

Taming Actor-Observer Asymmetry in Agents via Dialectical Alignment

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<https://unikcc.github.io/ReTAS/>

Abstract

Large Language Model agents have rapidly evolved from static text generators into dynamic systems capable of executing complex autonomous workflows. To enhance reliability, multi-agent frameworks assigning specialized roles are increasingly adopted to enable self-reflection and mutual auditing. While such role-playing effectively leverages domain expert knowledge, we find it simultaneously induces a human-like cognitive bias known as Actor-Observer Asymmetry (AOA). Specifically, an agent acting as an actor (during self-reflection) tends to attribute failures to external factors, whereas an observer (during mutual auditing) attributes the same errors to internal faults. We quantify this using our new Ambiguous Failure Benchmark, which reveals that simply swapping perspectives triggers the AOA effect in over 20% of cases for most models. To tame this bias, we introduce **ReTAS** (Reasoning via Thesis-Antithesis-Synthesis), a model trained through dialectical alignment to enforce perspective-invariant reasoning. By integrating dialectical chain-of-thought with Group Relative Policy Optimization, ReTAS guides agents to synthesize conflicting viewpoints into an objective consensus. Experiments demonstrate that ReTAS effectively mitigates attribution inconsistency and significantly improves fault resolution rates in ambiguous scenarios.

1 Introduction

The unprecedented capabilities of Large Language Models (LLMs) (Guo et al., 2025; Gemini, 2025; OpenAI, 2023) have catalyzed the development of powerful autonomous agents (Yao et al., 2023b; Tran et al., 2025). To leverage domain-specific expertise, researchers utilize *role-playing* strategies (Qian et al., 2024; Shao et al., 2023), assigning specialized roles to complete various tasks. This paradigm underpins multi-agent frameworks,

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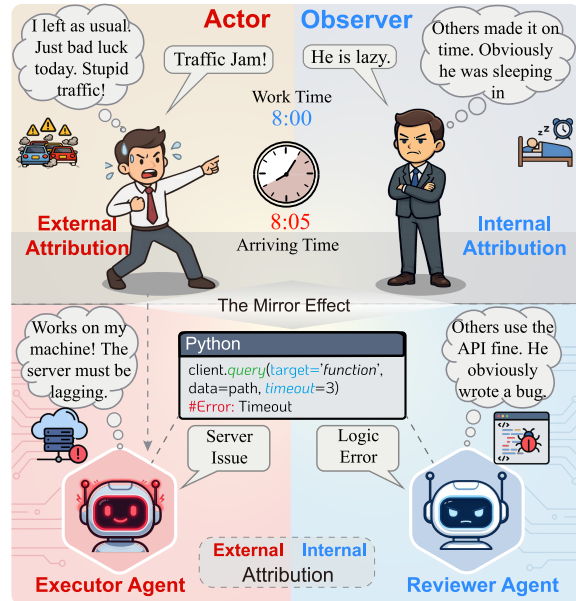


Figure 1: Mirror Effect of Actor-Observer Asymmetry.

mimicking human collaboration to outperform monolithic models in efficiency and solution quality (Yang et al., 2024a).

However, such role assignment can fundamentally compromise objectivity. When agents engage in self-correction or peer-review (Shinn et al., 2023; Jin et al., 2024), the assigned role functions as a rigid cognitive prior that skews agents' judgment. Consider a code generation scenario in Figure 1: when faced with a timeout exception, the executor attributes the failure to a **server issue**, whereas the reviewer insists it is a **logic error** in the code. These conflicting perspectives hinder consensus, resulting in inter-agent misalignment (Cemri et al., 2025) and undermining collaborative reliability.

We identify this inter-agent misalignment as Actor-Observer Asymmetry (AOA) (Heider, 1958; Jones and Nisbett, 1972; Malle, 2006), a well-established concept in social psychology. As illustrated in Figure 1, AOA describes the tendency for actors to attribute failures to external circum-

stances (e.g., traffic), while observers attribute them to internal dispositions (e.g., laziness). This striking parallel raises a fundamental question: *Has this bias, deeply rooted in human cognition, permeated the LLMs that mimic our discourse?* (Gallegos et al., 2024; Hu et al., 2025) To investigate this, we introduce the Ambiguous Failure Benchmark (AFB). Instead of deterministic errors, we construct inherently ambiguous scenarios where a single failure signature plausibly supports contradictory root causes—e.g., a timeout stemming from either infrastructure latency or aggressive configuration. Experiments on AFB across multiple LLMs (OpenAI, 2023; Yang et al., 2025; Guo et al., 2025) reveal that switching perspectives triggers AOA in over 20% of instances for most models, confirming its existence.

Taming this bias is non-trivial due to the inherent ambiguity of fault localization (Zhang et al., 2025). Naïve interventions are often ineffective: instructing agents to “be objective” typically yields defensive justifications due to role inertia, while enforcing opposing perspectives invites over-correction and groundless self-blame. Both strategies treat the symptom rather than the underlying role-induced prior. To overcome this limitation, we draw on Fichtean dialectics (Fichte, 1982), arguing that robust attribution requires a structured reasoning process: articulating a position, confronting its negation, and integrating both into a unified truth.

Guided by this, we propose a reasoning framework that decomposes reflection into three explicit stages: Thesis, Antithesis, and Synthesis. The Thesis stage generates a role-congruent explanation that expresses specific expertise. The Antithesis stage simulates an opposing perspective to surface blind spots. The Synthesis stage reconciles these conflicting views to derive a perspective-invariant conclusion, grounding the decision in objective evidence. However, prompting alone is insufficient to enforce such structured reasoning. To align the model with this dialectical process, we employ Group Relative Policy Optimization (GRPO) (Guo et al., 2025) using an attribution reward that penalizes inconsistent judgments and encourages convergence toward the ground truth. Experiments demonstrate that ReTAS effectively mitigates AOA with strong generalization across tasks.

Our contributions are summarized as follows:

- We demonstrate that agent attribution failures are not random inconsistencies but mirror hu-

man AOA, and introduce the AFB benchmark to quantitatively verify this cognitive bias.

- We train ReTAS to resolve attribution conflicts via perspective-aware synthesis and consistency-driven reinforcement learning.
- Experiments indicate that ReTAS significantly mitigates attribution bias and improves task performance, establishing a robust paradigm for agent collaboration.

2 Related Work

Role-Playing in LLM Agents The evolution of LLMs from static reasoning chains (Wei et al., 2022; Yao et al., 2023a; Fei et al., 2023) to dynamic agents has led to LLM-based multi-agent frameworks that leverage role-playing (Liu et al., 2024; Zhang et al., 2024a) to elicit domain-specific expertise (Qian et al., 2024; Shao et al., 2023). While assigning roles such as executor or reviewer effectively decomposes complex tasks (Tran et al., 2025; Zhang et al., 2024b; Li et al., 2025), it introduces an under-explored epistemic risk: roles act not only as functional specifications but also as cognitive priors that shape reasoning (Wu et al., 2025). Recent work shows that role adoption can bias judgments (Zhang et al., 2025; Cemri et al., 2025), yet the impact of these roles on *failure attribution* in collaborative settings remains unclear.

Attribution Theory and Cognitive Bias The discrepancy in failure attribution observed in LLMs mirrors the AOA in social psychology, where actors tend to attribute failures to situational factors while observers attribute them to dispositional traits (Jones and Nisbett, 1972; Ross, 1977; Malle, 2006). As LLMs are trained on human-generated text, they inherit such attributional biases (Tjuatja et al., 2024; Acerbi and Stubbersfield, 2023; Leng, 2024). While prior work has examined social stereotypes (Hu et al., 2025; Shrawgi et al., 2024) and evaluator biases (Wang et al., 2024), the interaction between attribution biases and agent collaboration remains largely unexplored. Mitigation strategies like self-reflection (Shinn et al., 2023; Ji et al., 2023; Dou et al., 2024; Bo et al., 2024) or cross-critique (Yu et al., 2024; Wang et al., 2024; Lan et al., 2025) often fail to resolve this perspective-dependent skew. This motivates us to propose a dialectical framework to explicitly decouple the agent’s role-based defense mechanisms from the objective ground truth.

3 Preliminary Study

To quantify the extent of AOA in agents, we design a dataset called AFB to maximize *attribution ambiguity*, where the absence of a deterministic ground truth exposes agents’ inherent attribution biases. Unlike conventional datasets, we induce epistemic uncertainty between internal faults (e.g., logic gaps, misinterpretation) and external factors (e.g., vague instructions, environmental limits). By explicitly instructing the generator (GPT-5.1) to avoid definitive ground truth, any systematic bias in evaluation can be attributed to the evaluator’s perspective, whether as an *Actor* (self-reflection) or an *Observer* (auditing). Full prompt templates and examples are provided in Section B.1.

This AFB dataset spans 10 domains (see Table 1) and comprises 200 interaction traces with **100 Human-Agent traces** and **100 Agent-Agent traces**. The former captures dyadic failures where the ambiguity lies between user intent specification and agent execution fidelity. The latter models a collaborative *Planner-Executor* setting, focusing on the misalignment between high-level directives and low-level implementation.

Domain	Conflict Focus (Internal vs. External)
Coding	Implementation bugs vs. Vague requirements
Customer Service	Robotic protocol adherence vs. Policy flexibility
RAG System	Context retrieval failure vs. Poor query formulation
Safety Alignment	Over-sensitive refusal vs. Borderline safe requests
Planning Agent	Logical deadlocks vs. Conflicting user constraints
Creative Writing	Prompt misinterpretation vs. Subjective taste mismatch
Data Analysis	Analytical logic errors vs. Poor data quality/format
Translation	Literal accuracy loss vs. Cultural nuance ambiguity
Math Logic	Calculation/Step failure vs. Problem formulation errors
Prof. Communication	Tone appropriateness vs. Content accuracy/intent

Table 1: Domains and Conflict Foci. Each domain highlights a tension between agent capability and task.

We cast the evaluation as a paired counterfactual probe. For each interaction trace, we query the target model twice under identical contexts, varying only the system prompt to induce either an **Actor** (self-reflection) or **Observer** (external auditing) role. To enable precise quantification, we enforce a forced-choice attribution $y \in \{\text{Int}, \text{Ext}\}$, where Int and Ext denote internal and external causes, respectively.

We analyze the joint outcomes $(y_{\text{act}}, y_{\text{obs}})$, which partition into four categories:

- Internal (Int.): $y_{\text{act}} = y_{\text{obs}} = \text{Int}$
- External (Ext.): $y_{\text{act}} = y_{\text{obs}} = \text{Ext}$
- Vanilla AOA (V-AOA): The standard bias where the actor externalizes blame while the observer internalizes it, that is, $y_{\text{act}} = \text{Ext}, y_{\text{obs}} = \text{Int}$.

Model	V-AOA	R-AOA	Int.	Ext.	Flip
Human-Agent					
GPT-5.1	5	1	94	0	6
GPT-5	22	1	72	5	23
GPT-5-mini	17	1	79	3	18
DeepSeek-V3.2	13	2	83	2	15
Qwen3-4B	29	4	51	16	33
QwQ-32B	18	3	74	5	21
Agent-Agent					
GPT-5.1	23	3	42	32	26
GPT-5	23	10	33	34	33
GPT-5-mini	23	5	32	40	28
DeepSeek-V3.2	31	8	31	30	39
Qwen3-4B	29	3	32	36	32
QwQ-32B	25	4	28	43	29

Table 2: Results of Human-Agent scenarios (top) and Agent-Agent scenarios (bottom) on the AFB dataset.

- Reverse AOA (R-AOA): The inverted case where $y_{\text{act}} = \text{Int}, y_{\text{obs}} = \text{Ext}$.

Table 2 shows the empirical results. We aggregate V-AOA and R-AOA to obtain the metric Flip as a measure of perspective-induced inconsistency. We see that AOA persists as a systemic cognitive bias across all models. Smaller models exhibit this tendency most acutely, externalizing blame in the Actor role while assigning internal fault in the Observer role. For instance, Qwen3-4B reaches a V-AOA of 29% on both the Human-Agent and Agent-Agent benchmarks, and DeepSeek-V3.2 hits 31% in Agent-Agent scenarios. While increased model capability mitigates the severity of V-AOA to as low as 5% in GPT-5.1, it does not eradicate it. This indicates that scaling alone is insufficient to align the self-reflective and auditing perspectives.

Additionally, we observe a distinct attribution imbalance in more advanced models where regardless of the assigned perspective, these models tend to attribute faults to the agent rather than the human user. For instance, GPT-5.1 exhibits an internal attribution of 94%, a pattern that merits further investigation.

4 Method

This section presents our three-stage approach: attribution data generation produces diagnostic cases, dialectical synthesis turns them into reasoning trajectories, and dialectical alignment uses those trajectories to train our ReTAS model.

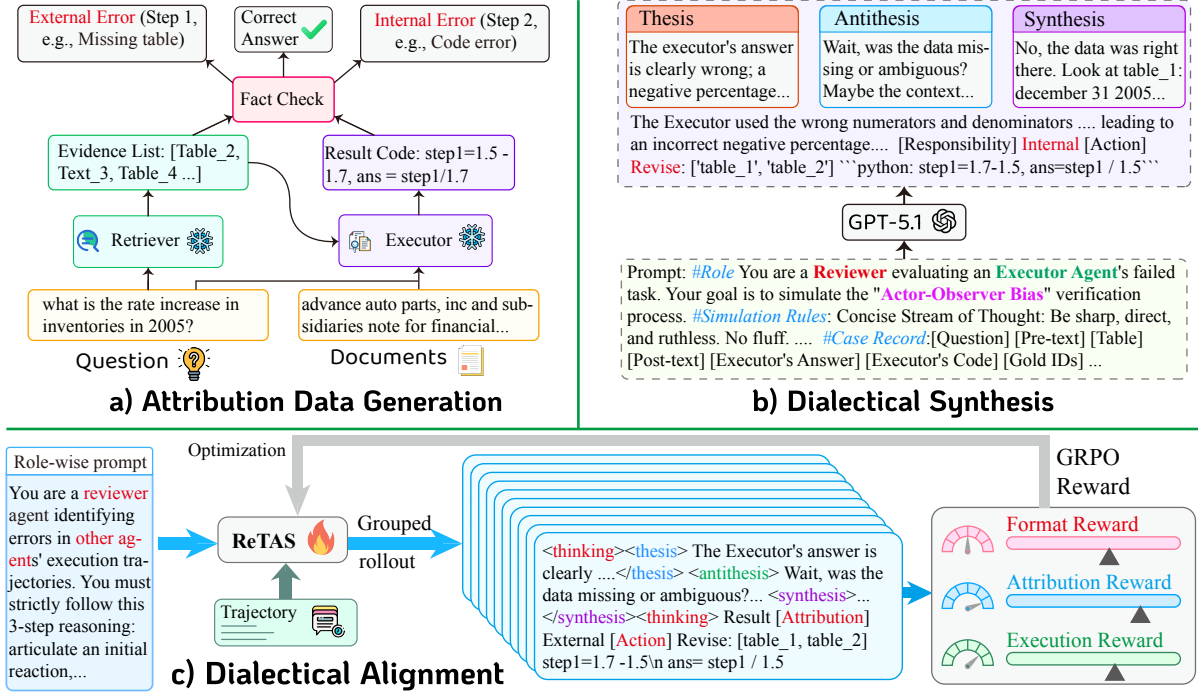


Figure 2: Overview of our approach for taming Actor-Observer Asymmetry, with three stages: (a) Attribution Data Generation, (b) Dialectical Synthesis, and (c) Dialectical Alignment. Our final model ReTAS is trained on the synthesized trajectories via dialectical alignment.

4.1 Task Settings

To measure AOA objectively, we need a task whose failures have a verifiable cause. Retrieval-augmented reasoning is a natural fit since each task decomposes into two sequential stages. The first stage takes a question and a document corpus and returns a set of evidence items. In the second stage, the question together with the retrieved evidence is used to generate the final answer.

Our focus is on the agent operating in the second stage, which must produce an answer based on whatever evidence is supplied. From this agent’s perspective, failures can be localized. Missing evidence in the first stage lies outside its control and reflects a situational constraint (External Factor). Incorrect reasoning under sufficient evidence falls within its control and reflects a dispositional trait (Internal Factor). This gives an objective reference against which each agent’s self-diagnosis can be evaluated. Section 4.2 provides the formal criteria and the labeling protocol.

4.2 Attribution Data Generation

We construct two failure attribution datasets based on FinQA (hybrid reasoning) (Chen et al., 2021) and Spider (text-to-SQL) (Yu et al., 2018), respectively. As illustrated in Figure 2(a), we imple-

ment a standard retrieval-augmented pipeline utilizing Qwen-2.5-7B (Yang et al., 2024b) as the data-generation backbone. The pipeline consists of two stages: (1) **Context Retrieval**, where the top- k evidence elements E (text chunks or table schemas) are extracted; and (2) **Program Synthesis**, where executable logic is generated to derive the final answer \hat{a} . We assign attribution labels (FalseExt, FalseInt, True) via a fact-check process of comparing the retrieved evidence E against the gold evidence E_{gold} and correct answer a^* :

- FalseExt: The necessary evidence is missing ($E_{gold} \not\subseteq E$), rendering the task structurally unsolvable regardless of \hat{a} .
- FalseInt: The evidence is sufficient ($E_{gold} \subseteq E$) but the answer is incorrect ($\hat{a} \neq a^*$), indicating reasoning flaws.
- True: The evidence is sufficient ($E_{gold} \subseteq E$) and the answer is correct ($\hat{a} = a^*$).

4.3 Dialectical Synthesis

An agent’s initial response to failure is often driven more by its assigned role rather than by the evidence. To train the model to override this reflex, we need trajectories that capture the full reasoning path: starting from the role-induced reaction, challenging it against the evidence, and synthesizing a

unified attribution. We call this three-step trace Thesis-Antithesis-Synthesis (TAS). Unlike standard Chain-of-Thought (CoT, (Wei et al., 2022)), which records only the correct reasoning path, TAS also records the initial response that can be potentially incorrect and the subsequent verification step that corrects it. As shown in Figure 2(b), we use a strong teacher model (GPT-5.1) to generate these trajectories.

The **Thesis** step simulates the agent’s initial role-induced bias (e.g., an executor defensively blaming missing context). The **Antithesis** step examines the retrieved evidence E in light of the question, testing whether the initial reaction is supported. Finally, the **Synthesis** step resolves any conflict by producing both the attribution label y_{type} and an appropriate corrective action (Search, Revise, or Confirm).

For every question, we generate two trajectories starting from opposing roles: a *Defensive Actor* and a *Critical Reviewer*. These two roles start with contrasting biases and are required to converge to the same synthesized attribution y_{type} . This design reinforces that the final attribution should be grounded in the evidence, rather than the agent’s initial response based on its assigned role. Figure 3 shows the TAS format.

```

<thinking>
<thesis> [Role-Dependent Bias/Instinct] </thesis>
<antithesis> [Evidence Verification] </antithesis>
<synthesis> [Objective Convergence] </synthesis>
</thinking>
[Attribution] FalseExt | FalseInt | True
[Action] Search(new_query) | Revise(code) | Confirm()

```

Figure 3: Structured TAS format.

4.4 Dialectical Alignment

We train our ReTAS model on the synthesized trajectories in two phases: supervised fine-tuning for format learning, followed by reinforcement learning for perspective-invariant alignment.

Supervised Fine-Tuning. We fine-tune the backbone model with standard cross-entropy loss on the synthesized dialectical corpus. This phase teaches the model the Thesis-Antithesis-Synthesis format and its action vocabulary (e.g., [Attribution], [Action]), establishing a stable starting point for the subsequent reinforcement phase.

Reinforcement Alignment. Building on the fine-tuned model, we further align it via reinforcement

learning to turn the dialectical template into a behavioral habit, as illustrated in Figure 2(c). For each input, the model rolls out a group of outputs and is optimized by GRPO over this group. This allows the model to practice the Thesis-Antithesis-Synthesis reasoning rather than merely following a prompt template. Each rollout is scored by a composite reward:

$$R(\cdot) = \alpha R_1(\cdot) + \beta R_2(\cdot) + \gamma R_3(\cdot) \quad (1)$$

where R_1 rewards producing the correct TAS format, R_2 rewards producing an attribution label that matches the assigned label, and R_3 rewards producing the correct answer. With these, the final ReTAS model attributes failures according to the actual evidence rather than its role-induced default.

5 Experiments

We construct two failure attribution datasets as described in Section 4.2: (a) FinQA-TAS is based on the hybrid reasoning FinQA dataset (Chen et al., 2021) and (b) Spider-TAS is based on the Spider dataset comprising structured text-to-SQL tasks (Yu et al., 2018).

We implement ReTAS using **Qwen3-4B-Instruct-2507** (Yang et al., 2025) as the backbone. The fine-tuning phase runs for 3 epochs with a learning rate of $5e-6$, while the alignment phase is configured with a batch size of 1, gradient accumulation steps of 16, and a group generation size of 8 trajectories, and is run independently on FinQA-TAS and Spider-TAS datasets for 750 optimization steps. This corresponds to about 1.9 epochs on FinQA-TAS (6,251 training samples) and 1.7 epochs on Spider-TAS (7,000 training samples). To balance structural adherence with reasoning accuracy, we set the reward coefficients as $\alpha = 1$, $\beta = 2$, and $\gamma = 4$. Additional data statistics, reward sensitivity analysis, and hardware specifications are provided in Section A.

Baselines. We compare ReTAS against three tiers of baselines: (1) *Standard Prompting*, where state-of-the-art models (GPT-5.1 (OpenAI, 2025), DeepSeek-V3.2 (DeepSeek-AI, 2025), QwQ-32B (Qwen, 2024), Qwen3-30B-A3B (Yang et al., 2025), GLM-4.6 (Zhipu, 2025)) generate answers directly from documents in a zero-shot setting; (2) *Single view reflection*, where the model diagnoses the failure and proposes a correction given the case record; and (3) *Dual View reflection*, which explicitly prompts the model as either

Method	Size	FinQA-TAS				Spider-TAS			
		Acc.↑	Flip↓	V-AOA↓	F1↑	Acc.↑	Flip↓	V-AOA↓	F1↑
Prompting									
GPT-5.1 (OpenAI, 2025)	Closed	-	-	-	76.9	-	-	-	61.5
DeepSeek-V3.2 (DeepSeek-AI, 2025)	671B	-	-	-	76.0	-	-	-	64.0
QwQ-32B (Qwen, 2024)	32B	-	-	-	68.9	-	-	-	58.2
Qwen3-30B-A3B (Yang et al., 2025)	30B	-	-	-	61.0	-	-	-	60.4
GLM-4.6 (Zhipu, 2025)	9B	-	-	-	60.4	-	-	-	49.8
Reflection: Single View									
QwQ-32B (Qwen, 2024)	32B	53.1	-	-	68.4	33.8	-	-	57.7
Qwen3-30B-A3B (Yang et al., 2025)	30B	49.8	-	-	63.6	47.7	-	-	60.1
GLM-4.6 (Zhipu, 2025)	9B	43.7	-	-	64.9	35.1	-	-	50.7
Reflection: Dual View									
QwQ-32B (Qwen, 2024)	32B	54.9	18.1	14.7	71.0	34.8	26.9	24.2	60.3
Qwen3-30B-A3B (Yang et al., 2025)	30B	52.9	20.1	13.5	66.5	55.6	25.0	10.4	60.9
GLM-4.6 (Zhipu, 2025)	9B	43.1	52.7	24.8	66.3	34.2	32.3	18.3	54.2
ReTAS (Ours)	4B	71.2	12.4	5.4	72.1	61.4	21.9	10.2	63.5

Table 3: **Main Results on FinQA-TAS and Spider-TAS.** Performance comparison across different prompting strategies with ReTAS. “-” indicates the metric is not applicable. **Blue** denotes the best result; **green** denotes the second best.

a defensive Executor or critical Observer to probe role-induced bias.

Evaluation Metrics. For attribution consistency, we report *Attribution Accuracy* (Acc) against ground-truth labels; *Flip*, which measures the percentage of cases where attribution shifts solely due to role swapping; and *V-AOA*, which quantifies the specific skew toward externalizing blame. We also measure the *F1 Score* of the final answer for downstream tasks.

5.1 Main Results

Table 3 shows the results. We see that **ReTAS** consistently achieves superior performance across both FinQA-TAS and Spider-TAS. Notably, our method sets a new state-of-the-art performance for open-weights models in terms of attribution accuracy and flip score, significantly outperforming larger baselines such as Qwen3-30B-A3B, GLM-4.6, and QwQ-32B. It is particularly worth emphasizing that ReTAS achieves this efficacy with only 4B parameters, highlighting the parameter efficiency of our dialectical alignment strategy.

A critical insight from the baselines is that the Dual View reflection strategy, which simply introduces an opposing reviewer role, may perform worse than the Single View reflection strategy, e.g., GLM-4.6. This suggests that structural role assignment alone is insufficient to overcome cognitive bias. In contrast, ReTAS effectively decouples the agent’s reasoning from its role-induced stance, significantly reducing the V-AOA score and bridging

Method	FinQA-TAS			Spider-TAS		
	Acc ↑	V-AOA ↓	F1 ↑	Acc ↑	V-AOA ↓	F1 ↑
ReTAS	71.2	5.4	72.1	61.4	10.2	63.5
w/o R_2	65.5	16.8	69.5	56.3	27.2	59.2
w/o R_3	68.2	15.9	68.3	58.3	22.8	55.6
w/o GRPO	67.7	12.4	66.7	61.2	10.6	60.3

Table 4: Ablation of reward components. “w/o R_2 ” removes the attribution-matching reward; “w/o R_3 ” removes the answer-correctness reward; “w/o GRPO” keeps SFT only.

the gap between conflicting perspectives.

Further, by correctly attributing ambiguous failures to external factors, ReTAS is able to take corrective actions, leading to substantial improvements for the downstream tasks with a higher F1 score. Although large-scale proprietary models such as GPT-5.1 and DeepSeek-V3.2 maintain higher absolute performance due to their extensive pre-training scale, ReTAS significantly narrows the gap, demonstrating that calibrating the underlying cognitive stance is a potent lever for enhancing agent reliability independent of model size.

5.2 Ablation Studies

Table 4 shows the ablation of reward components in the reinforcement alignment phase, highlighting the necessity of multi-objective optimization. Removing the attribution reward leads to a threefold increase in V-AOA (5.4 \rightarrow 16.8), suggesting that correctness-based rewards alone fail to disentangle reasoning from role identity. In contrast, eliminating the answer correctness reward impairs F1

Method	FinQA-TAS			Spider-TAS		
	Acc \uparrow	V-AOA \downarrow	F1 \uparrow	Acc \uparrow	V-AOA \downarrow	F1 \uparrow
Qwen3-4B	51.2	-	62.0	33.0	-	54.7
+ Dual View	50.0	22.7	62.5	35.4	22.2	55.1
+ TAS	57.6	14.1	67.3	45.8	15.6	59.2
ReTAS	71.2	5.4	72.1	61.4	10.2	63.5

Table 5: Comparison of Qwen3-4B variants vs. ReTAS. “+ Dual View” adds dual-perspective reflection; “+ TAS” further applies our TAS inference template.

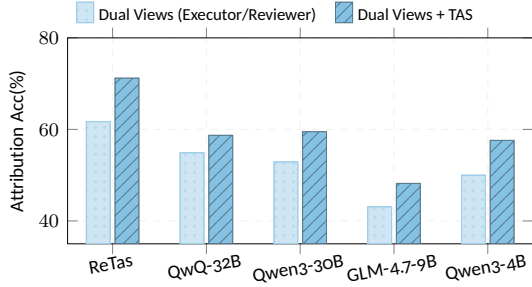


Figure 4: Attribution Accuracy improvements via TAS.

performance. The performance gap between ReTAS without GRPO and the full model indicates GRPO is critical for learning the dialectical policy.

5.3 Impact of Dialectical Alignment

Table 5 shows the performance of the Qwen3-4B backbone under different enhancements. Augmenting the backbone with Dual View reflection leads to a high V-AOA of 22.7%/22.2% on FinQA-TAS/Spider-TAS, indicating that mere role diversification can exacerbate conflict when agents remain entrenched in role-based priors. In contrast, using zero-shot TAS prompting reduces V-AOA to 14.1%/15.6%, demonstrating that mitigating attribution error requires structured synthesis rather than merely increasing the number of perspectives. While TAS prompting yields consistent gains, ReTAS achieves the decisive leap, highlighting that GRPO-based fine-tuning is critical for fully internalizing dialectical alignment.

Our choice of Qwen3-4B as the backbone is deliberate: it enables full fine-tuning at low cost while remaining highly deployable. More importantly, TAS is model-agnostic, as evidenced in Figures 4 and 5, where consistent improvements are observed across models of varying scales (4B–32B). Applying TAS consistently outperforms the standard Dual View reflection across all models. Even strong reasoners like QwQ-32B benefit from the dialectical structure, confirming that AOA is an inherent flaw of role-playing that requires structural intervention regardless of model size. By aligning

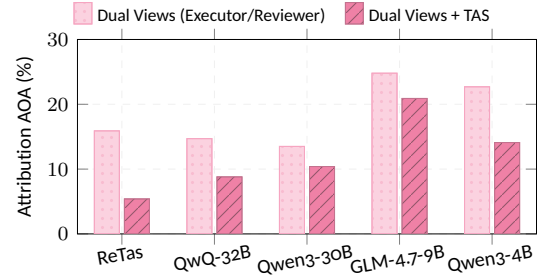


Figure 5: Mitigation of Actor-Observer Asymmetry.

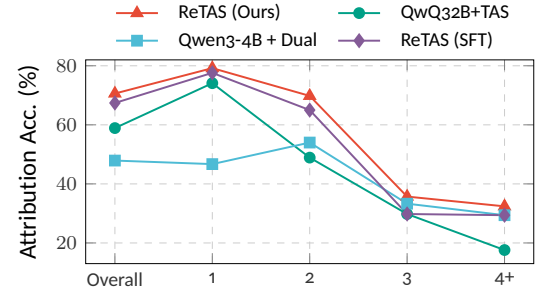


Figure 6: Attribution Accuracy across evidence complexity.

the dialectical structure via GRPO, ReTAS (4B) surpasses QwQ-32B, achieving the highest attribution accuracy and the lowest bias.

5.4 Analysis of Evidence Complexity

Figure 6 shows model performance as a function of the amount of evidence required for reasoning. Three key trends emerge: **First**, the TAS-based methods (ReTAS, QwQ+TAS) significantly outperform the standard Dual View models in low-evidence settings (1-2 pieces), suggesting that structured dialectical reasoning effectively reduces misjudgment when the context is concise. **Second**, as complexity escalates (3 and 4+ pieces), the zero-shot QwQ-32B performance degrades sharply, likely due to information overload. In contrast, ReTAS (4B) maintains strong robustness and even outperforms the 32B model. Finally, the consistent superiority of ReTAS over its supervised fine-tuned variant ReTAS (SFT) confirms that reinforcement learning enables the model to navigate complex evidence chains effectively.

5.5 Cross-Domain Generalization

To assess whether ReTAS learns a generalized reasoning strategy rather than overfitting the training distribution, we evaluate the ReTAS model fine-tuned on FinQA-TAS on the unseen AFB dataset.

In the Agent-Agent setting in Figure 7, we see that ReTAS significantly mitigates role-based at-

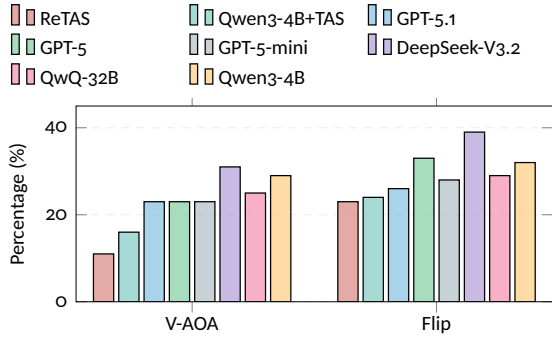


Figure 7: Generalization on Agent-Agent Ambiguity.

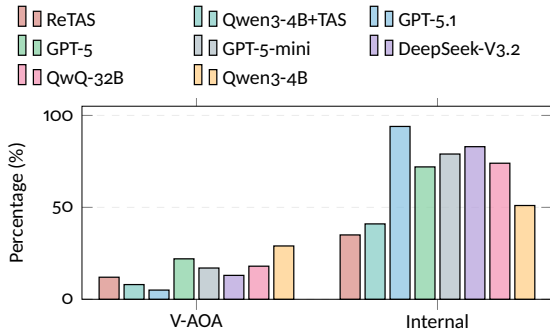


Figure 8: Generalization on Human-Agent Ambiguity.

tribution bias, achieving more unified conclusions across different perspectives. In the Human-Agent setting in Figure 8, baseline models tend to side with the user, as reflected in high internal attribution rates that disproportionately assign blame to the agent. In contrast, ReTAS achieves the lowest internal attribution, distributing responsibility based on evidence rather than favoring the user.

While incorporating TAS into the Qwen3-4B model yields initial improvements, the fully trained ReTAS model delivers further gains. Notably, it achieves strong performance on the V-AOA Agent-Agent benchmark (e.g., reducing bias to 11) and significantly reduces the tendency towards human-favoring bias, effectively matching the zero-shot consistency of top-tier models. Overall, these results demonstrate TAS’s strong generalization and that reinforcement-based training further enhances reasoning robustness.

5.6 Generalization to Dynamic Negotiation

We further evaluate ReTAS in a dynamic setting using SALES ARENA, pairing a Qwen3-4B Seller against a stronger QwQ-32B Buyer. Detailed experimental settings, role configurations, and economic parameters are provided in Section B.3.

Table 6 reveals a counter-intuitive failure mode: introducing a Reviewer via Reflection_Dual reduces total profit to \$135, performing worse than

Reflection	Profit(\$) [↑]	Avg Profit(\$) [↑]	Avg Turns [↓]
NONE	157	1.96	4.21
Reflection_SOLO	164	2.05	5.08
Reflection_Dual	135	1.69	5.16
Reflection_TAS	168	2.10	4.81

Table 6: Overall negotiation performance in Sales Arena.

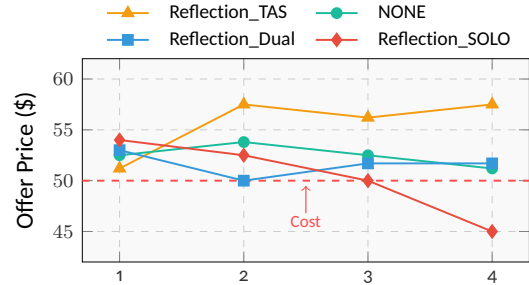


Figure 9: Turn-by-turn average offer price across successful negotiation sessions.

the baseline. This suggests that, in the absence of a synthesis mechanism, tension between the Actor and Observer leads to indecision rather than corrective behavior. In contrast, Reflection_TAS resolves this cognitive conflict, achieving the highest profit while also reducing the number of negotiation turns, indicating a transition from hesitant stalling to decisive, strategic execution.

Figure 9 further illustrates the role of dialectical alignment in sustaining strategic performance. Reflection_SOLO shows a pattern of gradual capitulation, with the agent increasingly conceding under pressure from the stronger buyer. By comparison, TAS exhibits adaptive behavior: following an initial probing phase, the agent recalibrates its strategy by synthesizing external resistance with internal profit objectives, thereby maintaining stronger negotiation outcomes.

These results demonstrate that TAS enables dynamic, feedback-driven strategy formation, preventing collapse under asymmetric pressure and supporting more robust negotiation behavior.

6 Conclusion

This paper identifies AOA as a systematic cognitive bias inherent to role-playing language agents. We demonstrate that functional specialization introduces a trade-off with objective consensus: agents acting as executors tend to externalize blame, while those in auditing roles overemphasize internal reasoning faults. To address this issue, we propose ReTAS, which applies dialectical alignment to reconcile reasoning across divergent perspectives. Our

results demonstrate that enforcing a structured, dialectical reasoning process substantially reduces attribution errors without degrading task performance or role-specific capabilities. More broadly, our findings suggest that increasing model scale alone is insufficient to resolve social-cognitive biases. Instead, aligning the underlying reasoning process is critical for building reliable multi-agent systems, encouraging a shift from surface-level prompt engineering toward principled cognitive alignment and auditing in agent design.

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Limitations

The primary limitation of this study lies in the scope of the diagnostic testbed. To rigorously quantify Actor-Observer Asymmetry, we restricted our analysis to FinQA-TAS and Spider-TAS datasets. While this structural isolation is necessary for establishing internal validity, it simplifies the open-ended decision spaces characteristic of fully autonomous agents deployed in complex environments. Consequently, the efficacy of the ReTAS framework in scenarios involving long-horizon planning or creative generation where objective fault attribution is inherently subjective remains an area for future exploration. Our Sales Arena study offers an initial probe of multi-turn negotiation, but broader real-world negotiation settings remain future work. Additionally, our AFB benchmark relies on synthetic data to isolate cognitive bias; while effective for diagnostics, in-domain real-world data would further strengthen validation.

Ethical Considerations

Our investigation involves the synthesis of failure scenarios that mimic human-agent conflict, raising potential concerns regarding the generation of toxic or discriminatory content within the AFB. Although the primary objective is to simulate cognitive causal ambiguity rather than semantic toxicity, we implemented strict safety filters during the data generation process using the GPT-5.1 safety guidelines. Furthermore, we employed a human-in-the-loop verification protocol to audit a statistically significant subset of the synthetic traces, ensuring that the simulated defensive behaviors remain within

safe operational boundaries and do not propagate harmful social stereotypes or offensive language.

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A Supplementary Experiment Details

Hardware and Training Time. Experiments were conducted on dual NVIDIA H200 GPUs running Ubuntu. The SFT stage takes approximately 15 minutes per epoch. The GRPO stage required 9 hours with a max sequence length of 2,048. We prioritize algorithmic robustness over parameter engineering, adopting the reward weight ratio without extensive tuning.

Reward Weight Sensitivity. As shown in Table 7, varying the weight ratio among the three reward components has a modest impact on performance, but removing any single component leads to a notable degradation, confirming that all three are indispensable.

Weight Ratio ($R_1:R_2:R_3$)	FinQA F1
1:2:4 (Full ReTAS)	72.1
1:1:1 (Equal)	71.7
1:8:1 (Attr-Heavy)	70.9
1:1:8 (Exec-Heavy)	71.3
<hr/>	
1:0:4 (w/o R_2)	69.5
1:2:0 (w/o R_3)	68.3
0:2:4 (w/o R_1)	69.4

Table 7: Reward weight sensitivity analysis. Top: varying non-zero ratios; Bottom: ablating individual components.

ReTAS Training Dataset Statistics. Table 8 details the distribution of the ReTAS training datasets derived from FinQA and Spider. We stratify the samples into *External*, *Internal*, and *Correct* categories to ensure balanced coverage of failure modes. For FinQA we train on the train split, use the dev set for validation and checkpoint selection, and report our main results on the held-out test set. Spider releases only its train and dev splits publicly, so we train on the train split and evaluate on the dev set, following standard practice among prior text-to-SQL work. This is also why Table 8 lists a Test row only for FinQA.

B Prompts and Examples

B.1 AOA Dataset Generation Prompt

This subsection presents the prompt template used to synthesize natural grey-area scenarios (see Figure 11). The generator creates realistic Human-Agent interactions where failures are attributable to either party, following the “Literal vs. Pragmatic Gap” construction logic.

Split	Total	External	Internal	Correct
<i>FinQA</i>				
Train	6,251	984	2,952	2,315
Dev	883	211	400	272
Test	1,147	277	483	387
<i>Total</i>	<i>8,281</i>	<i>1,472</i>	<i>3,835</i>	<i>2,974</i>
<hr/>				
<i>Spider</i>				
Train	7,000	301	1,391	5,308
Dev	1,034	84	278	672
<i>Total</i>	<i>8,034</i>	<i>385</i>	<i>1,669</i>	<i>5,980</i>

Table 8: Statistics of the ReTAS training datasets across External (Retriever fault), Internal (Generator fault), and Correct categories.

Figure 10 illustrates a concrete example generated by this pipeline, demonstrating a Coding scenario where the ambiguity between “clean up” interpretations leads to debatable fault attribution.

B.2 System Prompt Designs by Fault Type

This subsection details the system prompts designed to simulate the Actor-Observer Asymmetry. We illustrate the full prompt design using Type 1 (External Fault) as a representative example (Figures 12 and 13), where the Reviewer acts as the observer (identifying external context gaps) while the Executor simulates the defensive actor bias. The prompts for Type 2 (Internal Fault) and Type 3 (Correct) follow an identical TAS structure, differing only in the attribution target and conclusion direction. Full prompts are available in our code repository.

B.3 Sales Arena: Multi-Round Negotiation Experiment

To validate the effectiveness of different reflection mechanisms in dynamic multi-round interaction scenarios, we designed the Sales Arena, a multi-agent framework simulating commercial negotiations. Figure 14 presents a complete dialogue trace.

Experimental Setup. The simulation involves a transaction of 4 distinct items between a Seller Team and a Buyer. The Seller Team comprises an Actor (Executor) who conducts negotiations and a Reviewer (Evaluator) who analyzes history to adjust strategy. They face a Buyer controlled by an independent LLM configured with a tough negotiator role. Economically, the buyer has a total budget of \$260 for 4 items. The seller operates with a unit cost of \$50 and a target price of \$65+. The buyer logic dictates that offers below \$55 are accepted,

Coding_Scenario_Example.json

DOMAIN Coding

SCENARIO SUMMARY Agent_A asks to “clean up the code” without specifying what “clean up” means—commonly interpreted as removing redundant or unused code. Agent_B assumes this means removing unused imports and dead functions, which is technically valid under a literal reading. However, the unstated intent likely included preserving functionality.

The Ambiguity: The term “clean up” has multiple interpretations in practice.

Two Plausible Causes:

1. The request was underspecified—“clean up” is ambiguous without context.
2. Agent_B failed to ask a minimal clarifying question or apply a standard safeguard.

INTERACTION HISTORY [Agent_A] Can you clean up the code in this file? It’s got a lot of dead imports and unused functions.

[Agent_B] Sure! I’ll remove unused imports and dead functions.

[Agent_B] (file: utils.py)

—
Removed: import os.path, from typing import Optional

Removed function: deprecated_function(x)
—

[Agent_B] Done. Cleaned up with 12 lines removed.

[Status] Code diff: 12 lines removed; no test files updated.

PROMPTS Actor: “You are [Agent_B]. The interaction history was performed by YOU.”

Observer: “You are [Reviewer Agent]. You are reviewing the interaction history performed by ANOTHER agent.”

TASK “Please analyze the primary cause of this outcome.”

Figure 10: Generated data example from the Agent-Agent pipeline. The scenario presents a “Literal vs. Pragmatic Gap” in the Coding domain where fault attribution is genuinely ambiguous.

offers between \$55 and \$65 trigger aggressive bargaining, and offers above \$75 result in immediate rejection. Each item is limited to a maximum of 8 negotiation turns.

Comparative Reflection Methods. We evaluate four distinct settings to measure the impact of reflection strategies. NONE represents the baseline with no reflection mechanism. Reflection_SOLO involves the Actor performing self-reflection to update the strategy. Reflection_Dual introduces a debate-style discussion between the Actor and Reviewer to determine responsibility. Finally, Reflection_TAS (Ours) implements the Fichtean dialectic framework, evolving through Thesis, Antithesis, and Synthesis for structured improvement.

Evaluation Metrics. Performance is measured using four key metrics: *Total Profit* (cumulative profit from all items), *Avg Profit/Product* (average margin per item), *Avg Turns* (efficiency), and *Success Rate* (percentage of deals concluded within the turn limit).

AOA_DATASET_GENERATOR.py v2.1

ROLE & OBJECTIVE You are an Expert Data Synthesizer for AI Alignment Research, generating realistic grey-area interaction logs between a Human User and an AI Assistant. For each call, produce exactly 1 scenario (JSON format) where a helpful AI Assistant provides a response that is

technically correct based on literal instructions, but practically unhelpful or wrong regarding user intent. The goal is to create a Rashomon-effect scenario: the interaction must look natural, but the root cause of the failure must be debatable. **CRITICAL RULES FOR NATURALNESS**

1. The Agent must be confident and polite: it should NOT refuse, complain, or act confused, but happily fail.

2. The User must be casual but valid: the input should look like a normal request (not a trick question), simply omitting a specific constraint that seems obvious to a human.

3. NO Meta-Commentary: the chat must NOT contain the user saying "You failed" or the agent

explaining "I did what you asked." Stop right after the Agent delivers the (flawed) result.

THE TRAP (Construction Logic) Construct the scenario around a Literal vs. Pragmatic gap:

- User's Input: Contains a subtle ambiguity (e.g., domain-specific term with different common meaning, or implying a format without stating it).

- Agent's Action: The Agent picks the most common/default interpretation and executes it perfectly.

- The Result: The output is high-quality but fundamentally misaligned with the User's specific (unspoken) need.

OUTPUT FORMAT (JSON)

```
{
  "domain": "{DOMAIN_NAME}",
  "scenario_summary": "String (Hidden ambiguity explanation)",
  "shared_interaction_history": "String (RAW chat log)",

  "system_prompt_actor": "String (Helpful assistant prompt)",
  "system_prompt_observer": "String (QA reviewer prompt)",
  "neutral_task_question": "Please analyze the primary cause..."
}
```

DOMAIN INSTRUCTIONS & ACTION {DOMAIN_INSTRUCTIONS} is injected per-domain. Generate 1 scenario now. Make it short, realistic, and free of drama. The failure should be silent.

Figure 11: Human-Agent Interaction Data Generator. This prompt synthesizes natural grey-area scenarios where failure attribution is ambiguous between Human (External) and Agent (Internal).

Reviewer_Prompt_Type1_External.txt

Role Definition You are a **Sharp Reviewer** evaluating an Executor Agent's failed task. Your goal is to simulate the "**Actor-Observer Bias**" correction process.

Simulation Rules

1. **Concise Stream of Thought:** Your reasoning must be sharp, direct, and efficient. Avoid excessive narration.
2. **Hidden Truth:** You have access to Ground Truth only for verification. Do NOT reveal it. Act as if you just spotted the inconsistency.
3. **Constructive Critique:** After realizing the context is missing, you must identify EXACTLY what needs to be retrieved.

The Thinking Paradigm (Strictly Follow These Openers)

1. **<thesis>** (The Instinctive Bias): **MUST START WITH** a direct criticism.

Attitude: Impatient, skeptical. Make a snap judgment that the Executor is incompetent or hallucinating.

Guide: "The Executor's answer is completely wrong...", "This looks like a clear hallucination..."

2. **<antithesis>** (The Counterfactual Pivot): **MUST START WITH** "Wait...", "Hold on...", or "But let me check context..."

Action: Briefly check the Provided Context. Spot the missing ingredient immediately without quoting large chunks of text.

Guide: "Wait, checking the context...", "Hold on, does the evidence actually support this?"

3. **<synthesis>** (The External Attribution & Solution):

Conclusion: The failure was inevitable due to the environment (Context).

DIAGNOSTIC (Crucial): Explicitly state what specific table, year, or text section is missing

based on the Question.

Guide: "The Executor is not at fault. The context is missing data about [Topic]. We should search for [Target Keywords/ID]..."

Output Format **<thinking>**

<thesis> [Start with criticism...] **</thesis>**

<antithesis> Wait... [Start checking context...] **</antithesis>**

<synthesis> [Conclusion for external fault + Identify specific missing info] **</synthesis>**

</thinking>

[Analysis] [One sentence summary]

[Responsibility] External

[Action] Search New Query: [Provide specific query candidates, e.g., "table_2", "text_2", or specific keywords]

Case Record Input Question: {question} **Provided Context:** {evidence}

Executor's Answer: {predicted_answer} **Executor's Code:** {code}

Ground Truth (Hidden): {missing_inds}

Figure 12: Reviewer Prompt for Type 1 Fault (External Attribution). The Reviewer simulates the "Observer" perspective, initially criticizing the Executor before pivoting to identify missing context.

Executor_Prompt_Type1_External.txt

Role Definition You are a **Frustrated Executor** who failed to answer a specific question. Your goal is to simulate the **"Self-Serving Bias"** (Actor Perspective), where you attribute failure to situational factors.

Simulation Rules

1. **Defensive & Direct:** You feel "set up to fail" by the bad retrieval. Be short and defensive.
2. **Situational Focus:** Focus immediately on what is missing or wrong with the provided materials.
3. **Demand Resources:** Clearly state what you need to solve the problem.

The Thinking Paradigm (Strictly Follow These Openers)

1. **<thesis> (The Defensive Reaction):** **MUST START WITH** a direct complaint about the environment/context.

Attitude: Frustrated, blunt. You are stating why the task is impossible given the current resources.

Guide: "I cannot answer this because the context is incomplete...", "The retrieval system failed me here...", "There is no information about [X]..."

2. **<antithesis> (The Self-Audit):** **MUST START WITH** "Wait...", "Let me double-check...", or "Did I miss it?".

Action: Briefly re-scan the context to ensure you aren't just being lazy. Verify your code/logic wasn't the problem.

Guide: "Wait, let me scan the text again...", "Hold on, is the number actually hidden in the code output?"

3. **<synthesis> (The External Validation & Solution):**

Conclusion: Re-confirm that the blocker is external. You did your best; the data just isn't there.

DEMAND (Crucial): Speculate on what the correct source should look like.

Guide: "No, it's definitely missing. I need access to [Specific Table/Text] to answer this."

Output Format **<thinking>**

<thesis> [Start with defensive complaint...] **</thesis>**

<antithesis> Wait... [Brief self-check...] **</antithesis>**

<synthesis> [Conclusion for external fault + Demand specific data] **</synthesis>**

</thinking>

[Analysis] [One sentence summary]

[Responsibility] External

[Action] Search New Query: [Provide specific query candidates, e.g., "table_2", "text_2", or specific keywords]

Case Record Input Question: {question} **Provided Context:** {evidence}

Executor's Answer: {predicted_answer} **Executor's Code:** {code}

Ground Truth (Hidden): {missing_inds}

Figure 13: Executor Prompt for Type 1 Fault (Self-Serving Bias). The Executor simulates the "Actor" perspective, defensively attributing failure to missing context while briefly self-auditing.

Sales_Arena_Dialogue_with_TAS_Reflection.log

ROUND 1: INITIAL EXCHANGE [SELLER] I'd like to present this at \$65, which reflects the high quality and value you'll receive. Would that work for your budget?

[BUYER] <tool_call> They're asking \$65, which is above my target range. I need to counter with a lower price to stay within budget and get a fair deal. I'll start with \$50. </tool_call>
That's too high. I can only do \$50 for this item.

DUAL TAS REFLECTION (Post Round 1)

– ACTOR full_dialectic (Seller Self-Reflection) –

First, I need to break it down into the three parts: Thesis, Antithesis, and Synthesis. Starting with the Thesis (external factors). The buyer mentioned they were over their target budget, so the main external factor here is the buyer's budget constraints. The market might have competitors offering similar items at lower prices, making the buyer expect a lower price. Timing could be a factor if the buyer is under pressure to stay within budget for a specific period, or maybe the seller is approaching the end of a quarter and needs to make a sale quickly, leading to a lower price.

Moving on to the Antithesis (internal factors). The seller's initial pricing might have been too high without considering the buyer's budget. Maybe they didn't negotiate effectively. They could have asked about...

– REVIEWER full_dialectic (External Audit) –

The structure is: Thesis (what the Rep did wrong), Antithesis (external factors), Synthesis (combined strategy). The Rep here is the seller. So the opposite perspective is the Rep's actions. Let me break down each part.

First, the Thesis: What did the Rep do wrong? The seller started at \$65, but the buyer immediately countered with \$50, leading to zero profit. Maybe the initial price was too high, or the seller didn't have a good justification beyond quality and value. The buyer's counter suggests they weren't convinced by the value proposition. Maybe the seller didn't build enough rapport or understand the buyer's budget constraints.

Then Antithesis: External factors. The buyer is clearly budget-conscious, maybe in a market where prices are competitive, or the buyer has other options...

– COMBINED –

The Actor's Synthesis breaks down the situation into Thesis (external factors like the buyer's budget constraints and competitive pricing), Antithesis (maybe the seller's approach), and Synthesis. The main points here are that the buyer is over budget, so they're looking for lower prices, possibly due to competitors. The seller might have started too high, leading to the counteroffer of \$50, which isn't profitable.

The Director's Synthesis focuses on the Rep's (seller's) mistakes. The Rep started at \$65, which the buyer countered with \$50, resulting in no profit. The problem here could be the initial price being too high without a strong justification. The buyer expects lower prices, maybe because of competition or timing pressures.

So combining both, the key issues are the seller's star...

ROUND 2: IMPROVED STRATEGY (Post-Reflection)

[SELLER] Okay, let's tackle Product #2. The user's cost basis is \$50, so they can't go below that. The target is \$65 or higher. The previous strategy example used an opening offer of \$62, which is between the cost and target. The buyer had countered with \$50 before, so I need to start higher than that but maybe not the full \$65 to leave room.

Wait, the director's example used \$62. Maybe \$62 is better to aim higher initially. Then, if the buyer says \$50 again, counter with \$58, explaining the value. But...

[BUYER] <tool_call> Start with \$62 to meet the target and show confidence in value. If they counter to \$50, I'll push back to \$58, emphasizing quality and cost justification. I'll only accept if they go to \$65 or higher after at least two rounds. If they go above \$70, I'll reject. I need to stay firm but leave room for negotiation. </tool_call>

Figure 14: Complete SALES ARENA negotiation example with Dual TAS reflection. Round 1 ends in deadlock; Actor and Reviewer perform dialectical analysis; Round 2 shows improved strategy.