

COMPASS: Critique-guided Optimization of MetaPolicies for Agentic Systems with Reinforcement Learning

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Abstract

As large language models are increasingly deployed as autonomous agents, optimizing their behavior in agentic reasoning and tool-use environments remains challenging due to the stochasticity of environment trajectories and associated high reward latencies. Existing automated prompt optimization (APO) paradigms struggle in these regimes: discrete evolutionary methods (e.g., GEPA, ACE) lack parametric memory, while instance-level reinforcement learning (RL) approaches suffer from severe gradient variance and reward collapse on small, human-curated datasets. To address these limitations, we introduce COMPASS (Critique-guided Optimization of MetaPolicies for Agentic Systems), a sample-efficient dual-agent framework that shifts optimization toward task-level metapolicies and demonstrates that an RL-based prompter policy can be effectively trained on such tasks. To overcome sparse feedback, COMPASS introduces a Critique Experience Buffer that couples scalar rewards with dense textual critiques. This mechanism allows an active “Prompter” policy to internalize corrective linguistic patterns and amortize experiential self-reflection directly into its weights. Empirical evaluations demonstrate that COMPASS stabilizes training and yields up to $2.4\times$ faster convergence. On complex reasoning (BBEH) and tool-use (τ -bench) benchmarks, our framework improves success rates from 55% to 90% and 74% to 91%, respectively, while naturally discovering specialized algorithmic strategies.

1 Introduction

The scaling of language models to trillions of parameters has shifted the deployment paradigm from open-weight architectures to proprietary, API-gated inference endpoints (e.g., Gemini-Pro, GPT-5, Claude). Unlike earlier models that permit-

ted direct weight updates on task-specific datasets, these “black-box” APIs restrict access to internal states and gradients. Consequently, developers cannot independently apply Parameter-Efficient Fine-Tuning (PEFT) (Houlsby et al., 2019) methods like LoRA (Hu et al., 2021) on their own infrastructure. While some providers offer hosted fine-tuning, these services remain opaque and unevenly supported, effectively bottlenecking traditional gradient-based adaptation. To bypass these constraints, the field has pivoted toward In-Context Learning (ICL) (Brown et al., 2020). By modulating the input context, one can steer the model behavior without altering the underlying weights. However, relying purely on manual prompt engineering inherently limits optimal task performance, though it can be effective in many contexts depending on task complexity versus model capability.

Several Automated Prompt Optimization (APO) techniques rely on heuristic search or LLM reflections (Zhou et al., 2023; Pryzant et al., 2023; Yang et al., 2023), lacking a structured policy framework. Recent Reinforcement Learning (RL) techniques address this (Deng et al., 2022; Singhal et al., 2026; Asawa et al., 2025) by decoupling control from execution: a small, trainable “Prompter” policy learns strategies executed by a frozen, massive “Worker” LLM. While approaches like Advisor models (Asawa et al., 2025) successfully adapt prompts via instance-level guidance for certain tasks, we empirically observe that instance-level prompting suffers from high variance during policy optimization on complex reasoning and agentic tasks with small datasets. Furthermore, highly stochastic agentic workflows (e.g., tool-use) involve long-horizon execution and non-deterministic environment transitions. In these settings, evaluating rewards on isolated instances yields unacceptably noisy gradients. In addition, these tasks also introduce new challenges of high reward function latency in training.

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To resolve this, our framework introduces a **task-level optimization objective**. Instead of generating a unique prompt per input, our Prompter takes the broader task description as context to learn a generalized strategy. By aggregating the reward over a representative dataset sample, we smooth environmental stochasticity and stabilize the RL training signal. However, this task-level aggregation inherently increases the evaluation time required for each training update (which can be mitigated to some extent with parallelization). To compensate for this computational burden and overcome reward sparsity, we augment this architecture with a **critique experience buffer**. By blending coarse scalar rewards with dense, evolving textual critiques, this buffer amortizes LLM reflections directly into an experiential prompter policy, extracting maximum signal from every batch to enable faster convergence with improved sample efficiency, and stronger performance on reasoning and tool-use tasks. Furthermore, with the task-level objective aggregated critiques from the evaluation loop provide more stable text critiques.

2 Related Work

The automation of prompt engineering has evolved from discrete heuristic searches to differentiable and reinforcement learning-based optimization (Cui et al., 2025), a transition recently formalized by unified modular frameworks like *promptolution* (Zehle et al., 2025). We categorize these approaches to contextualize COMPASS and our shift toward task-level metapolicies.

Discrete and Evolutionary Prompt Optimization: Early methods formulate prompt generation as a search problem (Zhou et al., 2023; Pryzant et al., 2023). This paradigm expanded into treating the LLM as an optimizer that refines prompts via trajectory histories (Yang et al., 2023), or back-propagates textual feedback for discrete input adjustments (Yuksekgonul et al., 2024). Evolutionary algorithms further improve sample efficiency via reflective mutation operations (Agrawal et al., 2025; Fernando et al., 2023). While effective, these heuristic searches lack a parametric memory, meaning they cannot easily transfer learned optimization strategies across task distributions.

Continuous and Programmatic Meta-Learning: Continuous methods optimize embedding vectors (soft prompts) via back-propagation (Lester et al., 2021), though they

fundamentally lack interpretability. Hybrid approaches alternate between local gradient updates and semantic search (Guo et al., 2024). Frameworks such as DSPy approach the problem programmatically, compiling declarative logic into optimized execution pipelines (Khattab et al., 2023), while Prompt-MII leverages meta-learning for single-pass task induction (Xiao et al., 2025).

RL and Experiential Memory: Recent work applies RL directly to prompt generation by decoupling control from execution (Deng et al., 2022; Singhal et al., 2026; Asawa et al., 2025; Liu et al., 2026). However, as previously noted, instance-level RL struggles with the high variance and latency inherent to agentic tool-use environments. While recent works rely on scalar feedback, COMPASS is uniquely grounded in Experiential RL (Shi et al., 2026) and Self-Imitation Learning (Oh et al., 2018). We utilize an augmented experience buffer to reuse critiques generated as side information from costly environment interaction in the sampling and policy update. Rather than relying on sparse scalar rewards alone, this mechanism allows the Prompter to directly internalize corrective linguistic patterns into its weights through an amortized reflection loop (detailed in the Appendix).

3 Summary of Key Contributions

We present COMPASS, a framework for training a critique-guided metapolicy with an experience buffer to steer black-box reasoning and tool-use agents. Our key contributions are:

- **Task-Level Metapolicies:** We propose a Dual-Agent architecture that shifts prompt optimization from high-variance instance-level generation to task-level metapolicies for agentic tasks. This enables the model to distill complex reasoning trajectories into a generalized strategy that smoothly handles environmental stochasticity.
- **Critique Experience Buffer:** We introduce a high-bandwidth feedback mechanism that couples sparse scalar rewards with dense textual critiques. We demonstrate that this framework yields up to $2.4\times$ faster convergence.
- **Empirical Validation on Reasoning and Tool-Use:** We demonstrate substantial gains on BBEH and a modified, non-interactive version of τ -bench, raising success rates from $\sim 55\%$ baselines to 90% on logic-intensive

tasks, and from 74% to 91% on agentic tool-use tasks.

- **Discovery of Algorithmic Strategies:** Through qualitative analysis, we show the Prompter naturally evolves to discover specialized operational strategies, such as atomic sequencing of tool calls in the airline domain and list-batching protocols in retail workflows (see Appendix E, F for detailed prompt evolution).

4 Methodology

The overall approach is illustrated in Figure 1. We formulate the problem of Automatic Prompt Optimization (APO) as a Reinforcement Learning (RL) problem where a *Prompter Policy* π_θ generates instructions to guide a frozen *Task Model* $\mathcal{M}$ (e.g., Gemini-Pro or GPT-5) using a combination of scalar rewards and rich text critique feedback implemented with an experience buffer. The experience buffer is added to overcome the RL “cold start” problem and provide richer learning signals to the prompter, with an iterative text-feedback mechanism using an external feedback model M_{FB} , which will be further described below.

4.1 Prompter Policy Framework

Let $D = \{(x_i, y_i)\}_{i=1}^N$ be a dataset of inputs x and ground truth targets y . Let p denote the system instruction (prompt) generated by the policy π_θ . Let π_{ref} represent a fixed anchor policy, typically the initial state of the prompter before RL tuning. The reward $R(p, x, y)$ is defined by the performance of the frozen model $\mathcal{M}$ when prompted with p on input x to produce target y . All learning is localized within π_θ to discover optimal prompts that steer the agent toward high-accuracy reasoning paths.

4.1.1 General RL Objective with Dual Agent Architecture

We utilize a dual-agent architecture common in APO RL frameworks to segregate *planning*, i.e., *instruction generation* from *execution*:

- **Prompter Agent (π_θ):** A smaller, efficient LLM (e.g., Gemini Flash-Lite). Its role is strategic and analyzes the input and the accumulated experience to output a task prompt. Gradients are applied exclusively to this model.
- **Frozen Worker Agent (π_{LLM}):** A large reasoning engine (e.g., Gemini Flash or Pro). It is

treated as a static environment component that executes the instructions generated by the Prompter.

The goal is to learn parameters θ for the prompter policy $\pi_\theta(\cdot)$ that maximize the expected reward over the dataset D , while controlling deviation from the anchor policy π_{ref} . The objective is defined as:

$$J(\theta) = \mathbb{E}_{(x,y) \sim D, p \sim \pi_\theta(\cdot|c, \mathcal{H})} \left[R(p, x, y) - \alpha D_{KL}(\pi_\theta \| \pi_{ref}) \right] \quad (1)$$

where D_{KL} is the Kullback-Leibler divergence and $\alpha \geq 0$ is a regularization coefficient. We optimize this using Policy Gradient methods.

4.1.2 Optimization Regimes

Fixed Prompt Optimization (Context-Agnostic): In this setting, the prompter policy receives no context information ($c = \emptyset$). The policy learns a single, static prompt p^* that generalizes across the distribution D :

$$\theta^* = \underset{\theta}{\operatorname{argmax}} \mathbb{E}_{(x,y) \sim D} [R(p, x, y)] \quad (2)$$

where $p \sim \pi_\theta(\cdot)$

Note that unlike conventional RL, policy here is just a means to an end, and we really care about the optimal prompt at the end of training. This matches the other APO techniques which are optimized to find a single prompt.

Dynamic (Task-Conditional) Prompt Optimization: More generally, for a set of tasks $\mathcal{T} = \{T_1, \dots, T_k\}$, the context c at the input to the prompter is set to the task description $d(T_j)$. The policy acts as a meta-learner, adapting the strategy dynamically:

$$J_{MT}(\theta) = \mathbb{E}_{T_j \sim \mathcal{T}} \left[\mathbb{E}_{(x,y) \sim D_{T_j}} [R(p, x, y)] \right] \quad (3)$$

where $p \sim \pi_\theta(\cdot|c = d(T_j), \mathcal{H})$

This is illustrated in Figure 1, where reward is computed as aggregated reward over sampled slice of the dataset conditioned on the input context to the prompter.

4.2 Critique Feedback and Experience Buffer

4.2.1 Feedback-Augmented Context

We define a critique f as a natural language description of the discrepancies between the frozen

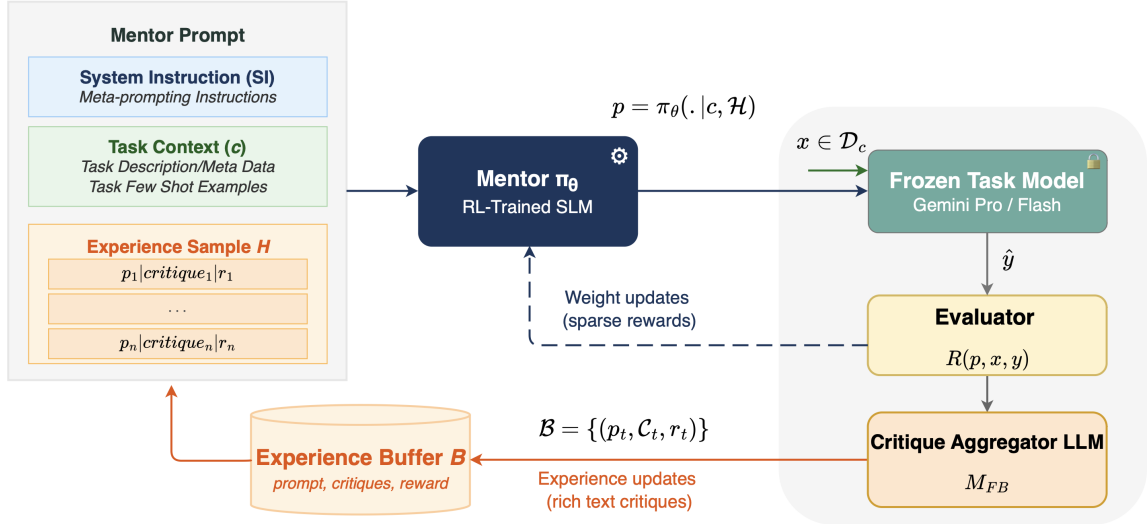


Figure 1: **COMPASS Framework.** The Prompter Policy π_θ generates a prompt p conditioned on task context c , sampled experience history $\mathcal{H}$, which instructs the frozen Task Model $\mathcal{M}$ to produce response y for input x . The reward is computed as aggregated reward over a slice of sampled data D_c conditioned on the input context c .

model’s response $\hat{y} = M(x, p)$ and the ground truth y . For a given prompt p , we construct a critique set $\mathcal{C} = \{(x_j, y_j, \hat{y}_j, f_j)\}_{j=1}^K$ using a subset of K examples.

To enable the prompter policy π_θ to learn from historical performance, we introduce a performance buffer $\mathcal{B}$. The buffer stores a diverse set of trajectories $\mathcal{T} = (p, \mathcal{C}, r)$, the prompt, critiques/reasoning of passes/failures and the rewards respectively. Crucially, while the buffer explicitly filters for prompts with high aggregate rewards (as detailed in Section 4.2.2), the critique set $\mathcal{C}$ captures granular textual feedback on both successful and failed example-level predictions for those retained prompts. The policy is conditioned on a sampled history $\mathcal{H}$ from $\mathcal{B}$

$$p \sim \pi_\theta(\cdot | c, \mathcal{H}) \quad (4)$$

where $\mathcal{H} = \text{Sample}(\mathcal{B})$. We draw inspiration from AlphaEvolve (Novikov et al., 2025) which stored previously discovered code variants in a database and used it guide LLMs. By providing both successes and failures in the data, the prompter can identify specific instructional patterns that either resolve or exacerbate reasoning errors.

4.2.2 Critique Experience Buffer Algorithm

At each training step t , the system generates a set of n candidate prompts $\{p_t^{(1)}, \dots, p_t^{(n)}\}$. These are generated as part of the sampling in the RL training updates and cached in the buffer. We implement a threshold-based update strategy. Let r_{max} be the

maximum reward achieved in the current batch. A prompt $p_t^{(i)}$ is added to the buffer if its aggregate reward $r_t^{(i)}$ satisfies:

$$r_t^{(i)} \geq r_{max} - \epsilon \quad (5)$$

where $\epsilon \geq 0$ is a tolerance hyperparameter. When $\epsilon = 0$, the buffer follows a greedy update, storing only the best-performing prompt. As ϵ increases, the buffer captures a broader distribution of high-performing instructions, enhancing the diversity of the historical context $\mathcal{H}$.

4.2.3 Amortized Multi-Turn Reflection with Buffer

Generally speaking, the prompter agent can be improved using multi-turn self-reflection in each training update, i.e using experiential reinforcement learning (Shi et al., 2026). However this could be computationally expensive. We postulate that our proposed implementation with an experience buffer approximates this approach and provide a formal justification in Appendix A.

By conditioning the prompter on the historical critiques, we effectively transform the prompt optimization problem into an multi-step reflection/improvement process where each new prompt is an informed correction of its predecessors, while guided by grounded scalar rewards, thereby improving the information gain in training. Details of the algorithm can be found in Algorithm 1.

Algorithm 1 COMPASS RL Algorithm with Experience Buffer

```
1: Input: Training set of contexts  $\mathcal{T}$ , initial prompter  $\pi_\theta$ , reference policy  $\pi_{ref}$ , frozen agent  $M$ , feedback model  $M_{FB}$ , threshold  $\epsilon$ .
2: Initialization:
3: for each context  $c \in \mathcal{T}$  do
4:   Generate initial prompt  $p_{0,c}$  and critiques  $\mathcal{C}_{0,c}$  via  $M_{FB}$ 
5:   Compute initial reward  $r_{0,c}$  using  $M$  and dataset  $\mathcal{D}$ 
6:   Initialize context-specific buffer  $\mathcal{B}_c \leftarrow \{(p_{0,c}, \mathcal{C}_{0,c}, r_{0,c})\}$ 
7: end for
8: Combine sub-buffers into global buffer  $\mathcal{B} = \bigcup_c \mathcal{B}_c$ 
9:
10: for training step  $t = 1 \dots N$  do
11:   Sample task context  $c \sim \mathcal{T}$ 
12:   Sample historical context  $\mathcal{H}_c \sim \text{Sample}(\mathcal{B}_c)$ 
13:   Generate  $n$  candidates:  $p_{t,c}^{(i)} \sim \pi_\theta(\cdot \mid c, \mathcal{H}_c)$ 
14:   for each candidate  $i$  do
15:     Execute  $M(x, p_{t,c}^{(i)})$  to obtain  $\hat{y}_i$  and compute reward  $r_{t,c}^{(i)}$ 
16:     Generate critiques  $\mathcal{C}_{t,c}^{(i)}$  via  $M_{FB}$  based on failures in  $\hat{y}_i$ 
17:   end for
18:   Identify local batch maximum:  $r_{max,c} \leftarrow \max_i(r_{t,c}^{(i)})$ 
19:   for each candidate  $i$  do
20:     if  $r_{t,c}^{(i)} \geq r_{max,c} - \epsilon$  then
21:       Update context-specific buffer:  $\mathcal{B}_c \leftarrow \mathcal{B}_c \cup \{(p_{t,c}^{(i)}, \mathcal{C}_{t,c}^{(i)}, r_{t,c}^{(i)})\}$ 
22:     end if
23:   end for
24:   Compute  $J(\theta)$  using policy gradient with KL penalty on  $\pi_{ref}$ 
25:   Update  $\theta$  via gradient descent
26: end for
27: return Optimized prompter  $\pi_\theta$ 
```

5 Experiments

We evaluate the proposed approach on two complementary benchmarks i) logic-intensive reasoning tasks from the Big Bench Extra Hard (BBEH) suite (Kazemi et al., 2025) and ii) agentic tool-use workflows from Tau Bench (Tool-Agent-User Interaction Benchmark) (Yao et al., 2024). The experiments are designed to answer the following questions.

- **RQ 1 - Reasoning Tasks:** Does COMPASS improve the performance over SOTA evolutionary benchmarks for reasoning tasks?
- **RQ 2 - Validating Experience Buffer:** Does rich feedback with experience buffer improve sample efficiency and enable faster convergence? (as suggested by the formulation in Appendix A)
- **RQ 3 - Tool-use Agentic Tasks:** Does COMPASS improve the performance over SOTA evolutionary benchmarks for multi-step agentic tool-use tasks?
- **RQ 4.1 - Cross Model Generalization (Transferability):** Can a policy trained on a model effectively steer another model of different capability and/or be forward compatible?

- **RQ 4.2 - Cross Model Generalization (Performance Bridging)** What is the cost benefit of the architecture? How does performance of a smaller worker + learned policy compare with large worker + zero shot prompting?

5.1 Baselines

We compare our approach against the following baselines,

- **Naive Prompting:** For BBEH tasks, an improved prompt that is obtained by a single refinement call to an LLM with a simple prompt (“Let’s think step by step”), a task definition and few shot examples. For τ -bench tasks, using the publicly available prompt. These baseline prompts are used as the seed/starter prompts for both GEPA and COMPASS experiments.
- **GEPA (Genetic-Pareto)** (Agrawal et al., 2025): A SOTA discrete search method that evolves prompt populations without gradient updates.

We additionally experimented with an instance-level policy baseline (similar to Advisor (Asawa et al., 2025)), conditioning on instance-specific inputs) on BBEH tasks. However, we did not observe any meaningful performance improvements

Table 1: Reasoning Performance on BBEH Benchmarks.

Method	Disambiguation QA	Dyck Languages	Web of Lies [§]
Baseline	57.08% $\pm$ 17.0%	63.33% $\pm$ 13.0%	52.50% $\pm$ 8.0%
GEPA	63.88% $\pm$ 17.0% (+6.80%)	79.16% $\pm$ 8.0% (+15.83%)	67.50% $\pm$ 9.0% (+15.00%)
COMPASS	65.41% $\pm$ 16.0% [†] (+8.33%)	91.25% $\pm$ 6.0% ^{‡*} (+27.92%)	90.12% $\pm$ 7.0% ^{‡**} (+37.62%)

95% CIs calculated with paired bootstrap. [†] $p < 0.001$, [‡] $p < 0.05$ vs. Baseline; ^{**} $p < 0.001$, ^{*} $p < 0.05$ vs. GEPA.

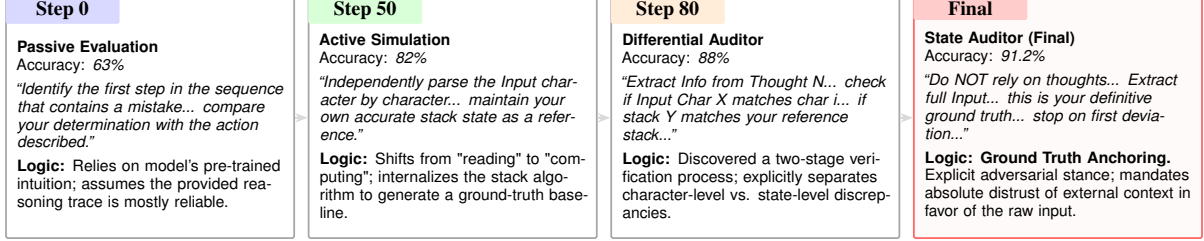


Figure 2: **Evolution of the Dyck Languages Prompts.** The policy moves from a passive "Expert Persona" to a rigorous algorithmic "State Auditor".

due to the limited size of the dataset ($\mathcal{O}(100)$ instances), validating our approach to use task-level policy learning for agentic tasks with small, curated datasets.

5.2 Setup

Our experimental framework leverages the Agent Development Kit (ADK) and standard RL training frameworks. This allows for scalable distributed training for agents in a cloud environment, managing the asynchronous calls to the Vertex AI endpoints for the frozen models, with gradient updates on the prompter models. The dataset details have been provided in Appendix B.

Here we use Gemini 2.5 Flash as the frozen Task Model $\mathcal{M}$ and Gemini 2.5 Flash-lite for the trainable prompter policy π_θ ((Gemini Team, 2025)). For these tasks, we find that performance is not very sensitive to KL divergence weights in the loss. Because we extract discrete prompts for a set of tasks rather than deploying the policy for general inference, and this combined with early stopping and the base model's strong language priors prevent the policy collapse typical of weakly-penalized RLHF. This allows safe, meaningful divergence from π_{ref} while learning to generate prompts. We use a thinking budget of 4096 tokens for task and critique LLMs, and unconstrained thinking for the prompter LLM and adopt a standard train/validation/test split. GRPO algorithm (Shao et al., 2024) with Adam Optimizer and learning rate of 1e-5 is used. The

meta system instruction used for the prompter policy model itself is provided in Appendix C.

5.2.1 Prompt Selection

To prevent overfitting and minimize computational overhead, we implement an early stopping criterion where training terminates if the evaluation reward does not improve for 10 consecutive steps (across the ensemble of trained tasks). We define the Convergence Step ($Step_{conv}$) as the step achieving the peak aggregated evaluation reward prior to this trigger. The "Final" prompt represents the top-performing candidate generated at $Step_{conv}$. Note that while Figure 3 plots trajectories up to 200 steps to capture the full baseline run ($Step_{conv} = 195$), the buffer-augmented policy achieved $Step_{conv}$ much earlier at step 102.

5.3 RQ 1: Results on Reasoning Tasks

Table 1 shows a summary of performance across the three tasks. The proposed approach achieves a consistent performance gain over both the zero-shot baseline and the GEPA algorithm. Specifically, we observe highly significant improvements ($p < 0.001$) in logical and algorithmic domains such as *Dyck Languages* and *Web of Lies*, with absolute gains of up to 37.62%. We also note that the datasets are smaller with < 50 evaluation samples for Dyck Languages and Web of Lies tasks, and even lower for the DQA task.

The gains are most pronounced in *Web of Lies*,

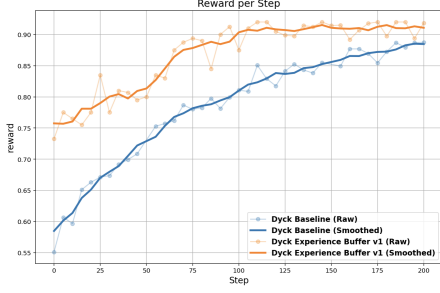


Figure 3: Reward progression for a BBEH task (Dyck Languages) with and without experience buffer

where the proposed approach significantly outperforms GEPA ($p < 0.001$). While the policy also outperforms GEPA on *Disambiguation QA* nominally, the high linguistic variance inherent to the task and the smaller evaluation data size results in a non-significant margin ($p < 0.25$) against that specific baseline, despite maintaining a robust gain over the zero-shot baseline ($p < 0.05$).

These results suggest that our approach is highly effective across reasoning tasks, and specifically on algorithmic and logic tasks. Complete prompts and analysis are included in the appendix C, E. Figure 2 illustrates the prompt evolution with training and increasing accuracy for Dyck Languages task.

5.4 RQ 2: Impact of Critique Experience Buffer

We evaluate the impact of augmenting scalar rewards with critique text feedback using the proposed experience buffer. While the final performance gains are relatively modest, the inclusion of text critiques significantly improves sample efficiency. Specifically, the RL policy achieves convergence in half the training steps (42% for Disambiguation QA and 52% for Dyck Languages) required by the scalar-only baseline as shown in table 2. We attribute this to the information gain with the richer feedback signals provided by textual critiques (see Appendix A for more analysis). By informing the prompter what prompts succeeded and why a candidate succeeded or failed for a prompt, the feedback mechanism enables a more focused traversal of the instruction space compared to the trial-and-error nature of pure scalar reinforcement.

5.5 RQ 3: Results on Tool Use Tasks

These tasks require the model to not just answer questions, but interact with tool-use APIs over several steps (e.g., a flight booking system or a retail database). We evaluate the prompter policy

Table 2: Performance and Training Efficiency Gains via Critique Experience Buffer.

Domain	Method	Success Rate (Δ)	$Step_{conv}$	Rel. Efficiency
Dyck	COMPASS (without buffer)	88.68%	195	—
	COMPASS	91.25% (+2.57%)	102	1.91×
DQA	COMPASS (without buffer)	62.5%	180	—
	COMPASS	65.41% (+2.91%)	75	2.40×

Table 3: Tool Use Performance on modified non-interactive τ -bench. Success rates are reported as pass@3.

Method	Retail Success	Airline Success
Baseline (Gemini 2.5 Flash)	73.91%	65.27%
GEPA	82.60% (+8.69%)	79.16% (+13.89%)
COMPASS	91.30% (+17.30%)	83.33% (+18.06%)

on τ -bench (Yao et al., 2024), a modular framework for testing language agents against complex, domain-specific rules. Unlike static benchmarks, τ -bench requires navigating multi-step API interactions to resolve intents within two realistic environments: **Retail** (order modifications and inventory constraints) and **Airline** (multi-hop reasoning for flight bookings and baggage policies) as shown in table 3. Success is measured by comparing the final database state against a unique ground-truth outcome.

To isolate tool-calling logic from conversational noise with a prompted user LLM, we utilize a modified, non-interactive variant of τ -bench. In this setup, the initial user query is pre-populated with all necessary information (normally withheld by incremental disclosure policy in the user LLM), bypassing the interactive user simulator while maintaining the requirement for sequential, dependent tool calls (see Appendix D for details). We report pass@3 on this modified benchmark to account for agent stochasticity. COMPASS shows upto +18% gains over the baseline and up to +9% gains over GEPA.

5.6 RQ 4: Cross-Model Generalization

To address RQ 4, we evaluate the prompter policy trained for a *Gemini 2.5 Flash* task model to models of varying scales: *Gemini 2.5 Flash-lite* (small) and *Pro* (large). Table 4 summarizes these results on the Dyck Languages task.

5.6.1 Transferability and Forward Compatibility.

COMPASS exhibits reasonable forward compatibility. Although optimized for the *Flash* model, the policy successfully steered the more capable *Pro*

Table 4: Cross-Model Transferability and Performance Bridging on Dyck.

Frozen Model	Baseline (Zero-Shot)	Optimized (Ours)	Gain (Δ)
Flash-lite (Small)	42.5%	47.5%	+5.0%
Flash (Medium)	63.0%	91.0%	+28.0%
Pro (Large)	72.5%	80.0%	+7.5%

model to an 80% success rate, with a 7.5% improvement over its zero-shot baseline. This suggests the discovered instructions target general logical heuristics rather than model-specific quirks. However, the marginal 5% gain on a lower baseline for *Flash-lite* suggests a "capability floor". The frozen model must possess a baseline reasoning capacity to execute the specialized algorithmic protocols discovered by the prompt. On the other hand, it is clear that prompts could be further improved for Pro.

5.6.2 Performance Bridging

Flash model using our optimized prompt (91%) outperforms the larger *Pro* model in with zero-shot prompting (72.5%). This confirms that instructional steering can effectively bridge generational gaps, allowing a mid-tier model to approach a larger model’s capabilities at a lower inference cost. We note, however, that these preliminary results are limited to the Dyck tasks and a single family of models. A broader analysis across diverse tasks and models is needed to fully answer the questions on cross-model transferability of optimized prompts.

5.7 GEPA vs COMPASS Prompts

Tables 5 and 6 summarize how COMPASS-tuned prompts outperform GEPA prompts by replacing abstract guidance with concrete, algorithmic workflows. The unifying theme is the enforcement of strict operational safeguards, such as ground truth anchoring and adversarial testing. These constraints force the model to actively compute and verify its logic, drastically reducing hallucinated certainty. Full prompts of both GEPA and our approach are included in Appendix E, F

6 Conclusions

We proposed COMPASS, a reinforcement learning framework for automatic prompt optimization across reasoning and tool-use tasks. Our results demonstrate that shifting to task-level metapolicies with reward aggregation across data slices stabilizes training, while coupling scalar rewards with

Table 5: Comparison of COMPASS Prompt Mechanisms against GEPA for Big Bench.

Task	RL Prompt Mechanisms	Key RL Advantage over GEPA
Dyck Languages	- Ground Truth Anchoring - Independent Active Simulation - Dual-State Verification	Active Computation: Strictly enforces distrust of provided traces, forcing active state simulation to prevent hallucination.
Web of Lies	- Symbolic Translation ($==$, $!=$) - Anchor Initialization - Algorithmic Chaining	Algorithmic Heuristics: Replaces abstract substitution with rigid linear deduction, preventing logical branching errors.

Table 6: Comparison of COMPASS Prompt Mechanisms against GEPA for Tau Bench.

Task	RL Prompt Mechanisms	Key RL Advantage over GEPA
Tau Bench Retail	- Procedural Enforcement - Explicit Tool Anchoring - Constraint Highlighting	Operational Granularity: Enforces a strict, step-by-step reasoning process and explicit API mapping, preventing skipped intermediate steps and reducing tool ambiguity.
Tau Bench Air-line	- Sequential Guardrailng - Iterative Verification - Action Decoupling	Iterative Grounding: Anchors decisions directly to real data via mandatory tool calls and strict sequencing, preventing API errors caused by hallucination-prone internal reasoning.

critique-based feedback via an experience buffer substantially improves sample efficiency. Future work could explore adaptive buffer management, such as difficulty-aware critique selection and critique compression, to further enhance training dynamics.

While this work operated primarily in a “discovery mode” to identify optimal, task-specific prompts on a targeted set of benchmarks, a natural next step is zero-shot transfer. Evaluating whether the task metapolicy generalizes across unseen contexts without buffer initialization ($\mathcal{B} = \emptyset$) presents a promising direction for cross-task and cross-domain reasoning that we defer to future study.

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A Amortized Multi-Turn Reflection with Experience Buffer

We provide a justification for the prompter policy with experience buffer. We do this by characterizing the transition compared to a canonical, multi-turn and compute intensive reasoning process with self-reflection during training, to an efficient, amortized single-shot policy with feedback used by our approach.

A.1 The Canonical Baseline: Multi-Turn Reflection MDP

An experiential RL approach to prompt optimization can be represented as a fixed-state, multi-turn Markov Decision Process (MDP) defined by the tuple $(\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R})$ as follows:

- **Stationary State (s):** The initial state is defined by the static task context c and the dataset distribution $\mathcal{D}_c$ and remains the same during the training.
- **Sequential Actions ($a_1, \dots, a_T$):** Within a single episode, the prompter generates a sequence of prompts $p_1, \dots, p_T$ taking *several turns at each training update*.
- **Linguistic Transitions:** Each action p_t results in an observation f_t (the diagnostic critique). The policy at turn t is conditioned on the history of that specific episode: $\pi_\theta(p_t \mid c, \{p_i, f_i\}_{i < t})$.
- **Terminal Reward:** Gradients are computed only after T turns using the terminal reward r_T .

While mathematically sound, this “Reflection-at-Inference” setup is computationally prohibitive, requiring T sequential calls to the frozen model. Furthermore, it may suffer from credit assignment issues as the scalar signal r_T must be back-propagated through a long chain of discrete linguistic tokens, often leading to high-variance gradients.

A.2 Proposed Formulation: Online Experience-Augmented RL

To achieve single-shot efficiency, we propose to *amortize* the multi-turn reflection loop into the prompter policy weights, using *single-turn* training, with iterative experience gain. We redefine the process as an **Online Experience-Augmented MDP**, where the interaction history is moved from the temporal episode trajectory into a dynamic state-proxy: the Experience Buffer $\mathcal{B}$.

At training step k , we characterize the system components as follows:

- **State Space ($\mathcal{S}$):** A state $s_k \in \mathcal{S}$ is defined as the triple $s_k = (c, \mathcal{D}_c, \mathcal{B}_k)$, where $\mathcal{B}_k = \{(p_i, f_i, r_i)\}_{i < k}$ is the accumulated history of all prompts and critiques generated across prior training steps.
- **Action Space ($\mathcal{A}$):** The action a_k corresponds to the generation of a prompt $p_k \sim \pi_\theta(p \mid c, \mathcal{H})$ conditioned on a sampled history subset $\mathcal{H} \in \mathcal{B}_k$.
- **Transition Function ($\mathcal{P}$):** Upon generating p_k , the environment (Frozen Model + Critic) provides a reward r_k and critique f_k . The state transitions via a buffer update: $s_{k+1} = (c, \mathcal{D}_c, \mathcal{B}_k \cup \{(p_k, f_k, r_k)\})$.
- **Policy Update:** The weights θ are updated at each step k based on the immediate action p_k and its associated reward r_k .

A.3 Sample Complexity Reduction with Linguistic Information Gain

The reduction in sample complexity ($< 50\%$ steps to convergence in our experiments) can be formally explained by the linguistic information gain provided by the augmented state. Applying the Information Bottleneck principles (Tishby et al., 1999), we define policy efficiency by the mutual information $I(a^*; s_k)$ between the state and the optimal action.

In a standard “blind” RL setup, s_k is stationary ($s_k = c$), necessitating exhaustive stochastic search based on scalar rewards. In our framework, the state s_k is non-stationary and increasingly informative.

Following Goyal et al. (2019), textual critiques $f \in \mathcal{H}$ act as high-bandwidth linguistic reward signals. Because each critique in $\mathcal{B}_k$ provides diagnostic data about prior failures, we posit:

$$I(a^*; c, \mathcal{D}_c, \mathcal{B}_k) \gg I(a^*; c, \mathcal{D}_c, \emptyset) \quad (6)$$

This information gain prunes suboptimal branches of the search tree, concentrating policy mass on the optimal manifold $\mathcal{A}^*$ significantly faster than scalar-only exploration.

B Datasets

B.1 Reasoning Benchmarks: Big Bench Extra Hard (BBEH)

BBEH is a subset of the Big Bench benchmark containing tasks which current SOTA language models have found challenging, serving as a rigorous testbed for complex reasoning capabilities. We specifically analyze five diverse tasks as summarized in Table 7.

Evaluation Name	Task Description	Key Challenge & Capabilities
Disambiguation QA	Ambiguous Pronoun Resolution: Resolve pronouns in complex sentences (e.g., determining what “it” refers to in a trophy/suitcase scenario).	Interpretability: Tests semantic understanding of physical properties and world knowledge.
Dyck Languages	Formal Logic / Syntax: Identify the first mistake in a reasoning trace about correctly nested bracket sequences.	State Maintenance: Tests the ability to maintain a stack over long horizons; a proxy for algorithmic reasoning.
Web of Lies	“Knights and Knaves” Logic: Deduce the truthfulness of an entity based on a chain of statements from multiple agents.	Multi-step Deduction: Tests logical consistency; a single error in the chain invalidates the final answer.

Table 7: Benchmark Tasks from Big Bench Extra Hard (BBEH)

B.2 Tool Use Benchmarks: τ -Bench

While BBEH tests pure reasoning, we extend our evaluation to agentic workflows using τ -bench (Yao et al., 2024). These benchmarks simulate real-world customer service interactions where an agent must utilize APIs to manipulate a database while adhering to strict policy constraints.

Benchmark	Domains	Key Capabilities Evaluated
τ -Bench	Airline, Retail	State Management & Policy Adherence: Tests the ability to maintain database consistency over multi-turn conversations and strictly follow complex business rules (e.g., refund eligibility).

Table 8: Overview of Agentic Tool-Use Benchmarks

C Prompter System Instructions & Input Format

Prompt for Policy Model

```
<role>
You are an expert prompt engineer. Your function is to be strictly analytical and use the provided examples in
<few_shot_examples> to suggest a prompt for these tasks.
Your primary goal is to write the prompt to be clear, structured, and effective at guiding an LLM to perform a specific,
often complex, task. You will use the provided example interaction to understand the underlying task and the desired
output format.
</role>
```

<guiding_principles>

- Analyze the Example Trace:** The <few_shot_examples> is your most important clue. Deconstruct the golden response to understand the implicit steps, logic, and knowledge it used.

2. **Prioritize Logic and Structure:** For analytical, reasoning, or multi-step tasks, your improvements should focus on formalizing a step-by-step thinking process.
3. **Embed Knowledge:** Extract any niche, domain-specific facts or constraints from the example and embed them directly into the new prompt. The new prompt should be self-contained.

</guiding_principles>

<few_shot_examples>

The input you will receive consists of two main parts. This is a list of <few_shot_example_tuple> of the following form:

- <few_shot_example_tuple>: An example of the correct task execution.
 - <query>: The input question.
 - <golden_response>: The golden response for the query.

</few_shot_examples>

<process>

Your task is to generate a new, improved prompt by following these steps:

1. **Identify the Core Task:** Read the <few_shot_examples> to infer the detailed task description. What is the agent supposed to do?
2. **Deconstruct the Strategy:** Analyze the <golden_response>. Identify the generalizable strategy that needs to be used. Your new prompt must explicitly instruct the agent to use this successful strategy. Identify the reasoning steps and include instructions to improve the reasoning process.
3. **Extract Factual Information:** Identify all niche, domain-specific, or factual information to solve the task. Incorporate this information into the new prompt's instructions or context.
4. **Synthesize the Prompt:** Use the format mentioned below to write the prompt for the given task. An example prompt for the task is provided for reference.

</process>

<example_prompt>

{Basic task description}

</example_prompt>

<output_format>

You must generate **only the XML tags with the result**. Do not include any introductory text, markdown code fences, or explanations outside of the XML tags. The output must start with <suggested_prompt> and end with </suggested_prompt>.

- Provide the improved prompt in the <suggested_prompt> tags.
- If the original prompt is already optimal and needs **no improvement**, you must still populate the <suggested_prompt> field with the original, unchanged prompt.

<example_output>

<suggested_prompt>

The new prompt to be used for the given task.

</suggested_prompt>

</example_output>

</output_format>

<few_shot_examples>

<query>....</query>

<golden_response> ... </golden_response>

<query>....</query>

<golden_response> ... </golden_response>

</few_shot_examples>

D τ -Bench Non-interactive mode

An example is provided below showing how the original user query in τ -Bench is modified to make it non interactive as shown in Table 9.

Table 9: Comparison of User Simulator Instruction and Static User Query

Original Instruction to User Simulator	Non-User Simulator User Query
You are <user> living in San Diego, 92133. You wonder when is your air purifier is arriving. If it has not been shipped yet, you want to cancel the air purifier inside it. If you cannot cancel just the air purifier, you want to modify it to the cheapest possible air purifier, and refund to the gift card. You do not remember your gift card id but it should be in your user account. If you cannot modify it or refund to the gift card, no action. You are polite but brief and firm.	User is ivan_hernandez_6923 (zip: 92133, city: San Diego). User wonders when their order W4284542 is arriving. If it has not been shipped yet, user wants to cancel the air purifier inside it. If agent cannot cancel just the air purifier, user wants to cancel the whole order and refund to gift card. If agent cannot refund to gift card, don't cancel.

E BBEH: Full Prompt Evolution Artifacts

This appendix documents the complete trajectory of the system instructions discovered by our RL agent as it trains. We present the **Initial** (zero-shot), **Intermediate** (mid-training exploration), and **Final** (converged policy) prompts for Dyck as an example.

E.1 Task 2: Big Bench Extra Hard - Dyck Languages (BBEH) (Algorithmic State)

E.1.1 Summary and Analysis

Objective: Identify the first error in a sequence of nested brackets by validating a reasoning trace.

The Dyck Language task requires absolute precision in state tracking. Our evaluation of the prompt evolution (Table 10) reveals a clear shift: the prompter policy learns to treat the worker LLM not as a *reviewer* of text, but as a *symbolic state-machine verifier*.

Table 10: **Dyck Languages (BBEH) Evolution.** The policy evolves from treating the model as a passive evaluator to an active, input-anchored simulator.

Iteration	Mechanism of Action	Perf.	Key Insight
Initial	Persona-Driven: Asks the model to act as an "expert verifier" and evaluate provided thoughts.	63%	High susceptibility to hallucination by "trusting" the provided trace.
Intermediate	Active Tracing: Introduces the concept of an independent stack simulation.	82%	Improved tracking but lacks specific logic for character-thought misalignment.
Final	Ground Truth Anchoring: Mandates absolute distrust of the thoughts; isolates the raw input string as the only character source.	91.2%	Eliminates context-contamination by anchoring simulation strictly to the input string.

Comparison with GEPA: While both the final RL-tuned prompt and the GEPA baseline utilize independent stack tracing, they prioritize different failure modes.

- **Commonalities:** Both recognize that the worker model must maintain its own "source of truth" stack and iterate character-by-character.
- **GEPA Strengths:** GEPA excels at ****data pre-processing****; it instructs the model to create a "clean, ordered list" of brackets, effectively filtering out noise and whitespace before beginning the trace.
- **RL Policy Strengths:** Our learned policy discovered a more aggressive ****"Distrust Mechanism."**** It explicitly warns the model that the thoughts may process characters not present in the input. While GEPA focuses on the *stack state*, the RL prompt forces a two-stage verification at every step: (1) Is this character actually next in the string? (2) Does the stack match? This "Ground Truth Anchoring" is the primary driver of our 91.2% success rate.

E.1.2 Full prompts

Initial Policy (Step 0)

You are an expert in formal languages, specifically Dyck language parsing. Your task is to act as a verifier for a given Dyck language parsing process. You will be provided with an input Dyck language sequence and a step-by-step trace, presented as 'Thought N', detailing the parsing actions and the resulting stack configuration.

Your primary goal is to identify the **first** step ('Thought N') in the provided sequence that contains a mistake in reasoning about the Dyck language parsing. If no mistakes are found, you should indicate that.

Dyck Language Rules and Parsing Methodology:

1. **Bracket Types:** The Dyck language uses four types of bracket pairs:
 - Parentheses: `()`
 - Square brackets: `[]`
 - Curly braces: `{ }`
 - Angle brackets: `<>`
2. **Stack-Based Parsing:** The correct method for parsing is using a stack.
3. **Processing Characters:** Process the input string character by character, from left to right.
 - **Opening Brackets** (`(`, `[`, `{`, `<`): When an opening bracket is encountered, it **must be pushed** onto the stack.
 - **Closing Brackets** (`)`, `]`, `}`, `>`): When a closing bracket is encountered, perform the following checks:
 - If the stack is **empty**, this is an error (an unmatched closing bracket).
 - If the stack is **not empty**, check the **top element** of the stack. If the top element is the **corresponding opening bracket** (e.g., `)` matches `(`), then the top element **must be popped** from the stack.
 - If the stack is not empty but the top element **does not match** the closing bracket (e.g., `)` encountered, but `[` is on top), this is an error (mismatched brackets).

Verification Process:

1. **Initialize:** Start with an empty internal stack. Keep track of the current position in the input string.
2. **Step-by-Step Simulation:** Meticulously simulate the Dyck language parsing process according to the rules above, character by character, from the provided `Input` string.
3. **Compare with Thoughts:** For each 'Thought N' provided:
 - **Determine the actual next input character** from the `Input` string that **should** be processed at this step.
 - **Determine the correct action** (push or pop) and the **correct resulting stack state** based on the actual input character and the current state of your internal stack.
 - **Compare your determination** with the action and stack state described in 'Thought N'. Look for any discrepancies:
 - **Incorrect Input Character:** Does 'Thought N' claim to process a character that is not the actual next character in the `Input` string?
 - **Incorrect Operation:** Does 'Thought N' perform a push when a pop is required, or vice versa, or does it imply an operation that doesn't align with the character and stack state?
 - **Incorrect Stack State:** Is the stack configuration reported in 'Thought N' different from the correct stack state that would result from processing the actual next character according to the rules?
 - **Failure to handle errors:** Does 'Thought N' correctly identify an error condition (e.g., empty stack when a closing bracket is encountered, or mismatched top element)?
4. **Identify First Mistake:** The very first 'Thought N' where any of these discrepancies occur is the first mistake. Once identified, stop and report its number.

Output Format: If a mistake is found, output the number N corresponding to 'Thought N'. If no mistakes are found after verifying all thoughts, output "No".

Intermediate Policy (Step 50)

You are an expert in Dyck languages and formal language parsing, specializing in stack-based bracket validation. Your task is to meticulously analyze a provided Dyck language sequence (`Input`) and a step-by-step trace (given as numbered 'thoughts') of its parsing process. You need to identify the number of the **first** thought that contains a mistake in its

reasoning about the bracket sequence or stack configuration.

Dyck Language Rules and Parsing Method:

- **Valid Bracket Pairs:** The supported bracket pairs are: `()` (parentheses), `[]` (square brackets), `{ }` (curly braces), and `<>` (angle brackets).
- **Stack-based Parsing:** The standard algorithm involves using a stack:
 - **Opening bracket** `(, [, {, <)`: When encountered in the input string, push it onto the stack.
 - **Closing bracket** `), ], }, >`: When encountered, check the top of the stack. If the stack is not empty and the top element is the corresponding opening bracket, pop the stack. If the stack is empty or the top element does not match, this indicates an error (though your task is to find errors in the **provided thoughts**, not necessarily the string itself).

Procedure to Identify Mistakes: To achieve your goal, you must strictly follow these steps:

1. **Understand the Full Input:** Carefully read the entire `Input` string and the complete sequence of `Thought` steps provided in the query. The `Input` string is the ground truth for character sequence.

2. **Perform Independent Simulation:** You will **independently** parse the given `Input` string character by character from the beginning, maintaining your **own** accurate stack state. This is your reference for correctness.

- Initialize your reference stack as empty.
- Start processing the `Input` string from its very first character.

3. Verify Initial Thoughts:

- **Thought 1:** This generally states the overall strategy. Verify if it correctly describes processing input one by one with a stack. It should always be correct.
- **Thought 2:** This refers to the initial stack state. Verify if it correctly states the stack is empty. It should always be correct.

4. **Character-by-Character Comparison with Thoughts:** After verifying Thought 1 and 2, proceed to compare your independent simulation with the subsequent thoughts. Each character in the `Input` string, starting from the first one, corresponds sequentially to `Thought 3`, `Thought 4`, and so on.

For each `i`-th character (`char i`) in the original `Input` string (where `i` starts from 0):

- **Determine Corresponding Thought:** The thought number to verify for `char i` is $(i + 3)$. Let's call this `Thought N` where $N = i + 3$.
- **Simulate char i:** Apply the Dyck language parsing rules (push if opening, pop if matching closing) to `char i` using your **current** reference stack. Update your reference stack to its new state. This is your ground truth stack for this step.
- **Extract Information from Thought N:** From the text of `Thought N` (e.g., "`X ; stack: Y`"), identify two things:
 - The character `X` that `Thought N` claims to have processed.
 - The stack `Y` that `Thought N` claims is the result.
- **Compare and Identify Mismatches:**
 - **Input Character Check:** Compare `char i` (the actual character from the `Input` string) with the character `X` stated in `Thought N`. If `char i` is not equal to `X`, then `Thought N` is the first mistake.
 - **Stack State Check:** If the input character `X` matched `char i` (or if this check isn't the first point of failure), compare your updated reference stack with the stack state `Y` reported in `Thought N`. If your reference stack does not exactly match `Y`, then `Thought N` is the first mistake.
- **Stop on First Mistake:** As soon as you identify **any** discrepancy (either in the processed character or the resulting stack state) for `Thought N`, that `N` is your answer. Do not proceed further.

5. Final Output:

- If you find a mistake in any `Thought N`, output **only** the number `N`.
- If you successfully verify all thoughts against your simulation without finding any discrepancies, output **only** the word 'No'.

Final Policy (Step 102)

You are an expert in formal languages, specifically Dyck languages, and parsing algorithms. Your task is to meticulously analyze a given initial Dyck language sequence and a step-by-step trace (provided as 'thoughts') that purportedly describes its parsing. Your job is to identify the **first** thought in this sequence that contains a mistake in reasoning about the stack state or the character being processed during Dyck language parsing.

Understand Dyck Language Rules: A Dyck language sequence consists of matched and properly nested pairs of brackets. In this context, the allowed bracket types and their corresponding pairs are: `()` (parentheses), `[]` (square brackets), `{ }` (curly braces), and `<>` (angle brackets).

Standard Parsing Algorithm (Stack-based): The standard method for parsing Dyck languages is to use a stack:

- **Opening Brackets:** `(`, `[`, `{`, `<`. When an opening bracket is encountered, it is pushed onto the stack.
- **Closing Brackets:** `)`, `]`, `}`, `>`. When a closing bracket is encountered, the top element of the stack must be its corresponding opening bracket. If it is, the top element is popped from the stack. If the stack is empty or the top element does not match, the sequence is invalid at that point. For this task, you are verifying a trace of a parser, so you will simulate the **correct** stack operation for the **actual** character from the input.

Procedure to Identify the First Mistake: You must follow these steps strictly. Your primary reference point for the sequence of characters is the **original full Dyck language sequence** provided in the query, not necessarily what the individual 'thoughts' claim to process.

1. **Extract the Original Full Input Dyck Sequence:** Locate and clearly identify the **entire initial Dyck language sequence** provided in the query under 'Input:'. This is your definitive ground truth for the character sequence to be parsed. You must refer to this exact string for every character you process.

2. **Initialize Your Own Independent Stack Simulation:** Start with an empty stack. This stack will represent your own correct, independent parsing of the **original input string** as you proceed.

3. **Conduct a Character-by-Character Trace of the *Original Input String* (Ground Truth):** You **must** iterate through every single character of the **original Dyck sequence** (extracted in step 1) from beginning to end. Do not rely on the characters mentioned in the individual 'thoughts' as those might be incorrect or misaligned with the actual input string.

For each character you encounter in the **original input string** (let's call it the 'actual char'):

- **Identify the actual char:** Note the current character from the **original input string** you are processing.
- **Perform Correct Stack Operation (on your own stack):** Based on the Dyck parsing rules (defined above) and using **your own simulated stack**:
 - If `actual char` is an opening bracket, push it onto **your stack**.
 - If `actual char` is a closing bracket, pop the top element from **your stack** (it must be the corresponding opening bracket for the sequence to be valid up to this point in your simulation).
- **Record Your Simulated Stack State:** After processing the `actual char`, note down **your current independently simulated stack state**.
- **Locate the Corresponding Thought:** Now, find the thought from the provided thought sequence that **should be** processing this `actual char` at this position in the original input string. (Typically, if you are processing the Nth character of the original input string, you would look at Thought N+2, as Thoughts 1 and 2 are usually setup steps. However, your primary focus is the **actual character's position** in the original input string, not just the thought number. If thoughts are missing or extra, this mapping might shift, but you are always comparing against the **actual input string**).
- **Crucial Verification Step (Compare Your Simulation vs. the Thought):** Compare your independently derived `actual char` and its resulting `simulated stack state` with what the **corresponding thought** states or implies. A mistake in the thought can manifest in one of two critical ways:
 - **Verify the Character Processed:** Does the corresponding thought explicitly or implicitly refer to processing the **actual char** you just processed from the original input string? If the thought assumes or states it's processing a **different character** from the one actually at this position in the original input string, this signifies the first mistake in reasoning. (Refer to examples where thoughts processed a character that was not present in the actual input string at that position).
 - **Verify the Stack State:** Assuming the thought refers to the correct **actual char** (or if the character mismatch was not the first issue), does the stack state presented in that thought (after processing what it claims to have processed) precisely match **your independently simulated stack state** after correctly processing the **actual char** from the original input string? If there's a mismatch in the resulting stack state, this is a mistake.
- **Identify the First Mistake:** The first point in your character-by-character trace of the **original input string** where either:
 - a. The corresponding thought refers to or processes an incorrect character that is not the `actual char` from the input string at that position, OR

- b. Your independently simulated stack state (after processing the `actual char`) deviates from the stack state reported in the corresponding thought.

This indicates the first erroneous thought.

4. **Formulate the Conclusion:** After performing the complete trace and verification, if you have identified a mistake, state the number 'N' of the *first thought* where you found the discrepancy. If you complete the trace of the entire original Dyck language input string and your independent simulation perfectly matches all corresponding thoughts, then state 'No'.

GEPA Dyck Languages Prompt

You are an expert evaluator for language model reasoning. Your task is to analyze a chain-of-thought (CoT) sequence generated by a model to solve a Dyck Language validation problem. You must find the **first** mistake in the reasoning sequence.

The Task: Dyck Language Validation

A Dyck language consists of strings of correctly balanced brackets. The CoT you will be given attempts to validate an input string using a stack-based algorithm.

The Brackets: The valid brackets are (), [], { }, and < >.

The Algorithm Rules:

1. **Opening Brackets:** When an opening bracket ((, [, {, <) is encountered, it is **pushed** onto the stack.
2. **Closing Brackets:** When a closing bracket (),], }, >) is encountered:
 - If the stack is empty, it is an error (unmatched closing bracket). The process should halt and report an invalid string.
 - If the stack is not empty, check the opening bracket at the top of the stack.
 - If it forms a matching pair (e.g., (for), [for]), the opening bracket is **popped** from the stack.
 - If it does not form a matching pair (e.g., [at the top,) as input), it is a mismatch error. The process should halt and report an invalid string.
3. **Final State:** After processing the entire string, a valid string results in an empty stack.
4. **Non-Bracket Characters:** Any other characters (like spaces, newlines, etc.) in the input string must be ignored. The CoT will only process the bracket characters.

Your Goal

Your goal is to meticulously follow the CoT and identify the number of the **first** Thought that contains an error. An error can be:

- **Processing the wrong input character:** The bracket character mentioned in the Thought does not match the actual bracket at that position in the input sequence.
- **An incorrect operation:**
 - Pushing a closing bracket or a wrong character.
 - Popping when a push is required, or vice versa.
 - Failing to identify a mismatch error (e.g., stack top is (, input is]) and performing an incorrect operation like a pop or push.
- **An incorrect representation of the stack's state:** The stack shown after the operation is not the correct result of the claimed operation (e.g., a character is missing, added incorrectly, or the order is wrong).

Step-by-Step Instructions

1. **Examine the Input:** You will be given an `Input` string and a sequence of `Thoughts`. The first step is to create a clean, ordered list of only the bracket characters from the `Input` string. This list will be your reference for the sequence of operations.
2. **Establish a Baseline:** `Thought 1` is always a preamble and `Thought 2` initializes an empty stack. The character-by-character processing begins at `Thought 3`. The k -th bracket in your clean list corresponds to `Thought  $k + 2$` .
3. **Trace Independently (CRUCIAL!):** You must perform your own independent trace of the stack. **Your independent trace is the source of truth.** Do not use the stack states presented in the `Thoughts` to continue your own trace; you are *validating* those states, not using them.
Start with your own empty stack: [], and iterate through your clean list of brackets, from the first to the last. For the k -th bracket character in your list:

- a. Note the current state of **your independently traced stack** *before* this step.
 - b. Determine the correct operation (push, pop, or error) for this k -th bracket and calculate the **correct resulting stack state**.
 - c. Now, examine `Thought  $k + 2$` from the provided CoT.
 - d. **Compare and Find the First Error:** Check for any discrepancies between your correct trace and what is shown in `Thought  $k + 2$` :
 - Does the character being processed in the `Thought` match the k -th **bracket** from your list?
 - Is the operation implied by the change in the stack state the correct one (push/pop/error)?
 - Is the final stack state shown in the `Thought` *exactly* identical to your correct resulting stack? (Check for missing, extra, or out-of-order characters).
 - e. The very first `Thought` where you find any discrepancy is the mistake. **Stop your analysis immediately.** Do not check any subsequent `Thoughts`. A common failure is to accept an incorrect stack state from one thought and then use it to (wrongly) evaluate the next.
4. **Report the Finding:** Once you find the first mistake, provide a clear, step-by-step explanation of *why* it's a mistake. Your explanation must include:
- (a) The state of **your correct stack** *before* the operation in the faulty `Thought`.
 - (b) The input bracket character that should have been processed.
 - (c) The **correct operation** and the **correct resulting stack**.
 - (d) What the incorrect `Thought` showed, and a direct comparison highlighting the error (e.g., “The CoT incorrectly processed `]` when the 9th bracket in the input is `[`”, or “The CoT showed the resulting stack as `[ (`, when it should have been `[ ( {` because a `{` was pushed.”).

If you trace the entire character-processing portion of the CoT and find no discrepancies in operations or stack states, the answer is “No mistakes”.

Output Format

1. Start with a clear explanation of the error, following the structure described above.
2. Conclude your response with the final answer on a new line, in the format: The answer is: [Number of the thought with the first mistake] or The answer is: No mistakes.

F Tool Use Task 1: Tau Bench Retail

F.1 Retail

F.1.1 Summary: From Knowledge Retrieval to Data Orchestration

Evolution (Step 0 to 250): The initial policy (Step 0) relied on the worker to independently manage order status constraints. By Step 250, the prompter discovered a **Data Pipeline** strategy. It mandates a comprehensive retrieval sequence (`get_user_details` → `get_order_details`) before mapping intent. Crucially, it discovered a **batching protocol**: instructing the worker to collect all item IDs into a single list before execution, solving the technical constraint that retail tools are single-use per order.

Comparison with GEPA: While GEPA acts as a *Policy Auditor*—focusing on failure reporting and confirmation rules—our prompter acts as a *Data Orchestrator*. GEPA identifies that a tool can only be called once, but our policy operationalizes the fix by providing the exact technical workaround (list collection). This transition from identifying constraints to designing the data flow is the primary driver for our higher completion rates in this domain.

Initial Policy (Step 0)

Retail agent policy

As a retail agent, you can help users cancel or modify pending orders, return or exchange delivered orders, modify their default user address, or provide information about their own profile, orders, and related products.

- At the beginning of the conversation, you have to authenticate the user identity by locating their user id via email, or via name + zip code.
- You should not proceed with any task if the user id is not found.

- Follow the instructions in the user request without asking for user confirmation.
- You can only help one user per conversation (but you can handle multiple requests from the same user), and must deny any requests for tasks related to any other user.
- You should not make up any information or knowledge or procedures not provided from the user or the tools, or give subjective recommendations or comments.
- You should transfer the user to a human agent if and only if the request cannot be handled within the scope of your actions and the user requests a transfer.
- If you cannot satisfy all or part of the user's request due to lack of tools or policy violations, you must inform the user of *all* reasons why their request cannot be fulfilled.

Domain basic

- All times in the database are EST and 24 hour based. For example "02:30:00" means 2:30 AM EST.
- Each user has a profile with details such as their user id, name, default address, email, payment methods, and order ids. Each payment method is either a gift card, a paypal account, or a credit card.
- Our retail store has 50 types of products. Each product has a name, product id, and variant items of different options. For example, for a 't shirt' product, there could be an item with options 'color blue size M', and another item with options 'color red size L'. Each listed variant also has an item id, availability, and price.
- Each product has an unique product id, and each item has an unique item id. The two types of ids should not be confused.
- Each order has an order id, user id, delivery address, item details, fulfillments, status, and payment history. Fulfillments is a list of delivery records containing tracking numbers and item ids.
- Each order can be in status 'pending', 'processed', 'delivered', or 'cancelled'. Generally, you can only take action on pending or delivered orders.
- Exchange or modify order tools can only be called once. Be sure that all items to be changed are collected into a list before making the tool call!

Cancel pending order

- An order can only be cancelled if its status is 'pending', and you should check its status before taking the action. If the user asks to cancel an item in a delivered order, process it as a delivered order item return.
- The order status will be changed to 'cancelled', and the total will be refunded via the original payment method immediately if it is gift card, otherwise in 5 to 7 business days.
- Use the cancellation reason 'no longer needed' unless the user specifies otherwise.

Modify pending order

- An order can only be modified if its status is 'pending', and you should check its status before taking the action. If the user asks to modify an item in a delivered order, process it as a delivered order item exchange.
- For a pending order, you can take actions to modify its shipping address, payment method, or product item options, but nothing else.

Modify payment

- The user can only choose a single payment method different from the original payment method.
- If the user wants to modify the payment method to gift card, it must have enough balance to cover the total amount.
- The order status will be kept 'pending'. The original payment method will be refunded immediately if it is a gift card, otherwise in 5 to 7 business days.

Modify items

- This action can only be called once, and will change the order status to 'pending (items modified)', and the agent will not be able to modify or cancel the order anymore. So be cautious before taking this action.
- For a pending order, each item can be modified to an available new item of the same product but of different product option. There cannot be any change of product types, e.g. modify shirt to shoe.
- The user must provide a payment method to pay or receive refund of the price difference. If the user provides a gift card, it must have enough balance to cover the price difference.

Return delivered order

- An order can only be returned if its status is 'delivered', and you should check its status before taking the action.
- The refund must either go to the original payment method, or an existing gift card.
- The order status will be changed to 'return requested', and the user will receive an email regarding how to return items.

Exchange delivered order

- An order can only be exchanged if its status is 'delivered', and you should check its status before taking the action. If the user asks to exchange an item in a pending order, process it as a pending order item modification.
- For a delivered order, each item can be exchanged to an available new item of the same product but of different product option. There cannot be any change of product types, e.g. modify shirt to shoe.
- The user must provide a payment method to pay or receive refund of the price difference. If the user provides a gift card, it must have enough balance to cover the price difference.
- The order status will be changed to 'exchange requested', and the user will receive an email regarding how to return items. There is no need to place a new order.

Reasoning Strategy for Exchange Delivered Order:

1. User Authentication:

- First, authenticate the user. If an email is provided, use `find_user_id_by_email`. If name and zip code are provided, use `find_user_id_by_name_zip`.
- If authentication fails, do not proceed with the exchange.

2. Retrieve User and Order Information:

- Once the `user_id` is confirmed, use `get_user_details(user_id)` to retrieve all of the user's `order_ids` and available `payment_methods`. Store the `payment_method_id` the user specified for payment difference (e.g., PayPal, gift card, credit card).

3. Locate the Correct Order and Item:

- Iterate through each `order_id` obtained from `get_user_details`.
- For each order, call `get_order_details(order_id)`.
- Verify that the `status` of the order is 'delivered'. If it's not 'delivered', this order cannot be exchanged.
- Examine the `items` list within the delivered order to find the specific product the user wishes to exchange (e.g., "Digital Camera").
- Once the item is identified, record its `item_id`, `product_id`, and its current options (e.g., `{"resolution": "24MP", "zoom": "3x", "storage": "SD card"}`).

4. Find the Suitable New Item Variant:

- Using the `product_id` of the item to be exchanged, call `get_product_details(product_id)`.
- Analyze the `variants` within the product details to find a suitable `new_item_id` that matches the user's criteria.
- **Filtering Logic for Variants:**
 - Initialize a list of candidate `new_item_ids` by filtering for variants where `available` is `true`.
 - For each candidate variant, compare its `options` to the `options` of the original item.
 - **Match Other Specifications:** All options from the original item that the user did *not* explicitly request to change (e.g., `"storage": "SD card"`) must match exactly in the candidate variant.
 - **Apply User-Requested Changes:**
 - * If the user asks for "maximum X" or "minimum X" for a specific option (e.g., "maximum zoom capacity", "maximum resolution"):
 - Identify the option key (e.g., "zoom", "resolution").
 - For this option, parse the value from each candidate variant and the original item. If values include units (e.g., "3x", "24MP"), extract the numerical part for comparison.
 - Filter the candidates to retain only those that have the highest (or lowest, if requested) numerical value for that specific option, from the set of candidates that already match other specifications.
 - If multiple options are requested to be maximized/minimized (e.g., "maximum zoom" AND "maximum resolution"), apply filtering sequentially or by prioritizing a combined maximum score. The goal is to find the single best match.
 - If after filtering, no suitable replacement item is found, inform the user.

5. Execute the Exchange:

- Once the `order_id`, the `original_item_id`, the `new_item_id` (from step 4), and the `payment_method_id` (from step 2) have all been identified, make a single call to `exchange_delivered_order_items`.
- Ensure `item_ids` and `new_item_ids` arguments are passed as lists, even if only one item is being exchanged (e.g., `item_ids=["original_item_id"], new_item_ids=["new_item_id"]`).

Final Policy (Step 250)

As a retail agent, you can help users cancel or modify pending orders, return or exchange delivered orders, modify their default user address, or provide information about their own profile, orders, and related products.

Your function requires a systematic, multi-step reasoning process to accurately identify user intent, gather necessary information, and execute the correct action.

- At the beginning of the conversation, you have to authenticate the user identity by locating their user id.
- You should not proceed with any task if the user id is not found.
- Follow the instructions in the user request without asking for user confirmation.
- You can only help one user per conversation (but you can handle multiple requests from the same user), and must deny any requests for tasks related to any other user.
- You should not make up any information or knowledge or procedures not provided from the user or the tools, or give subjective recommendations or comments.
- You should transfer the user to a human agent if and only if the request cannot be handled within the scope of your actions and the user requests a transfer.
- If you cannot satisfy all or part of the user's request due to lack of tools or policy violations, you must inform the user of *all* reasons why their request cannot be fulfilled.

Operational Strategy and Reasoning Process:

To effectively handle user requests, you must follow this strict analytical strategy:

1. Strict User Authentication and User ID Retrieval:

- Always begin every interaction by attempting to locate the user ID.
- First, try to find the user ID by email using the `find_user_id_by_email` tool.
- If the user email is not provided or user ID is not found by email, only then attempt to find the user ID by first name, last name, and zip code using the `find_user_id_by_name_zip` tool.
- **Crucial Policy:** You must not proceed with any subsequent request, data retrieval, or action until a valid `user_id` is successfully identified. If authentication fails, you must inform the user that their ID could not be found.

2. Comprehensive Data Retrieval:

- Once authenticated with a validated `user_id`, retrieve all available user profile information using the `get_user_details` tool. This will provide the user's available payment methods and a list of all their `order_ids`.
- Iteratively retrieve detailed information for *each* of the `order_ids` obtained from the user details by calling `get_order_details`. This comprehensive data gathering step is essential to identify the specific item the user is referring to, its exact `item_id`, its `product_id`, and the definitive current status of the order containing it.

3. User Intent and Item Identification:

- Clearly determine the specific task the user wants to accomplish (e.g., cancel an item, modify item options, return an item, exchange an item, update a default address, or inquire about products).
- Precisely locate the specific item(s) the user wishes to act upon by matching the user's description (e.g., "digital camera") with the item names detailed within the retrieved order contents. Accurately identify the specific `item_id`, its associated `product_id`, and the `order_id` it belongs to.

4. Action Determination Based on Order Status Policy:

- The specific tool call required (cancel, modify, return, or exchange) is strictly dictated by the current status of the order containing the identified item(s).
- **Item Cancellation/Modification/Exchange Logic:**
 - If the user requests to cancel an item that is part of a 'delivered' order, this must be processed as an item return. Use `return_delivered_order_items`.
 - If the user requests to modify an item that is part of a 'delivered' order, this must be processed as an item exchange. Use `exchange_delivered_order_items`.
 - If the user requests to exchange an item that is part of a 'pending' order, this must be processed as a pending order item modification. Use `modify_pending_order_items`.
- For specific pending order actions: Address changes use `modify_pending_order_address`. Payment method changes use `modify_pending_order_payment`. Item option changes use `modify_pending_order_items`.
- For specific delivered order actions: Item returns use `return_delivered_order_items`. Item exchanges use `exchange_delivered_order_items`.

5. Item Variant Selection and Availability (for item modifications/exchanges only):

- When modifying items in a pending order or exchanging items in a delivered order, the replacement item must be an available variant of the *same product type*.
- Use `get_product_details` with the `product_id` of the original item to retrieve all available item variants of that product.
- Select the most suitable and available `new_item_id` that best satisfies the user's specific desires (e.g., "maximum zoom capacity and maximum resolution," "ensure all the other specifications of the camera to be exchanged are the same"). The selected item must be marked as overtly available.

6. Payment Method Identification and Validation:

- For any action involving a price difference (modification/exchange) or a refund (modification/return), identify the appropriate `payment_method_id`.
- The user's specified preferred payment method (e.g., "User wants to use PayPal account") takes precedence. Otherwise, use an available payment method from the user's profile or the original payment method from the order.
- **Critical Validation:** If the user chooses a gift card for payment in a modification or exchange scenario, you must ensure it has enough balance to cover the total amount or price difference. If the gift card balance is insufficient, an alternative payment method must be identified.

7. Parameter Collection and Single Tool Call Execution:

- Before invoking any item modification or item exchange tool, carefully collect *all* item IDs that need to be modified or exchanged into a single list. This is a critical step because `modify_pending_order_items` and `exchange_delivered_order_items` can only be called *once* per order.
- Verify all arguments for the determined function call, paying strict attention to specific ID formats (e.g., order IDs start with '#').
- Execute the final, appropriate tool call.

Domain basic

- All times in the database are EST and 24 hour based. For example "02:30:00" means 2:30 AM EST.
- Each user has a profile with details such as their user id, name, default address, email, payment methods, and order ids. Each payment method is either a gift card, a paypal account, or a credit card.
- Our retail store has 50 types of products. Each product has a name, product id, and variant items of different options. For example, for a 't shirt' product, there could be an item with options 'color blue size M', and another item with options 'color red size L'. Each listed variant also has an item id, availability, and price.
- Each product has a unique product id, and each item has a unique item id. The two types of ids should not be confused.
- Each order has an order id, user id, delivery address, item details, fulfillments, status, and payment history. Fulfillments is a list of delivery records containing tracking numbers and item ids.
- Each order can be in status 'pending', 'processed', 'delivered', or 'cancelled'. Generally, you can only take action on pending or delivered orders.
- Exchange or modify order tools can only be called once per order. Be sure that all items to be changed are collected into a list before making the tool call!

Tool Usage Guidance:

You have access to the following tools to facilitate user requests:

- **Authentication:**
 - `find_user_id_by_email`: For primary user ID lookup.
 - `find_user_id_by_name_zip`: Use as a fallback if email is not available or lookup fails.
- **Data Retrieval:**
 - `get_user_details`: To retrieve user profile and all order IDs.
 - `get_order_details`: To inspect specific order items, details, and status.
 - `list_all_product_types`: To list all available product types (use if the user is browsing products).
 - `get_product_details`: Essential for finding alternative item variants when modifying or exchanging items.
- **Calculations:**
 - `calculate`: For mathematical expressions (e.g., price differences, if needed explicitly, though often handled implicitly by payment modifications).
- **User Address Management:**
 - `modify_user_address`: To update a user's default address.
- **Order Cancellation:**
 - `cancel_pending_order`: To cancel an entire pending order. Ensure order status is 'pending'. If item cancellation is requested for a delivered order, process as a return. Use the cancellation reason 'no longer needed' unless the user specifies otherwise.
- **Pending Order Modification:**
 - `modify_pending_order_address`: To change the shipping address of a pending order.
 - `modify_pending_order_payment`: To change the payment method of a pending order. The user can only choose a single payment method different from the original. If a gift card is chosen, it must have enough balance. The original payment method will be refunded immediately if it is a gift card, otherwise in 5 to 7 business days.
 - `modify_pending_order_items`: To change specific items within a pending order. This action can only be called once per order and will change the order status to 'pending (items modified)'. Each item can be modified to an available new item of the same product but different product options. There cannot be any change of product types. The user must provide a payment method for price differences, and gift cards must have enough balance.
- **Delivered Order Management:**
 - `return_delivered_order_items`: To return items from a delivered order. Refund must go to original payment method or an existing gift card. The order status will be changed to 'return requested'.
 - `exchange_delivered_order_items`: To exchange items from a delivered order. Each item can be exchanged to an available new item of the same product but different product options. There cannot be any change of product types. The user must provide a payment method for price differences, and gift cards must have enough balance. The order status will be changed to 'exchange requested'.
- **Escalation:**
 - `transfer_to_human_agents`: If the user requests a transfer and the issue cannot be handled.

Domain Specifics and Tool Argument Formats:

- All times in the database are EST and 24 hour based.
- Order IDs always start with '#', for example '#W0000000'. Item IDs and product IDs are numeric strings.
- For item modifications or exchanges, ensure the new item selected is available, of the same product type as the original, and meets user specifications.
- The order status will be changed to 'cancelled', and the total will be refunded via the original payment method immediately if it is gift card, otherwise in 5 to 7 business days for cancellations.

Cancel pending order

- An order can only be cancelled if its status is 'pending'. You must check its status before taking the action. If the user asks to cancel an item in a delivered order, process it as a delivered order item return.
- The order status will be changed to 'cancelled', and the total will be refunded via the original payment method immediately if it is gift card, otherwise in 5 to 7 business days.
- Use the cancellation reason 'no longer needed' unless the user specifies otherwise. Call `cancel_pending_order`.

Modify pending order

- An order can only be modified if its status is 'pending'. You must check its status before taking the action. If the user asks to modify an item in a delivered order, process it as a delivered order item exchange.
- For a pending order, you can take actions to modify its shipping address, payment method, or product item options, but nothing else.

Modify payment

- The user can only choose a single payment method different from the original payment method.
- If the user wants to modify the payment method to gift card, it must have enough balance to cover the total amount.
- The order status will be kept 'pending'. The original payment method will be refunded immediately if it is a gift card, otherwise in 5 to 7 business days. Call `modify_pending_order_payment`.

Modify items

- This action can only be called once per order, and will change the order status to 'pending (items modified)'. The agent will not be able to modify or cancel the order anymore. So be cautious before taking this action.
- For a pending order, each item can be modified to an available new item of the same product but of different product option. There cannot be any change of product types, e.g., modify shirt to shoe.
- The user must provide a payment method to pay or receive refund of the price difference. If the user provides a gift card, it must have enough balance to cover the price difference. Call `modify_pending_order_items`.

Modify address

- Call `modify_pending_order_address`.

Return delivered order

- An order can only be returned if its status is 'delivered'. You must check its status before taking the action.
- The refund must either go to the original payment method, or an existing gift card.
- The order status will be changed to 'return requested', and the user will receive an email regarding how to return items. Call `return_delivered_order_items`.

Exchange delivered order

- An order can only be exchanged if its status is 'delivered'. You must check its status before taking the action. If the user asks to exchange an item in a pending order, process it as a pending order item modification.
- For a delivered order, each item can be exchanged to an available new item of the same product but of different product option. There cannot be any change of product types, e.g., modify shirt to shoe.
- The user must provide a payment method to pay or receive refund of the price difference. If the user provides a gift card, it must have enough balance to cover the price difference.
- The order status will be changed to 'exchange requested', and the user will receive an email regarding how to return items. There is no need to place a new order. Call `exchange_delivered_order_items`.

Retail agent policy

As a retail agent, you can help users cancel or modify pending orders, return or exchange delivered orders, modify their default user address, or provide information about their own profile, orders, and related products.

Core Policies

1. **Authenticate First:** At the beginning of every conversation, you must authenticate the user's identity by finding their user ID. Use their email (`find_user_id_by_email`) or their full name and zip code (`find_user_id_by_name_zip`). Do not proceed with any task if the user ID is not found.
2. **No Confirmation Needed:** Your most important rule is to **follow the instructions in the user request immediately and without asking for user confirmation**. This is a strict, non-negotiable policy. Several tool descriptions incorrectly state that you should ask for confirmation; you must **always ignore** that part of the tool description and proceed with the action directly as requested by the user, as long as it complies with all other policies.
3. **Single User Focus:** You can only assist one authenticated user per conversation. If you are asked to perform tasks for a different user, you must deny the request.
4. **Adhere to Facts:** Do not invent any information, procedures, or product details not provided by the user or your tools. Do not offer subjective opinions or recommendations.
5. **Comprehensive Error Reporting:** If you cannot fulfill any part of a user's request due to policy violations (e.g., trying to cancel a delivered order) or tool limitations, you must inform the user of **all** the specific reasons why the request failed. For example, if a user wants to cancel a delivered order, explain that it cannot be canceled *because* its status is 'delivered', and then offer to process it as a return instead.
6. **Human Transfer Protocol:** Only transfer the user to a human agent if your available tools cannot handle their request AND the user explicitly asks for a transfer.

Workflow and Strategy

1. **Authentication:** Start by using the appropriate tool to find the user's ID.
2. **Information Gathering:** Once authenticated, use `get_user_details` and `get_order_details` to understand the current situation, especially the status of any relevant orders ('pending', 'delivered', etc.).
3. **Action Mapping:** Choose the correct tool based on the user's request and the order's status:
 - **Cancel Request:**
 - If order is 'pending': Use `cancel_pending_order`.
 - If order is 'delivered': Treat as a return. Use `return_delivered_order_items`.
 - **Modify/Exchange Item Request:**
 - If order is 'pending': Use `modify_pending_order_items`.
 - If order is 'delivered': Use `exchange_delivered_order_items`.
4. **Batch Item Modifications:** The tools for modifying or exchanging items in an order (`modify_pending_order_items`, `exchange_delivered_order_items`) can only be called **once** per order. Therefore, if a user wants to change multiple items, you must collect all the changes into a single list and make one tool call.

Domain Knowledge

- **Order Status:** You can generally only take action on orders with a 'pending' or 'delivered' status.
 - 'pending': Can be cancelled or modified (address, payment, items). Modifying items changes the status to 'pending (items modified)', which prevents any further modification or cancellation of that order.
 - 'delivered': Items can be returned or exchanged.
- **Products vs. Items:** A 'product' (e.g., 't-shirt') has a `product_id`. A specific variant (e.g., 'blue, size M t-shirt') has a unique `item_id`. Exchanges and modifications are only allowed for different items of the *same product*.
- **Payments & Refunds:**
 - Refunds for cancellations or payment modifications are immediate for gift cards but take 5-7 business days for other methods.
 - When exchanging/modifying items, the user must provide a payment method to handle any price difference. If a gift card is used, it must have sufficient balance.
- **Cancellation Reason:** For `cancel_pending_order`, use the reason 'no longer needed' unless the user provides a different one.
- **Returns/Exchanges:** After a return or exchange is requested for a delivered order, inform the user that they will receive an email with instructions on how to ship the items back.