MIGRATE $[\alpha, \gamma, \beta]$	[2, 2, 1]

Table 3: MIGRATE hyperparameters for Dockstring

Hyperparameter	Value
Model	BARC Li et al. (2024)
Learning rate	1e-5
Group size	16
LoRÂ rank	128
LoRA alpha	32
Training steps	64
Iterations per step	1
GRPO $[\alpha, \gamma, \beta]$	[16, 0, 0]
GRPO-Greedy [α , γ , β]	[15, 0, 1]
MIGRATE $[\alpha, \gamma, \beta]$	[11, 4, 1]

Table 4: MIGRATE hyperparameters for ARC

ARC. The black-box function we use is a hamming-distance based metric. We run all input grids with the sampled program and compute the proportion of cells in the ground-truth grid that matches the output grid. We assign a reward of 0 if the program does not terminate within 10 seconds of execution. During training, the reward is given by averaging the score across all training input grids of the given ARC task. If the output grid is larger than the ground-truth, then we assign a score of 0.

For the Random baseline, we sample 1024 programs using the task prompt. For the NS baseline, we sample 12 programs using the task prompt and 4 programs using the NS prompt for 64 iterations. We note that this Random baseline is equivalent to the main evaluations ran by Li et al. Additionally, our TTT baselines on ARC in the inductive setting are not an entirely fair comparison to prior works that do TTT in the transductive setting. We select $\mathcal{O}_{\text{greedy}}$ as the top-1 program found so far for both NS and MIGRATE. Similarly, for the OPRO baseline, we sample 12 programs using the task prompt and 4 programs using the OPRO prompt for 64 iterations. Due to hardware limitations and to maintain a fair comparison with MIGRATE, we only provide one program in-context for the OPRO prompt.

Discoverybench. The main black-box function we use is a belief-based score which represents the extent a model believes a generated hypothesis matches the gold hypothesis. In our implementation, we create a Beta belief distribution from 10 samples from a base Qwen 2.5 7B-Instruct model Yang et al. (2024a). We observed that using the Qwen model for this task performed similarly to sampling from GPT-40 OpenAI et al. (2024).

Hyperparameter	Value
Model	Qwen 2.5 7B Instruct Yang et al. (2024a)
Learning rate	1e-5
Group size	5
LoRA rank	128
LoRA alpha	32
Training steps	40
Iterations per step	2
MIGRATE $[\alpha, \gamma, \beta]$	[2, 2, 1]

Table 5: MIGRATE hyperparameters for Discoverybench

A.2 GRPO FORMULATION

We remove the KL term in the original GRPO objective. Following DAPO Yu et al. (2025b), we utilize token-level normalization, which assigns more balanced rewards to individually generated tokens—alleviating the bias towards longer responses. We also set $\varepsilon_{\rm low}=0.2$ and $\varepsilon_{\rm low}=0.28$ which DAPO finds to promote exploration of low-probability tokens that perform well. Dr. GRPO Liu et al. (2025) also divides the sum of loss by a constant instead of the total sequence length to completely remove any completion length bias. Although we did not use this formulation in our experiments, there should be no substantial differences since there is not high variability in the solution lengths in the domains we studied. Following Dr. GRPO, we do not scale the advantage by the standard deviation of the group's rewards. By doing so, we avoid biasing weight optimization on groups that perform extremely well or poorly on a given prompt. While our online prompt always remains constant, this bias is relevant for our NS prompt which can vary across iterations.

A.3 COMPUTATIONAL RESOURCES

All experiments were conducted on a cluster of NVIDIA GPUs. We utilize a mixture of A100 (40GB and 80GB), L40S, and A40 GPUs. TTT methods on ARC-Full were only ran with A100 (80GB) GPUs due to the higher memory requirements. Our implementation of MIGRATE is based on the TRL 0.19.0 implementation of GRPO from Hugging Face von Werra et al. (2020). We also utilize Unsloth Daniel Han & team (2023) and vLLM Kwon et al. (2023) to enable higher inferencing throughput and lower memory usage. The average runtime for MIGRATE on each Semantle problem was 93 seconds on an A100 GPU. The average runtime for MIGRATE across all GPU types on each molecule optimization task was 7.5 minutes. The average runtime for MIGRATE on each ARC task with early stopping is 51 minutes on an A100 GPU. The average runtime for MIGRATE on each DiscoveryBench query with early stopping is 61 minutes across all of the mentioned devices.

B APPENDIX B: ADDITIONAL EXPERIMENTS

B.1 ISLAND-BASED EVOLUTION ALGORITHM

We implement an island-based evoluationary algorithm as an alterative to top-k for selecting $\mathcal{O}_{\text{greedy}}$. We created a database inspired by Ellenberg et al. (2025) to store generated solutions and sample them for constructing neighborhood sampling. The island model organizes the solutions into isolated islands of solutions that are evolved independently.

At every training step, we iterate to another "island" in the database in a cyclic order. We then sample a solution stored at this island to construct our neighborhood sampling prompt. We note that unlike prior works Ellenberg et al. (2025); Surina et al. (2025) we do not construct additional subclusters of solutions within each island. This was done due to the low sampling constraints of our experiments but can also be seen as using a single cluster per island. Sampling from an island is carried out by an exploitation strategy with probability p and an exploration strategy with probability p. With the exploitation strategy, we randomly select a top solutions on the island that is also considered a globally top-k solution across all islands. If the island does not have a solution that is in

the top-k solution for all islands then we fall back on the exploration strategy. With the exploration strategy, we randomly select among the top solutions on the island that are *not* one of the globally top-k solutions.

We periodically migrate a percentage of the top-performing solutions from each island to their neighboring islands according to a ring topology. This maintains a balance of exploring diverse solutions in isolation and preventing the algorithm from spending too much time on low-performing solutions.

We conduct a comparison of using NS and MIGRATE with three different strategies for selecting the solution to sample neighbors from: Top-1, Top-3, and Evolution. For each of these configurations we use 10 neighborhood samples, 0 online samples, and 0 greedy samples. Fig. 5 shows that Top-3 outperforms Top-1 and that using our evolution-based strategy outperforms Top-3 in both NS and MIGRATE methods. While Top-3 shows the better initial gains in both NS and MIGRATE, the evolution-based strategy narrowly outperforms it by 1000 samples. Much like our other results in Table. 1, we also observe that the MIGRATE equivalent of each NS variation performs better – reinforcing the pattern that TTT improves search performance.

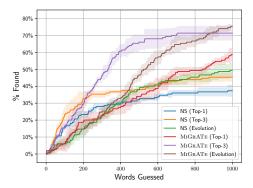


Figure 5: Comparing selection methods for NS. Evolution-based selection shows slower initial gains but results in more consistent improvements than using a top-k sampling strategy–resulting in better final performances.

B.2 CAN RELATED TASKS BOOTSTRAP SEARCH?

We investigate whether fine-tuned weights from TTT can generalize to other tasks. After running MIGRATE on every task, we perform TTT again on unsolved tasks and bootstrap the method with the learned weights of its "nearest" solved task.

In this experiment, we attempt to solve ARC tasks that were not solved by MIGRATE. For each unsolved task, we determine its "nearest" solved task by evaluating this task using the solution program from every solved task. We pass the training inputs of the unsolved task into each program and determine the nearest solved task to be the one whose solution program achieve the highest reward from our hamming distance-based reward function.

Once the nearest solved task is identified, we use its fine-tuned weights from MIGRATE as the initializing point for solving the unsolved task. This procedure aims to transfer inductive biases that may have been learned from structurally similar tasks, enabling the model to efficiently explore more viable programs on the unsolved task. This tests whether there is an advantage to initializing search via TTT from a more informed starting point on problems where starting with the base model fails.

We see marginal improvements from bootstrapping search with learned weights from MIGRATE. Fig. 6 shows that initializing Random Sampling and MIGRATE with the nearest solved task's weights allowed each respective method to solve tasks that were initially unsolvable by the base model. Notably, bootstrapping Random Sampling with nearest weights was able to solve more tasks than executing MIGRATE on the base model.

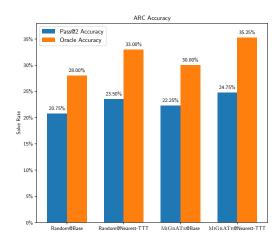


Figure 6: **Bootstrapping with nearest weights on ARC-Full.** Bootstrapping Random and MI-GRATE with initial weights learned from one round of MIGRATE shows slight improvement on total tasks solved.

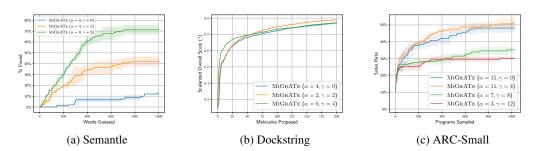


Figure 7: Varying α and γ . We vary the number of online and NS samples per group in MIGRATE. (a) On Semantle, we found that the strategy of using no online samples to be the most successful by a significant margin. (b) On Dockstring, we found that using only NS samples yield better performances at smaller budgets and a configuration of equal amounts of online and NS samples to achieve the best final performance. (c) On ARC-Small, we found the mixed configuration of $\alpha=11$ and $\gamma=4$ to perform the best.

B.3 SENSITIVITY ANALYSES

B.3.1 VARYING α AND γ SAMPLES

We conduct experiments on Semantle, Dockstring, and ARC-Small to investigate the tradeoff involved in varying the ratio of online to neighborhood samples within a GRPO group in MIGRATE. ARC-Small is a subset consisting of 54 tasks with grids up to a maximum of 64 cells, created to measure variance across search methods via repeat runs.⁵

Throughout these experiments, we fix the number of greedy samples at $\beta=1$. The results in Fig. 7 reveals that the optimal configuration of online sand NS samples vary across domains. Particularly, Semantle benefits from more NS samples, Dockstring performs the best with an equal ratio of samples, while ARC prefers a higher proportion of online samples. These results highlights the importanced of tuning α and γ when applying MIGRATE to different domains.

B.3.2 VARYING β SAMPLES

We explore varying the number of greedy samples on Semantle. In these experiments, we run MIGRATE with $\alpha=0$ onlines amples, β greedy samples, and $N-\beta$ neighborhood sampless. As

⁵Note that we ensure ARC-Small maintains the same difficulty distribution as ARC-Full.

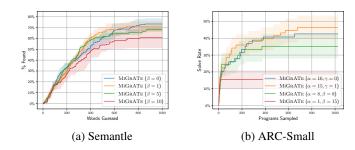


Figure 8: Comparing β on Semantle and ARC. MIGRATE shows a bias towards smaller β for better performance on Semantle and ARC-Small.

shown in Fig. 8a, performance remains relatively similar over $\beta=0,1,5,10$ with a small trend of better performance with smaller β . In tandem with the results on varying γ , this supports the potential of more off-policy methods of performing TTT with GRPO.

	Semantle		Dockstring	
Method	% Found	QED (†)	Vina Score (↓)	Overall Score (†)
NS OPRO	$\frac{45.30 \pm 2.49}{40.70 \pm 1.89}$	0.87 ± 0.01 0.90 ± 0.00	-9.65 ± 0.21 -9.94 ± 0.06	0.71 ± 0.00 0.74 ± 0.00
MIGRATE MIGRATE (OPRO)	71.30 ± 4.11 $\underline{65.3\% \pm 2.49}$	$0.90 \pm 0.00 \\ 0.90 \pm 0.00$	-11.00 ± 0.07 -10.80 ± 0.10	0.79 ± 0.00 0.78 ± 0.00

	ARC-Small			
Method	Pass@2 (%)	Oracle (%)		
NS OPRO	$48.15 \pm 0.00 \underline{50.62 \pm 1.75}$	$55.56 \pm 1.51 \\ \underline{59.26 \pm 0.00}$		
MIGRATE MIGRATE (OPRO)	51.23 ± 3.49 $44.44\% \pm 3.02$	62.35 ± 0.87 55.56 ± 0.04		

Table 6: **Comparing Prompt Optimization Techniques.** We compare the inference-only and MI-GRATE (TTT) performance of different prompt optimization techniques. All results are averaged over three random seeds, with the standard deviation reported. The best result in each column is marked in bold and the second best result is underlined. MIGRATE achieves the best performance across all metrics and ties with MIGRATE (OPRO) on optimizing QED for Dockstring. Notably, OPRO beats NS in every metric with the exception of accuracy on Semantle.

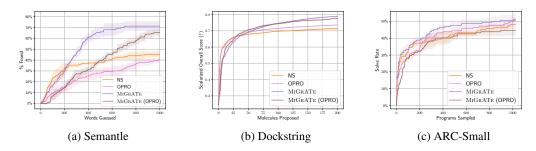


Figure 9: **Comparing Prompt Optimization Techniques.** MIGRATE (OPRO) shows similar performance to MIGRATE on Semantle and Dockstring and noticeably worse performance on ARC-Small.

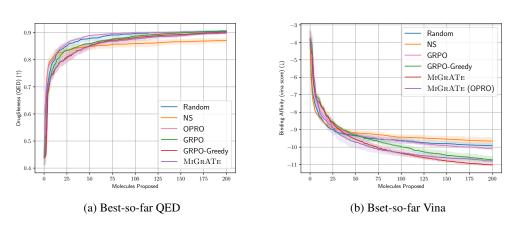


Figure 10: QED and Vina Score plots for Dockstring.

B.4 ALTERNATIVE LOCAL STRUCTURE SAMPLING IN MIGRATE?

We experiment with the alternative of using OPRO in place of neighborhood sampling (NS) in MIGRATE. Our results in Table. 6 and Fig. 9 show similar results between MIGRATE and MIGRATE (OPRO) on Dockstring and more favorable results towards MIGRATE on Semantle and ARC-Small. Compared to other baselines in Table 1, MIGRATE (OPRO) only underperforms relative to MIGRATE on Semantle and Dockstring. Notably, on ARC-Small, incorporating TTT into OPRO substantially degrades performance compared to inference-only OPRO. We also observe that OPRO achieves better performance than NS across most metrics. The varying performance of MIGRATE (OPRO) across domains suggests that NS is more compatible than OPRO with MIGRATE. In addition, the greater improvement achieved by using NS over OPRO suggests that the NS strategy of generating diverse variations may be better suited to TTT than OPRO, which focuses more on direct improvement of previous solutions.

C APPENDIX C: LLM PROMPTS

C.1 SEMANTLE: TASK PROMPT

Your task is to guess a hidden word from the English dictionary. Stick to proper, single-word English words. Now, guess exactly n=%s new word(s) that could be the hidden word. Be creative! (Note: give only a list of word(s) in the provided JSON format, e.g. "response": ["word1", "word2",...])

C.2 SEMANTLE: NEIGHBORHOOD SAMPLING PROMPT

Your task is to guess words related to a word from the English dictionary. Stick to proper, single-word English words. Now, guess exactly n=%s new word(s) that could be related to the word(s):

Word: %s

Be creative! (Note: give only a list of word(s) in the provided JSON format, e.g. "response": ["word1", "word2",...])

C.3 DOCKSTRING: TASK PROMPT

Your task is to find the optimal drug molecule that has both a high druglikeness (QED) as well as a strong binding affinity (vina) with the protein %s. For docking, lower is better (less than --10 is considered good) and for druglikeness, 1 is the best and 0 is the worst (greater than 0.8 is considered good). While both properties are important, the docking score is 10 times as important as the druglikeness score. If you propose an invalid molecule or make a repeat guess, you will get no score, so stick to valid SMILES strings.

Now, guess exactly n=%s new molecule(s).

(Note: give only a list of SMILES string(s) in the provided JSON format, e.g. "response": ["SMILES1", "SMILES2", ...])

C.4 DOCKSTRING: NEIGHBORHOOD SAMPLING PROMPT

Your task is to find the optimal drug molecule that has both a high druglikeness (QED) as well as a strong binding affinity (vina) with the protein %s. For docking, lower is better (less than --10 is considered good) and for druglikeness, 1 is the best and 0 is the worst (greater than 0.8 is considered good). While both properties are important, the docking score is 10 times as important as the druglikeness score. If you propose an invalid molecule or make a repeat guess, you will get no score, so stick to valid SMILES strings!

```
Here is my guess for a molecule:

SMILES: %s

Now, guess exactly n=%s new variation(s) of my molecule that could improve the scores to reach the optimal molecule.

(Note: give only a list of SMILES string(s) in the provided JSON format, e.g. "response": ["SMILES1", "SMILES2", ...])
```

C.5 ARC: TASK PROMPT

1358 1359

1386

1387

```
1360
1361
       Given input-output grid pairs as reference examples,
1362
       carefully observe the patterns to predict the output grid
1363
       for new test input. Each pair follows the same transformation
1364
       rule. Grids are 2D arrays represented as strings, with cells
       (colors) separated by spaces and rows by newlines. Here are
1365
       the input and output grids for the reference examples:
1366
1367
       Example 1:
1368
       Input:
1369
       [[1,1,1,\ldots,1]]
1370
       Output:
1371
       [[2,2,2,...,2]]
1372
       Example 2:
1373
       Input:
1374
       [[2,2,2,...,2]]
1375
       Output:
1376
       [[3,3,3,...,3]]
1377
1378
      Here is the input grid for the test example:
1379
       Input:
1380
       [[3,3,3,...,3]]
1381
1382
      Write a Python function 'transform' that can convert any
1383
       given input grid to its corresponding output grid based on
1384
       the pattern observed in the reference examples.
1385
```

C.6 ARC: NEIGHBORHOOD SAMPLING PROMPT

```
1388
1389
       Given input-output grid pairs as reference examples,
1390
       carefully observe the patterns to predict the output grid
1391
       for new test input. Each pair follows the same transformation
       rule. Grids are 2D arrays represented as strings, with cells
1392
       (colors) separated by spaces and rows by newlines.
1393
1394
       Here are the input and output grids for the reference
1395
       examples:
1396
       Example 1:
1397
       Input:
1398
       [[1,1,1,...,1]]
1399
       Output:
1400
       [[2,2,2,...,2]]
1401
1402
      Here is the input grid for the test example:
1403
```

```
1404
       Input:
1405
       [[3,3,3,\ldots,3]]
1406
1407
       The goal is to write a Python function 'transform' that can
1408
       convert any given input grid to its corresponding output
       grid based on the pattern observed in the reference examples.
1409
1410
       Here is my guess for the function:
1411
       '''python
1412
       def transform(input: np.ndarray) -> np.ndarray:
1413
          # Code
       . . .
1414
1415
       Provide a variation of my quess that could be the correct
1416
       answer.
1417
```

C.7 DISCOVERYBENCH: TASK PROMPT

You are a research scientist who is interested in data-driven research using the provided dataset(s) and query. Be creative and think of an interesting new experiment to help answer the provided scientific query. Explain in natural language the experiment plan that the programmer should follow (do not provide the code yourself). Here are a few instructions that you must follow:

- 1. Strictly use only the dataset(s) provided and do not simulate dummy/synthetic data or columns that cannot be derived from the existing columns.
- 2. The experiment plan should be creative, independent, and self-contained.
- 3. Use the prior experiments (if any) as inspiration to think of an interesting and creative new experiment. However, do not repeat the same experiments.

Here is a possible approach to coming up with a new experiment plan:

- 1. Find an interesting context: this could be a specific subset of the data. E.g., if the dataset has multiple categorical variables, you could split the data based on specific values of such variables, which would then allow you to validate a hypothesis in the specific contexts defined by the values of those variables.
- 2. Find interesting variables: these could be the columns in the dataset that you find interesting or relevant to the context. You are allowed and encouraged to create composite variables derived from the existing variables.
- 3. Find interesting relationships: these are interactions between the variables that you find interesting or relevant to the context. You are encouraged to propose experiments involving complex predictive or causal models.
- 4. You must require that your proposed experiment plan is based on robust statistical tests. Remember, your programmer can install python packages via pip which can allow it to write code for complex statistical analyses.

5. Multiple datasets: If you are provided with more than one dataset, then try to also propose an experiment that utilize contexts, variables, and relationships across datasets, e.g., this may involve using join or similar operations.

"Generally, in typical data-driven research, you will need to explore and visualize the data for possible high-level insights, clean, transform, or derive new variables from the dataset to be suited for the investigation, deep-dive into specific parts of the data for fine-grained analysis, perform data modeling, and run statistical tests.

Examples of valid experiment plans:

Experiment plan #1:

- 1. Merge the datasets offshore, immigration, and native_employment on the common columns 'year' and 'beaind'.
- 2. Replace infinite values with NaNs and drop rows with NaNs in any column.
- 3. Independent variables: 'iv_offshoring_1', 'penetration'
- 4. Fit the OLS regression modela

Experiment plan #2:

- 1. Chose BMI as dependent variable.
- 2. Time preference (independent) variables as 'DISSAVED' and 'SAMESAVE'.
- 3. Fit an OLS regression model and returned the model summary.

Plan an experiment to answer the question about the following dataset.

{dataset_metadata}

Now create exactly {n} new experiment plans that could answer the scientific question. Note: give only a list of experiment plans in the provided JSON format, e.g. {"response": ["experiment_plan_1", "experiment_plan_2", ...]})

C.8 DISCOVERYBENCH: NEIGHBORHOOD SAMPLING PROMPT

You are a research scientist who is interested in data-driven research using the provided dataset(s) and query. Be creative and think of an interesting new experiment to help answer the provided scientific query. Explain in natural language the experiment plan that the programmer should follow (do not provide the code yourself). Here are a few instructions that you must follow:

- 1. Strictly use only the dataset(s) provided and do not simulate dummy/synthetic data or columns that cannot be derived from the existing columns.
- 2. The experiment plan should be creative, independent, and self-contained.

1512
1513
3. Use the prior experiments (if any) as inspiration to think
1514 of an interesting and creative new experiment. However, do

not repeat the same experiments.

Here is a possible approach to coming up with a new experiment plan:

- 1. Find an interesting context: this could be a specific subset of the data. E.g., if the dataset has multiple categorical variables, you could split the data based on specific values of such variables, which would then allow you to validate a hypothesis in the specific contexts defined by the values of those variables.
- 2. Find interesting variables: these could be the columns in the dataset that you find interesting or relevant to the context. You are allowed and encouraged to create composite variables derived from the existing variables.
- 3. Find interesting relationships: these are interactions between the variables that you find interesting or relevant to the context. You are encouraged to propose experiments involving complex predictive or causal models.
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- 5. Multiple datasets: If you are provided with more than one dataset, then try to also propose an experiment that utilize contexts, variables, and relationships across datasets, e.g., this may involve using join or similar operations.
- "Generally, in typical data-driven research, you will need to explore and visualize the data for possible high-level insights, clean, transform, or derive new variables from the dataset to be suited for the investigation, deep-dive into specific parts of the data for fine-grained analysis, perform data modeling, and run statistical tests.

Examples of valid experiment plans:

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- 1. Merge the datasets offshore, immigration, and native_employment on the common columns 'year' and 'beaind'.
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- 3. Independent variables: 'iv_offshoring_1', 'penetration'
- 4. Fit the OLS regression modela

Experiment plan #2:

- 1. Chose BMI as dependent variable.
- 2. Time preference (independent) variables as 'DISSAVED' and 'SAMESAVE'.
- 3. Fit an OLS regression model and returned the model summary.
- Plan an experiment to answer the question about the following dataset.

```
1566
        {dataset_metadata}
1567
1568
        PRIOR EXPERIMENTS
1569
        Now create exactly \{n\} new experiment plans that could
1570
        answer the scientific question and are **similar** to the
1571
        prior experiments. Note: give only a list of experiment
1572
        plans in the provided JSON format, e.g. {"response": ["experiment_plan_1", "experiment_plan_2", ...]})
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```