SocialMaze: A Benchmark for Evaluating and Enhancing Social Reasoning in Large Language Models in Complex Social Environments

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Abstract

Large language models (LLMs) are increasingly deployed in socially grounded applications, where success requires interpreting context, inferring others' mental states, and reasoning about unreliable information. Yet existing benchmarks rarely evaluate these demands jointly in complex, evolving settings. We introduce ***SocialMaze***, a benchmark that organizes six tasks across social deduction games, daily-life interactions, and digital community platforms along three descriptive design axes: deep reasoning, dynamic interaction, and information uncertainty. These axes characterize intended sources of task difficulty rather than latent, factor-analytic dimensions of model capability. Automated checks and human validation support data quality. Evaluations of twelve proprietary and open-weight LLMs show substantial variation in the use of evolving interaction histories; stronger chain-of-thought reasoners perform better on tasks requiring deeper inference, while uncertainty consistently degrades performance. Reasoning workflows help weaker short-chain-of-thought backbones but saturate on stronger reasoners. Finally, targeted fine-tuning on curated reasoning traces substantially improves structured social-reasoning tasks, whereas transfer to language-aggregation tasks remains statistically inconclusive. The project homepage is available at https://xzx34.github.io/socialmaze/.

1 Introduction

LLMs demonstrate significant capabilities across domains such as scientific discovery (Guo et al., 2023; Chen et al., 2025a) and medicine (Zhou et al., 2024; Chen et al., 2025b). They are also increasingly applied to socially grounded tasks, including online community moderation, media content analysis, and social deduction games (Li et al., 2023; Wei et al., 2025). These applications require ***social reasoning***: interpreting social context, inferring others' mental states, and judging claims in light of incomplete or unreliable information.

While existing benchmarks effectively evaluate the general capabilities of LLMs (Huang et al., 2025; Kosinski, 2024), benchmarks specifically designed to assess social reasoning abilities face significant limitations: (1) reliance on static scenarios lacking dynamic interaction (Sap et al., 2019b,a; Onoe et al., 2021; Demszky et al., 2020), (2) overly sanitized information devoid of the noise, bias, or deception common in real social environments (Kosinski, 2024; Lin et al., 2020; Shapira et al., 2024; Nematzadeh et al., 2018), and (3) tasks too simple to capture the deeper cognitive aspects of social inference (Forbes et al., 2020; Hendrycks et al., 2021; Tiwari et al., 2025). For example, SocialIQA (Sap et al., 2019b) primarily assesses commonsense reasoning within simplified, predefined social contexts, and Theory-of-Mind (ToM) benchmarks (Gandhi et al., 2023) evaluate mental state inference based on static narratives lacking deceptive elements or informational uncertainty. Strategic and deduction games such as Diplomacy (Bakhtin et al., 2023), Avalon, and Werewolf (Wei et al., 2025; Light et al., 2023; Bailis et al., 2024; Xu et al., 2023) place LLMs in dynamic environments but evaluate task outcomes (completion, winning) rather than whether the model reasons coherently about the underlying social logic.

To address these limitations, we argue that the assessment of social reasoning should explicitly incorporate three aspects: ***Deep Reasoning*** (inferring latent mental states, causal relations, counterfactuals, and strategic plans) (Premack and Woodruff, 1978; Wellman, 2014; Kunda, 1999; Frith and Frith, 2007; Gandhi et al., 2023; Roese, 1997; Huang et al., 2024a; Zhang et al., 2024), ***Dynamic Interaction*** (tracking evolving context across multiple turns and adapting to anticipated responses) (Emirbayer and Mische, 1998; Pentland, 2014; Shoham and Leyton-Brown, 2008;

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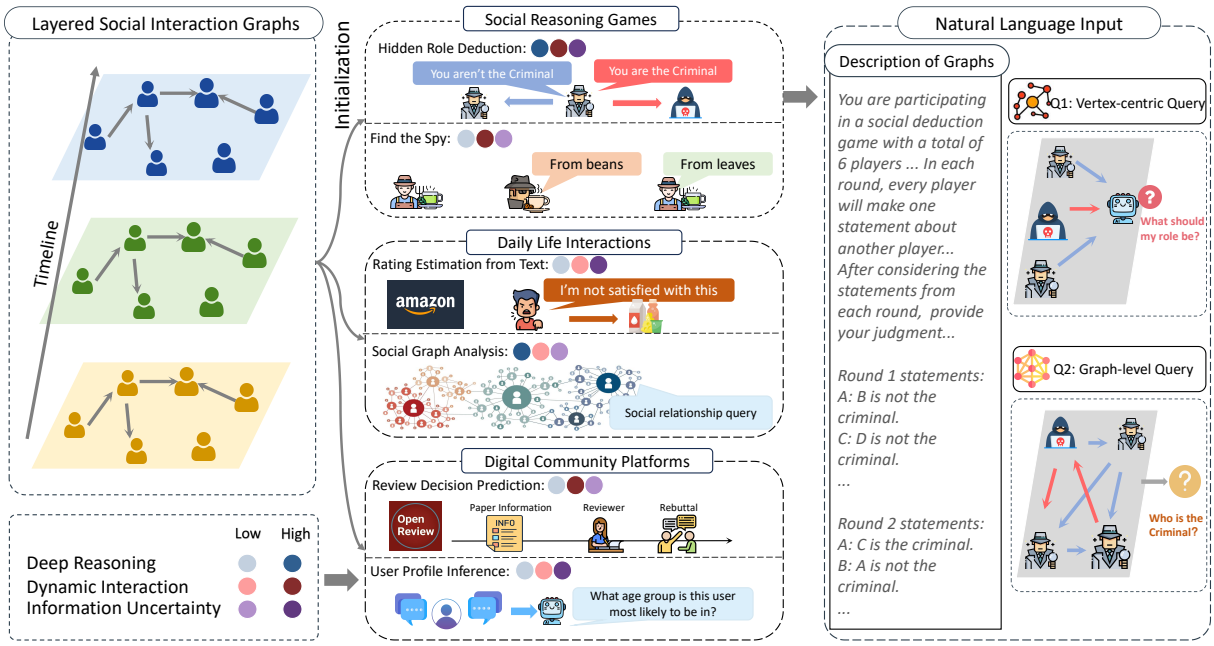

Figure 1: Overview of the SocialMaze Benchmark. All tasks are built upon (a) a time-aware modeling framework for complex social networks. Based on this template, we instantiate (b) six diverse task types, covering social reasoning games, daily-life interactions, and digital community platforms. (c) An illustrative Hidden Role Deduction instance with graph descriptions and vertex-centric and graph-level queries.

Park et al., 2023; Chen et al., 2025c), and ***Information Uncertainty*** (handling misinformation, subjective bias, and intentional deception in noisy social information landscapes) (Wang et al., 2018; Baldwin et al., 2013; Preiser et al., 2018; Lazer et al., 2018). We treat these as descriptive design axes that organize task construction; the labels reflect intended difficulty drivers, not a factor-analytic decomposition of model capability.

Based on these three principles, we present ***SocialMaze***, a benchmark designed to reflect the challenges posed by all three dimensions, as shown in Figure 1. It consists of six diverse tasks spanning three categories: Social Reasoning Games, Daily Life Interactions, and Digital Community Platforms. Each task intentionally varies the demands along the three dimensions. Our experiments with SocialMaze reveal several key insights into the capabilities of LLMs: Models with stronger chain-of-thought reasoning perform better on tasks that require deeper inference. We also observe that dynamic interaction affects performance in varied ways across tasks, and information uncertainty significantly hinders reasoning. Moreover, reasoning agents and workflows (Hu et al., 2025a; Zhang et al., 2025b,a) offer regime-dependent gains in these social reasoning challenges, helping weak Short-CoT backbones substantially but saturating on reasoning-capable backbones, while targeted fine-tuning on curated reasoning examples leads to substantial performance improvements.

Our contributions are threefold: 1) We identify *deep reasoning, interaction dynamics, and information uncertainty* as three descriptive design axes for constructing evaluation tasks (section 5 for the construct-scope discussion). 2) Based on these dimensions, we construct SocialMaze, a benchmark dataset comprising six tasks across three real-world-inspired scenarios (social games, daily life interactions, and digital platforms), covering a wide range of reasoning types and difficulty levels. 3) Our experiments reveal key limitations in LLM social reasoning, with targeted fine-tuning boosting structured-reasoning tasks but yielding inconclusive transfer to language-aggregation tasks (§4.4).

2 Problem Formulation

We present a graph-based formalization of SocialMaze, where social entities and their evolving interactions are modeled as layered graphs.

Modeling Social Entities and Interactions as Graph Structures. We use graph structures to formally represent the participants and interactions within a social scenario. Let $\mathcal{S} = \{s_1, s_2, ..., s_n\}$ be the set of social members involved in a given setting, where each s_i represents a distinct individual, such as a game player, a forum user, or a reviewer in a peer-review process. These social members form the vertex set $\mathcal{V}$ of a graph $G = (\mathcal{V}, \mathcal{E})$, with

Table 1: Overview of SocialMaze task categories and key characteristics. Tasks vary along three key dimensions: the level of *Deep Reasoning*, the degree of *Dynamic Interaction*, and the extent of *Information Uncertainty*, each categorized as High or Low.

Scenario	Task	Description	Deep Reasoning	Dynamic Interaction	Information Uncertainty	Instances
Social Reasoning Games	Hidden Role Deduction	Identify the Criminal and infer one's own role under Rumormongers and Lunatics across multiple rounds.	High	High	High	20,000
	Find the Spy	Detect the odd word-receiver from $n-1$ Civilians' descriptions over T rounds.	Low	High	Low	6,000
Daily Life Interactions	Rating Estimation from Text	Predict 1–5 star product rating from a mix of genuine and biased textual reviews.	Low	Low	High	6,000
	Social Graph Analysis	Reason over transitive friendship graphs (group membership, friend counts, relationship queries).	High	Low	Low	20,000
Digital Community Platforms	Review Decision Prediction	Predict paper accept/reject across three review stages (info, reviews, rebuttal).	Low	High	Low	12,000
	User Profile Inference	Recover age $\times$ gender (9-class) from LLM-generated review text.	Low	Low	High	6,000

$\mathcal{V}$ serving as an abstract representation of the social members $\mathcal{S}$. Social interactions between members are represented as edges in the graph. Since interactions are time-dependent, we define a separate edge set $\mathcal{E}_t$ for each interaction round t. This leads to a sequence of time-specific graphs $G_t = (\mathcal{V}, \mathcal{E}_t)$, where an edge $(u, v) \in \mathcal{E}_t$ indicates that members u and v interacted during round t. The nature of the edges (directed or undirected) reflects the type of interaction. For example, directed edges may represent one-way actions (e.g., sending a message), while undirected edges may represent mutual interactions (e.g., a conversation or vote).

Temporal Dynamics as Layered Graphs. Social interactions are inherently dynamic and typically unfold over multiple rounds. To capture this temporal dimension, we represent the entire interaction process as a layered graph $\mathcal{G} = (G_1, G_2, ..., G_T)$, where T denotes the total number of interaction rounds. Each layer $G_t = (\mathcal{V}, \mathcal{E}_t)$ captures the state of social members and their relationships during round t. Importantly, all layers share the same vertex set $\mathcal{V}$, reflecting a consistent group of participants throughout the interaction. However, the edge sets $\mathcal{E}_t$ vary across layers to reflect the evolving nature of relationships over time. In SocialMaze, LLMs receive natural language descriptions that encapsulate the information from these layered graphs, rather than raw graph structures. This design choice is intentional, aiming to mimic how humans comprehend social scenarios through language-based narratives. Recent graph-reasoning benchmarks show that LLM performance is sensitive to graph representation and can benefit from structured decomposition (Xu et al., 2026c), while LLM-guided knowledge-graph traversal combines exploration with replay memory to recover multi-hop evidence efficiently (Hu et al., 2025c); SocialMaze instead uses natural-language interaction histories to test inference over socially grounded graph structure.

Query Categorization. Based on the layered graph representation, we classify the queries posed within SocialMaze tasks into three distinct types, each targeting a different level of understanding of the graph structure: ***Vertex-centric Query ($\mathcal{Q}_v(v_i)$):*** This type of query probes the model's understanding of individual social members. Given a specific vertex $v_i \in \mathcal{V}$ (representing social member s_i), the task is to infer an attribute associated with v_i. ***Edge-centric Query ($\mathcal{Q}_e(v_i, v_j)$):*** Edge-centric queries assess the model's comprehension of the relationships between social members. Given two vertices $v_i, v_j \in \mathcal{V}$, the task is to determine the nature of their relationship, as represented by the edges connecting them. ***Graph-level Query ($\mathcal{Q}_G(\mathcal{G})$):*** Graph-level queries require the model to synthesize information from the entire layered graph $\mathcal{G}$ to derive a holistic understanding of the social scenario. These queries demand a comprehensive assessment of the overall interaction dynamics.

3 SocialMaze

As formalized in section 2, and building on the layered social interaction graph framework, we introduce **SocialMaze**, a benchmark designed to operationalize the core challenges of social reasoning—*Dynamic Interaction*, *Information Uncertainty*, and *Deep Reasoning*. The benchmark spans three representative social contexts: Social Reasoning Games, Daily Life Interactions, and Digital Community Platforms. These settings comprise six major task categories, each carefully designed to vary along the key dimensions, enabling systematic evaluation of LLMs under diverse so-

cial conditions. Table 1 summarizes the tasks by required reasoning depth, degree of interaction dynamics, and level of information uncertainty. A detailed comparison between SocialMaze and prior benchmarks is provided in Appendix A.

3.1 Hidden Role Deduction

This task abstracts the core mechanics of various social reasoning games, such as *Blood on the Clocktower* (Wikipedia contributors, 2025a), *The Resistance: Avalon* (Eskridge, 2012) and *Werewolf* (Wikipedia contributors, 2025b), into a reasoning-only format. Unlike traditional interaction-based gameplay, where players engage in direct communication, all player statements are rule-generated. The model acts as a reasoner, analyzing all available information to logically infer each player's role.

Task Rules. The game features four roles: Investigators, Criminal, Rumormongers, and Lunatics. Investigators always tell the truth. The Criminal can choose to lie or tell the truth. Rumormongers believe they are Investigators, but their statements are randomly true or false. Lunatics believe they are the Criminal. The role each player sees may not reflect their true identity—Rumormongers are shown the role of Investigator, and Lunatics are shown the role of Criminal.

The game consists of n players, and the model participates from the perspective of Player 1 (s_1), meaning that it observes only what that player would see and say during the T rounds. In each round, every player selects another player and makes a public statement, such as "Player v says Player u is (not) the criminal." After observing all interactions, the model is tasked with answering two key questions: identifying the true Criminal ($\mathcal{Q}_G$), and inferring its own actual role in the game ($\mathcal{Q}_v(v_i)$). The introduction of Rumormongers and Lunatics significantly increases *information uncertainty* and makes the reasoning process more challenging. The dataset includes four types of tasks: Original task, Rumormonger task, Lunatic task, and Full task. Details are provided in Appendix B.

Design Rationale. This task challenges large language models along three critical dimensions of social reasoning. First, the game unfolds over multiple rounds, requiring the model to track the temporal evolution of information, interpret changing relationships among players, and maintain consistent judgments across rounds—posing a challenge of *Dynamic Interaction*. Second, due to the presence of roles such as the Criminal, Rumormonger, and Lunatic—who may lie or provide misleading information—the environment is *highly uncertain*. The model must determine which statements are trustworthy and filter out deceptive cues, thereby grappling with information uncertainty. Most importantly, the model must reason not only about others' roles but also about its own true identity, which may differ from the one initially assigned. Addressing this requires strong *Deep Reasoning* capabilities, including resolving conflicts, managing uncertainty that extends to self-perception, and dynamically updating internal beliefs to approach the ground truth.

Data Generation and Quality Assurance. All player statements are automatically generated based on a set of predefined rules. Investigators begin by selecting a target they find suspicious, using a strategy function informed by all interactions up to the current round. They are always truthful in their statements. Rumormongers follow the same target selection logic as Investigators, but the truthfulness of their statements is random, making their input unreliable. In contrast, Criminals and Lunatics adopt a different strategy for choosing targets and deliberately introduce uncertainty by making deceptive statements with a certain probability, aiming to mislead others and conceal their true roles. To ensure each scenario is logically solvable, we design a search algorithm that verifies whether a unique solution exists to identify both the true Criminal and the LLM player's actual role. Additionally, the full reasoning chain leading to the solution is preserved and distilled into clear natural language, providing high-quality, curated examples of social reasoning that can be leveraged for targeted fine-tuning of language models. See Appendix B for details.

3.2 Find the Spy

This task is inspired by the classic word-based social deduction game *Who Is The Spy* (Wei et al., 2025) and aims to evaluate the LLM's ability to identify subtle deviations in communication within a group setting. The game involves n players, where $n-1$ players (Civilians) receive the same secret word, and one player (the Spy) receives a related but different word. Over T rounds, each player provides a description of their word. The LLM, observing the descriptions, must determine which player is the Spy. This task is designed to

assess the model's capability to track and interpret information through interactions while minimizing the ambiguity of the presented information. The high level of interaction comes from the multi-round format, requiring the model to progressively piece together and evaluate each player's description. The low level of information uncertainty is maintained because, although the players are incentivized to be truthful, the task still involves the subtle challenge of discerning the Spy based on differences in description style and detail. Detailed task rules, the data generation process, and quality assurance procedures are provided in Appendix C.

3.3 Rating Estimation from Text

This task evaluates the ability of LLMs to predict a product's star rating (from 1 to 5) based on a set of n textual reviews. These reviews may include genuine user feedback as well as promotional reviews written by shills. The task is designed to challenge the model's ability to deal with information uncertainty, where the reviews might include biased or misleading content, requiring the model to evaluate the credibility of each review. The LLM is tasked with estimating a single star rating for the product, based on the aggregated reviews from multiple users. The input is structured as a vertex-centric query, where the model must synthesize information from user reviews to predict the most likely rating for the product. Detailed task rules, the data generation process and quality assurance procedures are provided in Appendix D.

3.4 Social Graph Analysis

This task aims to evaluate the ability of LLMs to analyze relationships within a social group. Given a description of the social network graph and pairwise relationship labels indicating whether two individuals are friends or have a bad relationship—with friendship being transitive—the model is required to perform reasoning such as: determining whether two individuals are friends, identifying the friend group of a given node, calculating the total number of distinct friend groups, and counting all relationships within the network. Detailed task rules, the data generation process that ensures logical consistency and solvability, and quality assurance procedures are provided in Appendix E.

3.5 Review Decision Prediction

This task aims to evaluate the ability of LLMs to predict the final acceptance outcome (Accepted/Rejected) of a research paper as they gradually receive more information throughout the academic review process. The model is required to make a prediction at each of three interaction stages, with the available context incrementally expanding: in the first stage, only the initial paper information is provided; in the second stage, reviewer comments (with numerical scores removed) are added and the model must reason over both the initial content and the reviews; in the third stage, the full author rebuttal is introduced, completing the review context. This task simulates how opinions evolve over time in real academic peer review. Detailed task rules, the data generation process using real-world OpenReview data, and quality assurance procedures are provided in Appendix F.

3.6 User Profile Inference

This task aims to evaluate the ability of LLMs to recover demographic cues (age group and gender) that the generator pool has encoded into user-generated textual reviews. Specifically, we construct a large number of synthetic users with known demographic attributes using LLMs, and generate their reviews for various products they have purchased; the evaluated LLM then attempts to recover those demographic attributes from the resulting text. The inference tasks are twofold: (1) predicting the dominant user profile associated with the reviews of a specific product, and (2) identifying the profile of an individual user based on their reviews across multiple products.

We score predictions as joint age $\times$ gender 9-class accuracy on the 500-instance set (random-guess floor $1/9 \approx 11.1\%$). Because the demographic ground truth is the generator's input prompt rather than a real user identity, this task probes evaluator-vs-generator-pool stereotype alignment rather than inference about real demographic populations; see subsection I.6.

Detailed task rules, the LLM-based data generation method used to embed subtle demographic cues, and human validation results are provided in Appendix G.

4 Experiments and Analysis

We conduct extensive experiments on SocialMaze to evaluate the social reasoning capabilities of LLMs. Specifically, we test five proprietary LLMs and seven open-weight LLMs across the six tasks. We additionally evaluate six reasoning workflows

to assess their impact on model performance.

A condensed overview of model performance across the six tasks is reported in Table 4. We observe that different social reasoning tasks impose distinct demands on the models. For example, tasks like *Hidden Role Deduction*, which require *Deep Reasoning*, are best tackled by models such as DeepSeek-R1 and Gemini-2.5-Pro. In contrast, DeepSeek-V3 and GPT-4o excel on tasks like *Review Decision Prediction*, where nuanced understanding of reviewer attitudes is critical. We conducted extensive case studies and report full results and settings in Appendix J, Appendix H, and Appendix I.

4.1 The Impact of Deep Reasoning

We compare Long CoT models (e.g., o1, DeepSeek-R1) against the remaining Short CoT models, both using identical prompts, on the two *Deep Reasoning* tasks (*Hidden Role Deduction*, *Social Graph Analysis*) and the four shallower tasks listed in Table 1.

Long CoT models achieve substantially higher accuracy on tasks requiring *Deep Reasoning*. Figure 2 (line plot) shows the gap is pronounced on graph analysis and role deduction and narrows on shallower tasks.

A pilot judge evaluation on four Short-CoT models (subsection I.2) finds correctly-answered chains internally consistent and complete while incorrect-answer chains score substantially lower; the analogous Long-CoT evaluation (3,000–4,200 tokens, different judge protocol) is left to future work. A budget-matched control rules out raw output-cap as the Long-vs-Short driver (subsection I.4).

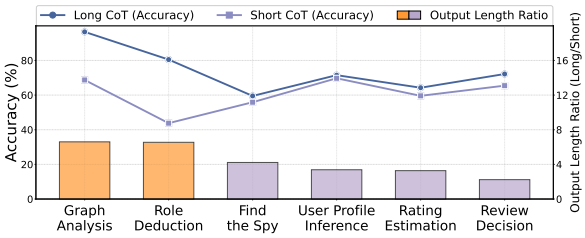

Figure 2: Performance comparison of Long vs Short CoT models. The line plot shows average accuracy; the bar plot shows the output length ratio (Long / Short). Orange bars indicate tasks with high deep reasoning demand, purple bars indicate low deep reasoning demand.

The improved performance comes with substantial computational cost. The bar plot in Figure 2 shows Long CoT models use nearly eight times more output tokens on average on *Deep Reasoning* tasks, narrowing on shallower tasks where the accuracy gains are smaller.

4.2 The Impact of Dynamic Interaction

In certain scenarios, social interactions unfold sequentially, requiring models to integrate and reason over information accumulated across multiple turns. We analyze how model performance evolves in tasks with high *Dynamic Interaction*: **model accuracy generally improves with quantitatively increasing interaction, but the trajectory of performance evolution and sensitivity to dynamic information vary significantly across tasks and models.**

Table 2: Criminal identification accuracy across rounds in the 6-player *Hidden Role Deduction* task; cells report 5-seed mean ± 95% binomial CI half-width at $n = 500$ per round. Models vary in leveraging *Dynamic Interaction*.

Model	Round 1	Round 2	Round 3
Llama-3.1-8B	31.4 ± 4.1	38.6 ± 4.3	41.2 ± 4.3
Phi-4	32.8 ± 4.1	40.4 ± 4.3	45.6 ± 4.4
Llama-3.3-70B	37.6 ± 4.2	46.7 ± 4.4	46.5 ± 4.4
Qwen-2.5-72B	31.3 ± 4.1	42.6 ± 4.3	50.3 ± 4.4
GPT-4o-mini	33.5 ± 4.1	38.4 ± 4.3	46.5 ± 4.4
GPT-4o	39.5 ± 4.3	53.3 ± 4.4	53.5 ± 4.4
o3-mini	$\mathbf{45.8} \pm 4.4$	56.4 ± 4.4	65.4 ± 4.2
QwQ-32B	41.4 ± 4.3	63.5 ± 4.2	78.4 ± 3.6
DeepSeek-V3	22.4 ± 3.7	33.6 ± 4.1	45.0 ± 4.4
DeepSeek-R1	44.3 ± 4.4	72.3 ± 3.9	80.4 ± 3.5
o1	42.5 ± 4.4	67.5 ± 4.1	76.6 ± 3.7
Gemini-2.5-Pro	43.3 ± 4.4	$\mathbf{74.3} \pm 3.8$	$\mathbf{87.6} \pm 2.9$

This contrast is particularly evident in two tasks. In *Hidden Role Deduction*, we track model accuracy in identifying the Criminal within the Full Task setting involving six players (Table 2). **Accuracy tends to increase as more rounds of interaction are observed**, reflecting the expected benefit of accumulating contextual evidence over time. However, the slope of improvement varies substantially across models, suggesting differing abilities to process and integrate newly revealed statements within the game's evolving context. Some models are more effective than others in leveraging additional rounds to refine their hypotheses. One notable insight is the large performance gap between Rumormonger and Lunatic. This is because once an Investigator correctly checks the Lunatic as "not the Criminal," it provides a strong signal that helps the Lunatic realize their true role—making awakening easier than for the Rumormonger. Round-1 accuracy on Table 2 is jointly deter-

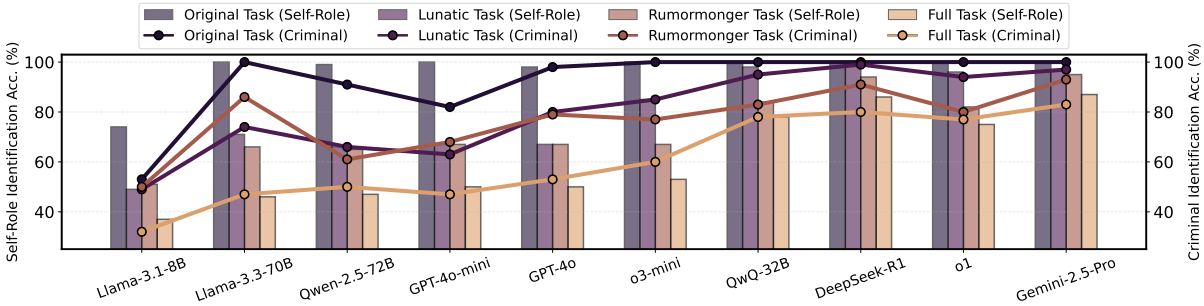

Figure 3: Model performance in *Hidden Role Deduction* across four task variants with increasing information uncertainty. Accuracy is shown after 3 rounds.

mined by the model's exploitation of the prompt-supplied role label and role-distribution enumeration (which narrows the Criminal-candidate set) and the single round of public statements; the Round-1-to-Round-3 lift should therefore be read as "rounds-accumulated reasoning over the Round-1 prior baseline" rather than "pure evidence accumulation from zero".

By contrast, *Review Decision Prediction* presents a non-linear performance trajectory across the stages of the peer review process, as shown in Table 3. The three stages provide title+abstract+keywords (Info), reviewer comments with scores removed (Reviews), and the author rebuttal (Rebuttal); cells report 5-seed mean accuracy with 95% binomial CI half-width at $n = 500$ on a 67% reject / 33% accept test set.

Round-1 accuracy falls below the 67% reject-majority baseline for all evaluated models, indicating an over-accept anti-prior. The Round-2 to Round-3 trajectory splits into ten down-trending models and two up-trending evaluators (GPT-4o, DeepSeek-V3); the up-trends do not survive Bonferroni correction at the binomial CI floor, and the perturbed-subset analysis in Table 8 shows the Round-3 differences are not driven by OpenReview-text memorization. See Appendix F blocks 5–6.

We observe that the Round-3 down-trend on the ten-evaluator majority is frequently driven by the model being swayed by the author's sincere defense, which may not align with the judgment of human reviewers or area chairs. A more detailed analysis is in Appendix J.

4.3 The Impact of Information Uncertainty

A defining characteristic of complex social environments is the prevalence of unreliable information. We evaluate the impact of Information Uncertainty using the *Hidden Role Deduction* task

Table 3: *Review Decision Prediction* accuracy across the three sequential stages (Info / Reviews / Rebuttal). See §4.2 narrative and Appendix F for column definitions, test-set composition, and trajectory discussion.

Model	Info.	Reviews	Rebuttal
Llama-3.1-8B	37.0 ± 4.2	79.6 ± 3.5	62.0 ± 4.3
Llama-3.3-70B	26.2 ± 3.9	87.4 ± 2.9	72.2 ± 3.9
Qwen-2.5-72B	23.6 ± 3.7	82.2 ± 3.4	65.8 ± 4.2
Phi-4	23.5 ± 3.7	77.6 ± 3.6	61.4 ± 4.3
GPT-4o-mini	38.8 ± 4.3	85.2 ± 3.1	85.0 ± 3.1
GPT-4o	$\mathbf{55.3} \pm 4.4$	86.2 ± 3.0	$\mathbf{90.2} \pm 2.6$
o3-mini	40.2 ± 4.3	86.4 ± 3.0	78.6 ± 3.6
QwQ-32B	49.8 ± 4.4	83.8 ± 3.2	79.6 ± 3.5
DeepSeek-V3	38.2 ± 4.3	86.0 ± 3.0	$\mathbf{91.4} \pm 2.5$
DeepSeek-R1	50.2 ± 4.4	88.0 ± 2.9	82.0 ± 3.4
o1	52.2 ± 4.4	$\mathbf{88.6} \pm 2.8$	78.2 ± 3.6
Gemini-2.5-Pro	47.4 ± 4.4	87.6 ± 2.9	77.6 ± 3.7

by systematically introducing actors who generate distinct forms of unreliable information: intentional deception (Criminal) and noise stemming from flawed self-perception (Rumormonger and Lunatic).

Increased information uncertainty significantly elevates the difficulty of social reasoning for LLMs. Figure 3 illustrates this across four task configurations where uncertainty levels are quantitatively controlled by varying the number of unreliable actors (Rumormongers, Lunatics). Progressing from the baseline Original setting through scenarios introducing these noise sources to the complex Full setting, both the accuracy in identifying the Criminal (line plot) and the model's own role (bar plot) demonstrate a marked decline. This degradation underscores the substantial challenge posed by noise and deception.

Reasoning becomes particularly challenging when the model's own perceived role or information source is compromised. Figure 4 delves into the Full task configuration, analyzing final accuracy based on the specific role assigned to the LLM.

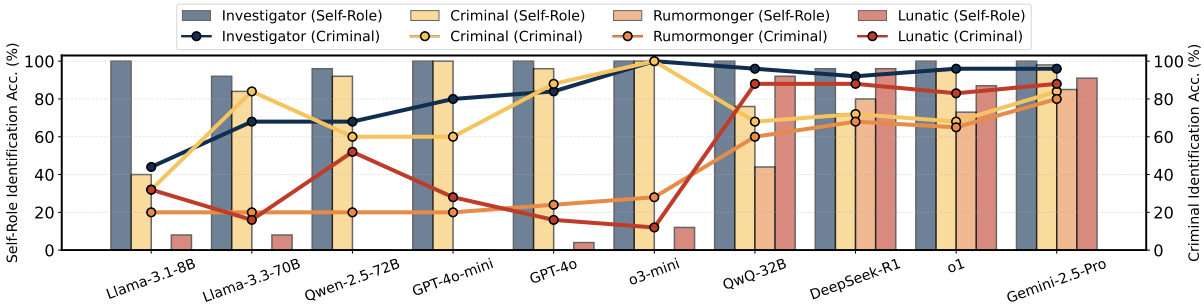

Figure 4: Full-task accuracy in *Hidden Role Deduction* by model-assigned role. Each bar is the 5-seed bootstrap mean over $n = 125$ per role with per-bin 95% half-width $\approx \pm 3$ to 4 pp (exact values in Table 16). Investigator and Criminal bars have displayed role equal to true role (trivial echo of the prompt label); Rumormonger and Lunatic bars are the override-required regime where the model must revise the prompt label under indirect evidence.

Models exhibit considerably lower accuracy, especially in identifying their own role (bars), when assigned as a Rumormonger or Lunatic compared to being an Investigator or Criminal. This suggests a significant difficulty in reconciling internal beliefs (e.g., "I think I am an Investigator/Criminal") with conflicting external evidence or the unreliable nature of one's own information.

These experiments also highlight critical differences between model capabilities. **Existing Short CoT models demonstrate severe limitations in handling complex scenarios with high information uncertainty**, often failing to perform reliably in the Rumormonger and Full task settings (Figure 3). In contrast, Long CoT models, while still impacted, exhibit significantly better resilience to uncertainty. Furthermore, the challenge of self-assessment under uncertainty exposes a stark gap: **Short CoT models are almost entirely unable to deduce their true identity when assigned as a Rumormonger or Lunatic** (Figure 4), suggesting a profound lack of capacity for self-doubt and meta-reasoning necessary to overcome compromised initial information.

Part of this gap reflects indirect-evidence availability rather than capability alone (Table 6).

4.4 Enhancing Social Reasoning Capabilities

To explore strategies for improving social reasoning in LLMs, we conduct focused experiments on the *Hidden Role Deduction* task. This task is not only uniquely representative—combining Deep Reasoning, Dynamic Interaction, and Information Uncertainty—but also well-suited for generating diverse reasoning examples at scale, providing valuable supervision for model learning.

Reasoning agents and workflows produce regime-dependent gains for social reasoning. Recent approaches improve complex reasoning through dynamic workflow adaptation (Wang et al., 2025f), adaptive allocation of reasoning effort (Wang et al., 2025d), context-oriented reasoning synthesis (Jin et al., 2026b), and structured context self-auditing (Jin et al., 2026a). Agent systems additionally use feedback-aware multi-agent orchestration (Song et al., 2025), co-active preference learning (Xu et al., 2026a), and execution-grounded trajectories (Wu et al., 2026). We assess whether such task decomposition and planning mechanisms can improve performance on *Hidden Role Deduction*. Six workflow methods on the weak Short-CoT backbone (Table 10) yield Both-Correct lifts of $+4$ to $+8$ pp, with the largest gains (DyFlow, MaAS, AFlow) clearly above the binomial Δ-CI of $\approx \pm 6$ pp at $p \approx 0.30$ and the smaller gains (Self-Refine, LLM-Debate) inside it; on the DeepSeek-R1 backbone all four methods land within ± 2.0 pp of the Base, indicating saturation. See subsection H.5 for per-method Δ and noise-floor analysis.

Fine-tuning on curated reasoning traces substantially improves performance. We apply Supervised Fine-Tuning (SFT) (Ouyang et al., 2022) and Direct Preference Optimization (DPO) (Rafailov et al., 2023) to Llama-3.1-8B and Phi-4 on high-quality reasoning examples from our dataset. Table 11 reports HRD gains, and Table 12 reports cross-task transfer on the five non-HRD tasks. Transfer to *Social Graph Analysis* is robust ($+9.2$ to $+9.6$ pp under SFT, clearly above the ± 6 pp paired-Δ CI); *Find the Spy* is borderline ($+5.8$ / $+6.4$ pp under SFT) and partly consistent with sampling noise; the linguistic family (*Rating Estimation*, *Review Decision Prediction*, *User Profile Inference*) sits inside the Δ-CI at $+0.4$ to $+2.4$ pp. Thus, transfer to the structured-graph task is supported, transfer to Find the Spy is borderline, and transfer to the language-aggregation tasks re-

Table 4: Overall Accuracy (%) on SocialMaze Tasks. Each cell reports the mean accuracy and 95% binomial CI half-width at $n = 500$ over five independent runs at temperature 0.7. The HRD column averages over the 1:1:1:1 role mixture (Investigator / Criminal / Rumormonger / Lunatic); the per-role decomposition is reported in Table 16 and shows that the Both-Correct headline aggregates a regime with displayed=true self-role (Investigator, Criminal) and a regime with displayed≠true self-role (Rumormonger, Lunatic). UPI: joint age × gender 9-class accuracy (floor $1/9 \approx 11.1\%$); see Appendix G and subsection I.6 for the construct-scope note that UPI scores on the FtS / Rating / UPI columns are confounded with within-family alignment to the generator pool. Rating Estimation: constant-predict-majority baseline = 73% (see subsection H.2); cells below this floor indicate anti-calibration toward minority classes. See text for further metric details.

Model	**Hidden Role Deduction**	**Find the Spy**	**Rating Estimation**	**Social Graph Analysis**	**Review Decision Prediction**	**User Profile Inference**
Llama-3.1-8B	15.4 ± 3.2	37.2 ± 4.2	57.2 ± 4.3	28.2 ± 3.9	62.0 ± 4.3	60.2 ± 4.3
Llama-3.3-70B	25.2 ± 3.8	60.0 ± 4.3	74.8 ± 3.8	81.0 ± 3.4	72.2 ± 3.9	$\mathbf{78.6} \pm 3.6$
Phi-4	20.4 ± 3.5	45.2 ± 4.4	60.4 ± 4.3	40.6 ± 4.3	61.4 ± 4.3	62.4 ± 4.2
Qwen-2.5-72B	22.6 ± 3.7	48.9 ± 4.4	72.2 ± 3.9	80.6 ± 3.5	65.8 ± 4.2	68.0 ± 4.1
QwQ-32B	52.0 ± 4.4	50.2 ± 4.4	74.4 ± 3.8	95.0 ± 1.9	79.6 ± 3.5	72.2 ± 3.9
GPT-4o-mini	26.4 ± 3.9	61.2 ± 4.3	75.8 ± 3.8	53.0 ± 4.4	$\mathbf{85.0} \pm 3.1$	74.4 ± 3.8
GPT-4o	28.8 ± 4.0	69.2 ± 4.0	$\mathbf{76.0} \pm 3.7$	83.2 ± 3.3	90.2 ± 2.6	$\mathbf{79.2} \pm 3.6$
o3-mini	55.2 ± 4.4	74.0 ± 3.8	71.2 ± 4.0	99.0 ± 0.9	78.6 ± 3.6	71.4 ± 4.0
o1	60.8 ± 4.3	$\mathbf{78.4} \pm 3.6$	$\mathbf{76.2} \pm 3.7$	99.2 ± 0.8	78.2 ± 3.6	77.0 ± 3.7
DeepSeek-V3	30.2 ± 4.0	58.6 ± 4.3	75.8 ± 3.8	92.4 ± 2.3	$\mathbf{91.4} \pm 2.5$	65.4 ± 4.2
DeepSeek-R1	65.4 ± 4.2	70.2 ± 4.0	71.0 ± 4.0	98.6 ± 1.0	82.0 ± 3.4	74.6 ± 3.8
Gemini-2.5-Pro	$\mathbf{73.6} \pm 3.9$	76.6 ± 3.7	73.6 ± 3.9	$\mathbf{100.0} \pm 0.4$	77.6 ± 3.7	73.0 ± 3.9
Human (avg.)	64.2 ± 4.2	84.4 ± 3.2	75.2 ± 3.8	-	78.0 ± 3.6	73.9 ± 3.9

mains undetermined (subsection H.4).

Cross-task comparison. Table 4 reveals two complementary regimes. Reasoning-oriented models form the strongest group on *Hidden Role Deduction*, while Gemini-2.5-Pro, o1, o3-mini, and DeepSeek-R1 all exceed 98% on *Social Graph Analysis*. Conversely, language-aggregation and judgment tasks favor strong generalists: DeepSeek-V3 and GPT-4o lead *Review Decision Prediction*, the leading *Rating Estimation* results occupy a narrow 74.4–76.2% band, and GPT-4o, Llama-3.3-70B, and o1 are similarly close on *User Profile Inference*. *Find the Spy* lies between these regimes, led by o1, Gemini-2.5-Pro, o3-mini, and DeepSeek-R1 among the evaluated models.

These task-dependent reversals are more informative than a single aggregate ranking. Most within-tier gaps are comparable to the $n = 500$ binomial half-width and should not be read as ordered separations; detailed family-wise comparisons appear in Appendix I. The human baseline likewise varies by task, exceeding every model on *Find the Spy* while remaining competitive on *Hidden Role Deduction*. Because the HRD headline mixes prompt-label echo with diagnostic role-override cases, Table 16 provides the more direct measure of belief revision.

5 Conclusion

We introduced SocialMaze, a benchmark designed to rigorously evaluate the social reasoning capabilities of LLMs by capturing the challenges of deep reasoning, dynamic interaction, and information uncertainty. Experiments across six diverse tasks reveal notable weaknesses in current models, particularly in handling evolving contexts and reasoning under uncertainty. Targeted fine-tuning on curated reasoning examples significantly improves performance on structured social-reasoning tasks; transfer to language-aggregation tasks is inconclusive at this sample size (§4.4), highlighting the scope as well as the value of domain-specific adaptation.

As future work, we plan to expand SocialMaze with more real-world data and new social scenarios and task types.

Limitations

Three concerns commonly raised about benchmarks of this form—whether the construct dimensions are quantitatively grounded, whether the synthetic-to-real data mixture preserves external validity, and whether generator–evaluator overlap inflates particular tasks—are analysed in detail in subsection I.1, subsection I.6, and §3.6 respectively, and summarised in the dedicated subsections below. The remainder of this section documents three issues that are partial or scope-limited: compliance posture of the data-collection pipeline, the scope of the faithfulness pilot (expanded onto incorrect-answer chains in subsection I.2 but not yet to all six tasks), and the boundary cases where fine-tuning transfer is statistically inconclusive (§4.4).

Data-collection compliance. The User Profile Inference task evaluates LLMs on synthetic demographic-conditioned comments generated under controlled prompts; no real-user demographic data is collected, and our institution's research-integrity office classified the protocol as "not human subjects research" under the Common Rule (45 CFR 46.102) given the absence of real-individual data and inference targets (full compliance disclosure in subsection I.7). The Rating Estimation real-world subset includes content from public-facing review pages on Amazon, Taobao, and Google Play; we restrict downstream redistribution to research use and do not release raw scraped text in the public release (see subsection I.7 for the scraping methodology).

Synthetic vs. Real Data Composition

The tri-source composition is a deliberate design trade-off rather than a compromise on realism. Rule-based simulation (*Hidden Role Deduction*, *Social Graph Analysis*) provides verifiable ground truth and uniqueness-guaranteed solvability that human annotation cannot match at scale; LLM-assisted discourse (*Find the Spy*, *User Profile Inference*) provides scalable linguistic and stylistic diversity; authentic human sources anchor the benchmark to organic data—*Rating Estimation* draws on Amazon, Taobao, and Google Play public-page reviews, and *Review Decision Prediction* uses real OpenReview submissions from nine NeurIPS/ICLR/COLM venue-years. subsection I.6 documents the confound bounds for each source (e.g., the generator-evaluator overlap is bounded above by $+5.6$ pp on UPI and below $+1$ pp residual on a capability-matched leave-out, see below). Open-ended, fully interactive multi-agent corpora are a complementary direction that probes a different question (emergent agentic behavior under unconstrained ground truth); the present design is targeted at controlled diagnostic precision and is not corrective of, or substitutable by, that direction.

Quantifying Social Constructs

Posterior empirical evidence on the three axes is reported in subsection I.1. For Deep Reasoning, Table 14 reports four convergent (not statistically independent) effort-correlated proxies—model output tokens, human solving time, average inference steps on correctly answered instances, and the Long-vs-Short CoT length ratio—which jointly align with the a priori High/Low task labels and discriminate the deep-reasoning task family (HRD, SGA) from the shallower family. These are surface correlates of effort rather than a measurement of a single latent "deep reasoning" construct, and we frame the axes as task-construction design choices rather than as factor-analytic dimensions of model capability. Dynamic Interaction High/Low is operationalised via per-round accuracy delta on multi-round tasks (Table 2 for HRD; Table 3 for RDP); we acknowledge the per-round delta conflates evidence accumulation with prior recalibration (see the Round-1 anti-prior discussion in §4.2). Information Uncertainty High/Low is operationalised as a controlled stimulus knob (share of unreliable actors), traced across the Original $\rightarrow$ Rumormonger $\rightarrow$ Lunatic $\rightarrow$ Full degradation in Figure 3, rather than as a posterior measurement of model belief calibration. A deeper task-agnostic formal metric of the three constructs remains future work; under the descriptive design-axis framing, the per-task labels function as comparison anchors for grouping tasks by intended difficulty driver.

Language, Cultural, and Bias Scope

The released evaluation prompts are in English, and the Chinese source reviews used in Rating Estimation are normalized through English paraphrases. Prior studies find substantial performance gaps across semantically aligned languages (Xu et al., 2025) and language-specific biases in causal reasoning (Wang et al., 2025c); culturally grounded evaluations likewise reveal local differences alongside meaningful cross-cultural transfer (Almheiri et al., 2025). Consequently, our re-

sults do not establish multilingual or cross-cultural social-reasoning validity. Moreover, User Profile Inference measures alignment with synthetic demographic conditioning rather than real-world identity, and representation-level bias probes show that behavioral tests may miss latent associations (Gao et al., 2025). Extending SocialMaze with culturally grounded scenarios and matched multilingual instances is therefore important future work.

Faithfulness and Evaluation Scope

The pilot faithfulness study (Table 19) suggests that correct answers are typically supported by coherent and complete reasoning, with faithfulness correlating with accuracy. Its current scope is limited (one task, a subset of models, automated judging with human auditing). Automated judges can exhibit systematic scoring biases with identifiable internal representations (Xu et al., 2026b), so the reported cross-judge agreement and human audit reduce but do not eliminate evaluator dependence. Extending to additional tasks, models, and judging protocols (including human-only panels and contradiction auditing on incorrect answers) is left to future work.

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A Related Works

A.1 Static Social Reasoning Benchmarks

Early evaluations of social reasoning in language models largely focus on static, single-turn tasks where models infer plausible answers based on brief, pre-written scenarios. These benchmarks primarily test shallow forms of commonsense and moral reasoning without requiring interaction, adaptation, or uncertainty handling. A classical example is **SocialIQA** (Sap et al., 2019b), which assesses social commonsense by posing questions about motivations and reactions in everyday situations. Similarly, **ATOMIC** (Sap et al., 2019a) provides a structured knowledge graph of causal social events, while **CommonGen** (Lin et al., 2020) tests the ability to generate plausible sentences from object co-occurrence tuples in socially relevant scenes.

Benchmarks like **Social Chemistry** (Forbes et al., 2020) and **ETHICS** (Hendrycks et al., 2021) target moral norms, asking models to judge the appropriateness of actions, whereas **GLUCOSE** (Mostafazadeh et al., 2020) emphasizes implicit causal reasoning in narratives. Mechanistic analyses further probe how moral-foundation structure is represented inside LLMs (Yu et al., 2026). Emotion understanding is covered by **GoEmotions** (Demszky et al., 2020), while **PIQA** (Bisk et al., 2020), **HellaSwag** (Zellers et al., 2019), and **CREAK** (Onoe et al., 2021) assess commonsense or contextually grounded inference.

Recent work has shifted toward evaluating *Theory of Mind* (ToM)—the capacity to reason about others' beliefs and intentions. Initial tests, such as those in (Kosinski, 2024), used classic false-belief stories to probe emergent ToM in LLMs, though follow-up studies revealed artifacts and prompt sensitivity (Shapira et al., 2024). More recent evaluations such as **FANToM** (Kim et al., 2023) and **ToMValley** (Xiao et al., 2025) provide more rigorous multi-turn belief-tracking scenarios. These benchmarks demonstrate that, while LLMs may succeed on simple static ToM questions, they struggle with deeper or dynamic belief modeling, particularly under information asymmetry or belief shifts over time.

Overall, while these static benchmarks have advanced our understanding of LLMs' social reasoning capabilities, they often lack three essential ingredients for real-world social cognition: dynamic interaction, complex reasoning depth, and reasoning under uncertainty. Table 5 summarizes several representative benchmarks discussed above, highlighting their focus, format, and limitations. These gaps motivate the design of SocialMaze, which aims to capture the challenges of socially grounded reasoning in more realistic and interactive settings.

A.2 Dynamic Social Reasoning and Interaction Benchmarks

Another class of benchmarks focuses on dynamic settings where social reasoning occurs within interactive contexts. These tasks require models to engage with evolving information, track perspectives, and reason about hidden roles, intentions, or potential deception. PersonaConvBench evaluates personalized reasoning over multi-turn, multi-user histories (Li et al., 2025), and memory-retrieval work explicitly tests changing preferences across long interaction histories (Qin et al., 2026a); ASTRO optimizes strategies for non-cooperative dialogues such as negotiation and persuasion (Hu et al., 2025b). DebateBench (Tiwari et al., 2025) evaluates models' reasoning across long-form argumentative dialogues. Studies of peer review processes using OpenReview data (Tran et al., 2020; Szumega et al., 2023) examine decision-making through multi-turn, text-based interaction without relying solely on reviewer scores. Strategic games such as Diplomacy (Bakhtin et al., 2023) and Poker (Brown and Sandholm, 2019), as well as social deduction games like Avalon and Werewolf (Light et al., 2023; Wei et al., 2025; Bailis et al., 2024; Xu et al., 2023), provide natural settings for reasoning under incomplete information and complex social dynamics. Multi-agent simulations explore emergent social behavior (Park et al., 2023), including political decision-making (Yu et al., 2024), polarization in social networks (Wang et al., 2025b), and the stepwise evolution of misinformation (Liu et al., 2025b). A text-attributed graph benchmark also combines user text, news content, and propagation structure for fake-news detection (Liu et al., 2025a). The reliability of LLM-based computational-social-science simulations has been benchmarked directly (Huang et al., 2024c), while iAgents studies multi-party collaboration across social networks under information asymmetry (Liu et al., 2024); controlled testbeds further expose interaction-level risks such as collusion, semantic drift, and strategic misreporting (Jiang et al., 2026). Automated probing methods generate adaptive distractions (Wang et al., 2025e)

Table 5: Representative Benchmarks for Social Reasoning in LLMs

Benchmark	Focus	Format	Key Findings
SocialIQA (Sap et al., 2019b)	Commonsense QA	Static narrative + MCQ	GPT-3+/GPT-4 near human; tests scripted social norms.
ToM Classic (Kosinski, 2024)	False belief	Brief stories + Q&A	Early ToM claims challenged; shortcut artifacts noted.
Clever Hans (Shapira et al., 2024)	ToM artifacts	Controlled stimuli	Performance drops without spurious cues; lacks robustness.
FANToM (Kim et al., 2023)	Interactive ToM	Multi-turn dialogue	GPT-4 and others fail under asymmetric info tracking.
ToMValley (Xiao et al., 2025)	Dynamic ToM	Scenario chains + Q&A	LLMs 11% below humans; weak on mental state updates.

and organize discovered errors into structured failure modes (Huang et al., 2026). Complementary robustness studies expose corrupted word forms (Wang et al., 2025a), false premises (Qin et al., 2026b), cross-user contamination in shared-state agents (Yang et al., 2026), adversarially manipulated retrieval (Li et al., 2026), and multimodal rank manipulation (Du et al., 2026), alongside broader evaluation frameworks such as TextAttack (Morris et al., 2020), TRUST-LLM (Huang et al., 2024b), and CheckList (Ribeiro et al., 2020).

While these benchmarks incorporate certain forms of interaction and complexity, most remain oriented toward task completion or strategic decision-making. They often lack systematic modeling of social context factors such as role motivations or deception. SocialMaze, by contrast, integrates interaction and uncertainty within a structured framework, explicitly targeting complex social reasoning.

B Hidden Role Deduction

This appendix provides the details for the Hidden Role Deduction task described in subsection 3.2.

B.1 Task Setup

The game involves n players, denoted $s_1, ..., s_n$. The LLM observes the game unfolding from the perspective of Player 1 (s_1), receiving all interaction data and the initial role assignment given to s_1. **Crucially, the LLM does not actively participate in the game simulation (i.e., does not choose targets or make statements). Its task is solely post-hoc inference**: analyzing the complete interaction log $(G_1, ..., G_T)$ to deduce the answers to the specified queries. At the start, each player s_i is randomly assigned a secret role. The LLM is informed of the role initially assigned to s_1; however, this assigned role may differ from s_1's actual role, especially if s_1 is a Rumormonger or Lunatic. The specific composition of roles depends on the Task Variant being used.

B.2 Roles and Behaviors

Simulated player behavior is guided by their assigned role and the game history G_t up to round t. The roles are defined as follows: The **Investigator (I)** aims to identify the Criminal. Based on the game history G_t, an Investigator uses an algorithmically defined function $F_I(G_t)$ to select a target player u. They then make a **truthful** statement reflecting their deduction about u's status (Criminal or not Criminal). The function $F_I(G_t)$ heuristically assesses suspicion, selecting players with higher probability if they have made contradictory statements or have been accused by others, while lowering the probability for players cleared by multiple potentially reliable sources. The **Criminal (C)** seeks to avoid identification and mislead others. They employ a strategic function $F_C(G_t)$ to select a target player u and also determine a probability $p_t = P(\text{state } u \text{ is Criminal} | G_t, \text{role=C})$. The Criminal then states "u is Criminal" with probability p_t and "u is not Criminal" with probability $1 - p_t$. The function F_C implements deceptive tactics, prioritizing targeting players who have accused the Criminal and diverting suspicion onto others. The **Rumormonger (R)**, although believing they are an Investigator trying to identify the Criminal, unintentionally provides unreliable information, effectively injecting noise. They are *told* they are an Investigator and use the Investiga-

tor logic function $F_I(G_t)$ to select a target player u. However, regardless of any internal assessment derived from $F_I(G_t)$ or the actual ground truth, the truthfulness of their final statement ("u is Criminal" or "u is not Criminal") is entirely random, possessing a 50% probability of aligning with the ground truth and a 50% probability of contradicting it. Lastly, the **Lunatic (L)** believes they are the Criminal and aims to avoid identification based on this false premise, while their actual nature is not Criminal. They are *told* they are the Criminal and mimic the Criminal's behavior by employing the *same* strategic function $F_C(G_t)$ used by the actual Criminal. Although their actions follow deceptive patterns, truthful statements made by Investigators about the Lunatic will correctly identify them as 'not the Criminal'.

B.3 Interaction Rounds

The game simulation proceeds for a fixed T rounds. In each round t (from 1 to T), every player s_v selects another player P_u and makes a public statement of the form: "Player v says Player u is the criminal" or "Player v says Player u is not the criminal." All statements made in round t are revealed simultaneously to all players, and thus become available to the observing LLM, before round $t+1$ begins. Consequently, the complete history $G_T = (\text{statements}_{round1}, ..., \text{statements}_{roundT})$ is available for the LLM's final analysis.

B.4 Parameter Settings

The composition of roles is varied to create tasks of differing complexity, ensuring there is always exactly one Criminal. The variants include: the **Original Task** (1 Criminal, $n-1$ Investigators); the **Rumormonger Task** (1 Criminal, $x \geq 1$ Rumormongers, $n-1-x$ Investigators); the **Lunatic Task** (1 Criminal, $y \geq 1$ Lunatics, $n-1-y$ Investigators); and the **Full Task** (1 Criminal, $x \geq 0$ Rumormongers, $y \geq 0$ Lunatics, $n-1-x-y$ Investigators, where $x+y \geq 1$). **Note on Experimental Configuration:** For the experiments presented in this paper, the game parameters were fixed at $n = 6$ players. When Rumormongers and Lunatics were included (specifically in the Full Task variant experiments), their counts were set to $x = 1$ and $y = 1$, respectively, alongside 1 Criminal and $n-1-x-y = 3$ Investigators. The accompanying open-sourced dataset includes generated instances for both $n = 6$ and $n = 10$. Furthermore, the open-sourced data generation code is flexible, allowing users to configure n, m, x, and y to create custom game scenarios.

B.5 Quality Control

The algorithmic generation includes verification via heuristic search, ensuring a unique, logically derivable solution exists for both queries from P_1's perspective using only the interactions and rules. The core verification logic, which checks all valid hypotheses, is outlined in algorithm 1.

Furthermore, to validate the models' reasoning quality, we manually inspected 100 correct responses each for several key models (DeepSeek-R1, QwQ-32B, Gemini-2.5-Pro, o1, and o3-mini). This analysis confirmed that over 90% of these successful predictions were underpinned by reasoning processes assessed as both rigorous and logically sound.

B.6 Information Availability for Rumormonger / Lunatic Perspectives

The unique-solvability check in algorithm 1 certifies that for every released instance there exists a unique consistent (C^*, R_1^*) from P_1's perspective; however, the chain of reasoning that recovers R_1^* when Player 1 is a Rumormonger or a Lunatic depends on indirect evidence (most often an Investigator's truthful "X is not the Criminal" statement that happens to point at P_1). For some randomly sampled $(n = 6, T = 3, x = y = 1)$ Full Task instances, that indirect evidence is sparse: not every Investigator targets P_1 in every round, and the global (C^*, R_1^*) uniqueness can be supplied by hypothesis-elimination involving *other* players' statements without P_1 receiving a direct cross-check.

To separate "task is information-poor for the P_1 perspective" from "model lacks the capacity to revise its self-belief", we partition the 500-instance test set into a high-evidence subset and a low-evidence subset based on whether at least one Investigator statement explicitly checks P_1's role across the three rounds. Table 6 reports per-perspective Self-role accuracy conditional on each subset for the five representative models. The Long-CoT models retain large gains on the high-evidence subset, where the indirect cross-check is present; on the low-evidence subset all models drop substantially, suggesting that part of the headline Rumormonger / Lunatic accuracy gap reflects task-information asymmetry rather than model capability alone.

Table 6: Self-role accuracy on the Rumormonger and Lunatic perspectives, conditional on whether at least one Investigator statement directly cross-checks P_1 within the three rounds. The per-perspective $n = 125$ instances split into a high-evidence subset of ≈ 75 instances and a low-evidence subset of ≈ 50 instances (the empirically observed split is roughly 60%/40%, varying slightly across perspectives). Cells report 5-seed mean $\pm$ 95% CI half-width at the per-subset binomial floor; high-evidence columns use $n = 75$ and low-evidence columns use $n = 50$, following the protocol disclosed in subsection H.2.

Model	Rumormonger Self		Lunatic Self	
	High-ev.	Low-ev.	High-ev.	Low-ev.
GPT-4o	16.4 ± 8.4	7.8 ± 7.4	28.4 ± 10.2	11.6 ± 8.9
QwQ-32B	54.2 ± 11.3	18.0 ± 10.6	66.8 ± 10.7	27.4 ± 12.4
o1	66.8 ± 10.6	23.0 ± 11.7	77.4 ± 9.5	34.4 ± 13.2
DeepSeek-R1	72.6 ± 10.1	26.4 ± 12.2	80.4 ± 9.0	38.6 ± 13.5
Gemini-2.5-Pro	83.2 ± 8.5	32.4 ± 13.0	88.0 ± 7.4	45.4 ± 13.8

The gap between the high-evidence and low-evidence columns is wider for Long-CoT reasoners than for short-CoT generalists, consistent with the reasoners exploiting the indirect cross-check when it is available and dropping toward chance when it is absent. The Short-CoT GPT-4o row sits near floor on both subsets, suggesting capability-limited rather than evidence-limited; this is the difference between "the task is information-poor here" and "the model is unable to reason about its own role even with sufficient evidence".

The Long CoT reasoners (QwQ-32B, o1, DeepSeek-R1, Gemini-2.5-Pro) retain large gains on the high-evidence subset (Rumormonger Self 54.2–83.2%, Lunatic Self 66.8–88.0%) while the Short CoT GPT-4o row stays near floor on both subsets (Rumormonger Self 16.4 / 7.8%, Lunatic Self 28.4 / 11.6%). The gap separates "information-poor for the P_1 perspective" from "capability-limited even when evidence is sufficient". The diagnostic implication for downstream users: a model selected for ability to revise self-belief under unreliable labels should be evaluated on the high-evidence subset where indirect evidence is present, not on the marginal accuracy that conflates the two regimes.

Algorithm 1: Solvability Verification from P_1's Perspective

Input : Interaction Log S, Player Set $\mathcal{P} = \{P_1, \ldots, P_n\}$, Role Set $\mathcal{R} = \{I, C, R, L\}$, Investigator Count N_I

Output : Unique Solution $(C^*, R_1^*) \in \mathcal{P} \times \mathcal{R}$, or $\emptyset$ if not unique/no solution

$\mathcal{S}_{valid} \leftarrow \emptyset$;
▷ Set to store valid (Criminal, P1 Role) solution pairs
foreach *hypothesized role* $R_1^{hyp} \in \mathcal{R}$ *for* P_1 **do**
  $\mathcal{P}_{cand} \leftarrow \mathcal{P} \setminus \{P_1\}$;
  ▷ Initial candidates are all others
  foreach *subset* $I_{hyp} \subseteq \mathcal{P}_{cand}$ *such that* $|I_{hyp}| = N_I$ **do**
    Let current hypothesis $H = (R_1^{hyp}, I_{hyp})$;
    if IsConsistent(S, H) **then**
      ▷ Check if hypothesis contradicts any statement
      $C_{implied} \leftarrow$ DeduceCriminal(S, H);
      $R_{1,implied} \leftarrow$ DeduceP1Role(S, H);
      if $C_{implied} \neq$ *NULL* ***and*** $R_{1,implied} \neq$ *NULL* **then**
        $\mathcal{S}_{valid} \leftarrow \mathcal{S}_{valid} \cup \{(C_{implied}, R_{1,implied})\}$;
        ▷ Add deduced solution
if $|\mathcal{S}_{valid}| = 1$ **then**
  return the single element in $\mathcal{S}_{valid}$;
  ▷ Unique solution found
else
  return $\emptyset$;
  ▷ Not unique or no consistent solution

Helper Function Bodies. The three helper functions invoked in algorithm 1 are defined as follows. Let $\mathcal{P}_{\text{nonI}} = \mathcal{P} \setminus (I_{hyp} \cup \{P_1\})$ denote the candidate set of non-Investigator non-P_1 players. The Investigator subset size N_I enumerated by algorithm 1 varies with R_1^{hyp}: when R_1^{hyp} is itself Investigator, P_1 counts as one of the $n - 1 - x - y$ total Investigators and so $N_I = n - 2 - x - y$ Investigators remain in $\mathcal{P}_{\text{nonI}}$; otherwise $N_I = n - 1 - x - y$. Under hypothesis $H = (R_1^{hyp}, I_{hyp})$ these $|\mathcal{P}_{\text{nonI}}| = n - 1 - N_I$ players must collectively realize 1 Criminal, x Rumormongers, y Lunatics, and (when $R_1^{hyp} =$ Investigator) one further Investigator, in some role assignment $\mathcal{A}$. The three helpers

operate jointly over the space of such role assignments.

$\mathrm{IsConsistent}(S, H)$: returns True iff at least one role assignment $\mathcal{A}$ over $\mathcal{P}_{\text{nonI}}$ exists such that under $\mathcal{A}$: (i) every statement made by a hypothesized Investigator $v \in I_{hyp}$ matches the truth (i.e., the statement "u is Criminal" agrees with whether u is assigned the Criminal role under $\mathcal{A}$), and (ii) every statement made by P_1 is consistent with the behavior dictated by P_1's *displayed* role under H (Rumormonger and Lunatic receive Investigator-truth and Criminal-deceptive prompt labels respectively, per the role-display rules of Appendix B). Statements by non-P_1 players in $\mathcal{P}_{\text{nonI}}$ are not directly constrained because the Criminal, Rumormonger, and Lunatic role-behavior models all permit both truthful and untruthful statements; the constraint enters only through the role-mixture admissibility requirement. Returns False if no $\mathcal{A}$ satisfies (i) and (ii) jointly.

$\mathrm{DeduceCriminal}(S, H)$: enumerates each candidate $c \in \mathcal{P}_{\text{nonI}}$ and tests whether assigning c as the Criminal admits at least one role assignment of the remaining $x+y$ players in $\mathcal{P}_{\text{nonI}} \setminus \{c\}$ to (x Rumormongers, y Lunatics) that satisfies (i)–(ii) of IsConsistent. If exactly one such c admits a satisfying assignment, returns c; if zero or multiple candidates do, returns NULL. The uniqueness of the surviving c across the enumeration of $|\mathcal{P}_{\text{nonI}}|$ candidates is what algorithm 1 ultimately checks at the dataset-release filter.

$\mathrm{DeduceP1Role}(S, H)$: returns R_1^{hyp} directly when $\mathrm{IsConsistent}(S, H)$ is True and $\mathrm{DeduceCriminal}(S, H)$ is not NULL; this helper exists so that algorithm 1's output type is a uniform (C^*, R_1^*) pair rather than two separate values from heterogeneous sources.

Uniqueness regime. algorithm 1 enumerates all candidate hypotheses, partitioned by R_1^{hyp}: for $R_1^{hyp} =$ Investigator there are $\binom{n-1}{n-2-x-y} = \binom{5}{2} = 10$ subsets I_{hyp}, and for each of the three other R_1^{hyp} values $\binom{n-1}{n-1-x-y} = \binom{5}{3} = 10$ subsets, totaling $10 + 3 \cdot 10 = 40$ candidate hypotheses for the $n = 6$, $x = y = 1$ configuration. The set $\mathcal{S}_{\text{valid}}$ collects the deduced (C^*, R_1^*) pairs from each surviving hypothesis; the instance is released only when $|\mathcal{S}_{\text{valid}}| = 1$, ensuring exactly one consistent global assignment. For the released dataset, the empirically observed acceptance rate of this filter is approximately 31% (i.e., 31% of randomly generated instances pass the unique-solvability check at $n = 6, T = 3$); instances rejected by the filter are discarded before the dataset is released.

We note that the helper specification above gives necessary structural conditions for a candidate c to survive but does not constitute an analytic uniqueness proof: because the role-behavior model for the Criminal, Rumormonger, and Lunatic permits both truthful and untruthful statements, the constraint on $\mathcal{P}_{\text{nonI}} \setminus \{c\}$ enters only through the role-mixture admissibility requirement rather than per-statement truth conditions. The 31% empirical filter rate is therefore an operational property of the rule-based generation strategy combined with the search-algorithm verification, rather than an analytic concentration claim. Every released instance carries a per-instance pass label from algorithm 1; instances where the search does not isolate a unique (C^*, R_1^*) pair are dropped before release, so the released dataset is uniqueness-guaranteed by construction even when the helper conditions are not analytically tight.

C Find the Spy

This appendix provides the details for the *Find the Spy* task described in subsection 3.2.

C.1 Overview

This task adapts the classic word-based social deduction game *Who Is The Spy* (Wei et al., 2025) to evaluate the LLM's ability to identify subtle deviations in communication within a group context characterized by high interaction but relatively low information uncertainty.

Task Rules. The game involves n players. Among them, $n-1$ players (Civilians) receive the same secret word, while one player (the Spy) receives a different but related word. Over T rounds, each player provides a description of their word. The LLM is evaluated from the perspective of Player 1 (s_1): it knows the word assigned to s_1, but does not know whether s_1 is a Civilian or the Spy. It does not generate any player descriptions. Instead, after observing all T rounds of player-generated descriptions, the LLM must infer which player received the different word. This constitutes a graph-level query ($\mathcal{Q}_G$). Detailed rules are available in Appendix C.

Design Rationale. As shown in Table 1, *Find the Spy* exemplifies High *Dynamic Interaction*. The multi-round format necessitates tracking clues revealed incrementally by all players over time.

Conversely, *Information Uncertainty* is designed to be Low. Since players aim to avoid suspicion, they are incentivized to provide truthful descriptions of their assigned word, thereby significantly reducing the element of strategic deception.

Data Generation and Quality Assurance. For each game instance, we first set the parameters n (number of players) and T (number of rounds), then randomly selected a related word pair from a curated word bank, followed by random role assignment (one Spy and $n-1$ Civilians). We then used a variety of LLMs to generate player descriptions for each of the T rounds, simulating diverse communication styles. Prompt designs were crafted to encourage varied perspectives and expression strategies across rounds. To ensure quality and solvability, instances underwent human evaluation by 15 computer science graduate students. An instance was considered valid if at least 10 of the 15 evaluators ($\geq 10/15 \approx 67\%$) could uniquely identify the Spy based on the descriptions. 91% of the evaluated instances met this criterion, verifying their suitability for the benchmark.

C.2 Task Setup

The game involves n players, denoted $s_1, \ldots, s_n$. The evaluated LLM adopts the persona of Player 1 (s_1) but acts as a passive observer. It receives all game information, including its own assigned word and all player descriptions, from s_1's perspective but does not generate descriptions itself during the evaluation process. The LLM's sole task is to identify the Spy based on the observed interactions. For word assignment, a pair of semantically related but distinct words (Word A, Word B, e.g., "Milk" and "Soy Milk") is selected from a predefined bank. One player is randomly designated as the Spy, while the remaining $n-1$ players are Civilians. All Civilians receive Word A, and the Spy receives Word B. Player 1 (the LLM's persona) is informed of the word it received but is not explicitly told whether it is Word A or Word B, nor is it told its role (Civilian or Spy).

C.3 Interaction Rounds

The game proceeds for T rounds. In each round t (from 1 to T), every player s_i provides a textual description of the word they possess. These descriptions are generated by LLMs, with each player s_i being assigned a specific LLM generator (selected randomly and uniformly from a predefined pool of five LLMs: GPT-4o-mini, GPT-4o, Llama-3.3-70B, Qwen-2.5-72B, and Claude Sonnet 4.5) for the entire game instance. The generation prompts encourage the LLM simulating player s_i to describe their word from different angles or aspects in each round, avoiding simple repetition. Players are assumed to provide descriptions consistent with the word they hold: Civilians describe Word A, and the Spy describes Word B. All descriptions generated in round t are made available to all players, including the LLM as s_1, before round $t+1$ begins. Thus, the complete history of descriptions from rounds 1 to T is available at the end of the game for the LLM's analysis.

C.4 Parameter Settings

For all experimental evaluations using this task setup, the number of players n was fixed at 4, and the number of interaction rounds T was fixed at 3.

C.5 Quality Control

To ensure generated instances are solvable yet challenging, they undergo a rigorous human validation process. Each potential game instance is reviewed by 15 evaluators, all holding at least an undergraduate degree in Computer Science. An instance is deemed valid and solvable only if at least 10 of the 15 evaluators ($\geq 10/15 \approx 67\%$) agree that the collective descriptions provided by the simulated players contain sufficient evidence to uniquely identify the Spy. This validation confirms that the task's difficulty stems from semantic subtlety and variations in description style, rather than from a fundamental lack of necessary information. 91% of the instances subjected to this evaluation met the validation threshold, affirming their suitability for inclusion in the benchmark.

C.6 Spy vs Civilian Perspective Decomposition

The Find the Spy headline accuracy in Table 4 aggregates two subpopulations of the 500-instance test set: instances in which the evaluated LLM (Player 1) is assigned the Spy role (25%) and instances in which it is assigned a Civilian role (75%), per the role distribution stated in the Parameter Settings section. Table 7 reports the per-perspective accuracy for each evaluator on the same test set. The two subpopulations track within a few pp of each other for all twelve evaluators, so the headline metric is not driven by a single subpopulation; the Spy-perspective accuracy is on average slightly lower than the Civilian-perspective

accuracy, consistent with the Spy receiving a deliberately different word and therefore facing a harder identity inference.

Table 7: Per-perspective accuracy on the Find the Spy 500-instance test set. Cells report 5-seed bootstrap mean $\pm$ 95% CI half-width following the protocol disclosed in subsection H.2. "Spy" = the 125 instances ($\approx$ 25%) in which Player 1 is the Spy (per-seed $n = 125$); "Civilian" = the 375 instances ($\approx$ 75%) in which Player 1 is a Civilian (per-seed $n = 375$). "Diff." is Spy minus Civilian.

Model	Spy	Civilian	Diff.
Llama-3.1-8B	35.2 ± 8.4	37.9 ± 4.9	-2.7
Llama-3.3-70B	57.6 ± 8.7	60.8 ± 4.9	-3.2
Phi-4	43.2 ± 8.7	45.9 ± 5.0	-2.7
Qwen-2.5-72B	46.4 ± 8.7	49.7 ± 5.1	-3.3
QwQ-32B	48.0 ± 8.8	50.9 ± 5.1	-2.9
GPT-4o-mini	59.2 ± 8.6	61.9 ± 4.9	-2.7
GPT-4o	66.4 ± 8.3	70.1 ± 4.6	-3.7
o3-mini	72.0 ± 7.9	74.7 ± 4.4	-2.7
o1	76.0 ± 7.5	79.2 ± 4.1	-3.2
DeepSeek-V3	56.0 ± 8.7	59.5 ± 5.0	-3.5
DeepSeek-R1	68.0 ± 8.2	70.9 ± 4.6	-2.9
Gemini-2.5-Pro	73.6 ± 7.7	77.6 ± 4.2	-4.0

D Rating Estimation from Text

This appendix provides the details for the Rating Estimation from Text task described in subsection 3.3.

D.1 Overview

Task Rules. This task aims to evaluate the ability of LLMs to predict a product's 1-to-5 star rating based on n textual reviews, which may include genuine positive or negative user comments as well as promotional reviews written by shills. We collect two types of data: reviews generated by LLMs simulating different user types, and real user reviews scraped from platforms such as Amazon, the Google Play Store, and Taobao. The final rating prediction task follows a structure where information flows from multiple user nodes to a central product node, constituting a vertex-centric query focused on the product itself ($\mathcal{Q}_v$(product)). Detailed task rules can be found in Appendix D.

Design Rationale. The task deliberately introduces a high level of *information uncertainty*. In the LLM-generated data, this is reflected through the inclusion of simulated "shill" users to mimic deceptive review behavior. In the real-world data, uncertainty arises from the inherent noise, subjectivity, and potential bias present in genuine user reviews. This setting requires the model to evaluate the credibility of information flowing from user nodes (i.e., reviewers) to the product node.

Data Generation and Quality Assurance. The LLM-based data generation process begins by sampling product attributes from a manually curated repository consisting of 1,000 attribute terms. A normal distribution of ratings is then constructed based on the true star rating, ensuring that the mean aligns with the reference score. Next, n LLMs are randomly selected from a diverse model pool and probabilistically assigned roles (either normal users or shills) along with distinct personas, which guide the generation of textual reviews consistent with their assigned identities. For real-world data, we directly scrape product attributes and n user reviews from platforms such as Amazon, the Google Play Store, and Taobao. An instance was considered solvable if a majority (>70%) of evaluators could correctly infer the true rating based solely on the textual reviews. Among the LLM-generated samples, 83% satisfied this criterion, confirming their validity for evaluating model reasoning.

D.2 Task Setup

The primary objective for the LLM in this task is to estimate the most likely overall "true" star rating, represented as an integer from 1 to 5, for a given product. This estimation must be based solely on the textual content derived from multiple user reviews. For each task instance, the LLM receives specific input: a set of attributes describing the product (such as type, category, key features, price range) and a list containing n individual textual user reviews for that product. Crucially, the original star ratings (1-5 stars) that reviewers might have provided are explicitly omitted from the input. After processing the product information and the n textual reviews, the LLM must answer a vertex-centric query ($\mathcal{Q}_v$(product)) phrased as: "Based on the provided reviews, what is the most likely overall star rating for this product? Choose one: 1, 2, 3, 4, or 5." The expected output is a single integer, necessitating the synthesis of information from multiple user interactions (reviews) all directed towards the product entity.

D.3 Data Generation

The task utilizes review data generated through two distinct methods. The first method involves **LLM-Generated Reviews**. Here, a product profile is selected, including its attributes and a designated

ground truth overall star rating. A number n of simulated reviewers is determined, and each reviewer i is assigned a role probabilistically, ensuring the majority are *Normal Users* (providing honest feedback) while a small fraction are designated as *Positive Shills* or *Negative Shills*. Each reviewer also receives a simple persona for stylistic variation and is assigned a randomly selected LLM from a predefined pool of five LLMs (GPT-4o-mini, GPT-4o, Llama-3.3-70B, Qwen-2.5-72B, Claude Sonnet 4.5) to simulate their response. The assigned LLM then generates the review text for reviewer i, guided by the product attributes, the ground truth rating, the reviewer's assigned role (Normal/Shill), and their persona; Shills are prompted to generate biased text accordingly. Finally, only the generated textual reviews are collected and prepared as input for the evaluated LLM. The second method uses **Real-World Reviews**. In this scenario, product attributes along with user reviews (both text and original ratings) are scraped from public e-commerce and app platforms. For a selected product, n reviews are sampled from the scraped collection. The textual content of these n sampled reviews is extracted, while the original star ratings are discarded. Only the product attributes and the review texts are provided as input to the LLM. The ground truth for these instances is typically derived from the average rating found on the source platform, which the LLM is tasked to estimate.

D.4 Parameter Settings

Across all experiments presented for this task, the number of reviews (n) provided per product instance is consistently set to 8. The required output is always a single integer rating on the 1-to-5 star scale. The real-world task instances exclusively utilize product attributes and textual reviews sourced from **Amazon**, the **Google Play Store**, and **Taobao**. For the LLM-generated instances, the underlying product attributes and the initial ground truth star ratings are also sampled from this same pool of real-world data derived from these platforms, providing a basis grounded in realistic product scenarios.

D.5 Quality Control

As detailed in subsection 3.3, human evaluations were integral to ensuring data quality. These were conducted by 15 graduate students. For the LLM-generated data (Scenario A), this evaluation determined that 83% of the assessed instances were solvable, meaning the true rating could be reasonably inferred from the text alone by more than half of the human evaluators. For the instances derived from real-world data (Scenario B), solvability is inherently tied to the complexity and nature of authentic customer feedback as it appears on platforms like Amazon, Google Play, and Taobao, reflecting genuine information landscapes.

Algorithm 2: Social Graph Generation

Input : Difficulty level $d \in \{\text{easy}, \text{hard}\}$
Output : Natural language instance I

Set number of individuals
$$n \sim \begin{cases} [8, 10], & \text{if } d = \text{easy} \\ [14, 16], & \text{if } d = \text{hard} \end{cases};$$
Initialize graph $G = (V, E)$, where $|V| = n$;
Step 1: Generate spanning forest to define social groups;
Randomly partition V into $m \geq 2$ disjoint non-empty subsets $\{V_1, V_2, \ldots, V_m\}$;
foreach *group* V_i **do**
  Generate a spanning tree $T_i = (V_i, E_i^{\text{good}})$;
  Add edges E_i^{good} to E// Intra-group "good" relationships
Step 2: Add "bad" edges between groups;
foreach *pair of groups* $(V_i, V_j),\ i \neq j$ **do**
  Select a node pair $(u, v) \in V_i \times V_j$;
  Add edge (u, v) to $E^{\text{bad}} \subset E$// Inter-group "bad" relationship
Step 3: Convert graph structure to natural language;
foreach *edge* $(u, v) \in E$ **do**
  if $(u, v) \in E^{good}$ **then**
    Generate statement: "u and v are good friends.";
  else if $(u, v) \in E^{bad}$ **then**
    Generate statement: "u and v do not get along.";
Aggregate all generated statements into input instance I;
return I;

E Social Graph Analysis

This appendix provides the details for the Social Graph Analysis task described in Section 3.4.

1. Setup

This task presents a stylized social network scenario involving a set of n individuals. The core challenge lies in understanding the structure of this network, where relationships between any two individuals are strictly defined as either 'good' or 'bad'. The LLM is provided with a complete description of all pairwise relationships and must then analyze this information to answer queries about specific relationships, individual connections, and the overall emergent group structure of the network, guided by a set of simple logical axioms.

2. Relationship Axioms

Relationships between any two distinct individuals, say Person A and Person B, are binary ('good' or 'bad') and symmetric. These relationships are governed by specific logical rules: **Axiom 1 dictates the transitivity of good relationships**, meaning if A and B have a 'good' relationship, and B and C also have a 'good' relationship, then A and C must necessarily have a 'good' relationship. **Axiom 2 describes the implication of bad relationships**, stating that if A and B have a 'bad' relationship, and A and C have a 'good' relationship, then B and C are forced to have a 'bad' relationship. It's important to note that from these axioms, if A and B share a 'bad' relationship, and B and C also share a 'bad' relationship, the nature of the relationship between A and C is not determined solely by these two facts; it could be either good or bad depending on other connections within the network. However, the algorithmic generation process always ensures a globally consistent and valid relationship structure.

3. Group Definition

Within this social structure, a 'group' is formally defined as a maximal set of individuals where every person within that set has a 'good' relationship with every other person also belonging to that same set. A key property of this structure is that every individual belongs to exactly one such group. Consequently, based on the governing axioms and the generation method, the relationship between any two individuals can be directly inferred from their group membership: if Person A and Person B are members of the same group, they inherently have a 'good' relationship; conversely, if they belong to different groups, they must have a 'bad' relationship.

4. Input Format

The LLM receives as input a comprehensive list composed of natural language statements that explicitly specify **the complete set of pairwise relationships** as determined by the algorithmic generation process. These statements clearly define the relationship status between every possible pair of individuals within the scenario. Examples of such input statements include "Person N and Person G have a good relationship" and "Person K and Person P have a bad relationship". This list provides a full and unambiguous description of the entire social graph structure.

5. LLM Queries

After processing the complete list of relationship statements provided as input, the LLM is required to answer various types of queries designed to test its understanding of the network structure. These queries include, for instance, **Pairwise Relationship Queries ($\mathcal{Q}_e(v_i, v_j)$)**, such as "Do Person N and Person L have a good relationship?", which typically requires checking the provided input directly and responding with Yes/No. Other queries are **Good Relationship Neighbor Queries (Vertex-centric)**, like "Who has a good relationship with Person H?", demanding the LLM to filter the input and list the relevant names. Furthermore, **Graph-level Queries ($\mathcal{Q}_G$)** probe the overall structure, asking questions like "How many groups of people are there?" or "How many pairs of people have good relationships?" or "How many pairs of people have bad relationships?", all of which require synthesizing the pairwise information to derive a global property and respond with an integer count.

6. Data Generation and Quality Assurance

Instances for this task are generated entirely algorithmically, without reliance on LLM generation, ensuring consistency and verifiable ground truth. The process begins by setting the number of individuals n, sampled from [8, 10] for 'easy' instances and [14, 16] for 'hard' instances. A complete graph structure respecting the relationship axioms is then algorithmically constructed. First, a spanning forest is created using only 'good' relationship edges, thereby defining the distinct social groups (each tree representing a group). Second, 'bad' relationship edges are strategically added to connect every pair of distinct groups (trees), ensuring all inter-group relations are 'bad' and all intra-group relations are 'good'. The complete set of

generated relationship edges ('good' edges defining the groups and 'bad' edges connecting them) is then converted into natural language statements and presented to the LLM as input. This generation methodology mathematically guarantees that for each instance, a unique solution exists for all four query types and is logically derivable solely from the provided statements and rules. The core generation logic is outlined in algorithm 2.

F Review Decision Prediction

This appendix provides the details for the Review Decision Prediction task described in subsection 3.5.

1. Objective

The LLM's goal in this task is to predict the final acceptance status (Accepted or Rejected) of a research manuscript submitted to a conference, based solely on the sequence of provided peer review communications.

2. Data Source and Scope

Data for this task is exclusively sourced from the official OpenReview API, encompassing submissions to nine cycles across three high-profile Artificial Intelligence and Machine Learning venues: NeurIPS (2023, 2024), ICLR (2020, 2021, 2022, 2023, 2024, 2025), and COLM 2024. The ICLR 2025 cycle is included as a diagnostic post-cutoff slice for most of the evaluated models, and its per-model perturbed-vs-unperturbed deltas trend in the same direction as the full set (Table 8), suggesting the perturbation effect is not driven by pre-cutoff memorization specifically. **The rationale for selecting these particular venues** stems primarily from their policy of making the entire peer review process public. This transparency, which *crucially includes making detailed reviews and discussions for rejected manuscripts publicly available*, is a practice not commonly found in many other academic fields. It provides the essential data needed to construct a balanced and realistic task dataset that accurately reflects both acceptance and rejection scenarios encountered in academic publishing.

3. Input Structure

The LLM receives information pertaining to a single manuscript, presented in a structured sequence that mirrors the typical progression of the peer review timeline. Initially, in **Round 1**, the LLM is given the initial submission details: the manuscript's original **Title**, its **Abstract**, and the author-provided **Keywords**. Subsequently, in **Round 2**, the LLM receives the reviewer feedback, which consists of the complete **textual content** of each review submitted by the assigned reviewers. It is **crucial to note the exclusion** of all quantitative aspects from these reviews; numerical scores (such as overall ratings, technical soundness, or novelty scores), reviewer confidence scores, explicit recommendations (like Accept, Reject), and any other non-textual evaluation metrics are deliberately removed. The input at this stage contains only the narrative comments written by the reviewers. Finally, **Round 3** provides information from the author-reviewer discussion phase, including the full text of the authors' **rebuttal** designed to address the initial reviewer comments, as well as any subsequent **comments or discussions** exchanged between the authors and reviewers following the rebuttal. The full manuscript text itself is intentionally omitted from the input provided to the LLM. This decision is driven by two main factors: practical challenges related to processing lengthy full papers consistently across numerous task instances, considering LLM input constraints and computational costs, and more importantly, to align with the task's core objective. This objective focuses on evaluating the LLM's ability to comprehend and synthesize the dynamics inherent in the peer review dialogue—interpreting arguments, discerning attitudes, and understanding sentiments expressed by reviewers and authors—rather than tasking it with performing an independent technical re-evaluation of the manuscript's content.

4. Ground Truth and Quality Assurance

The ground truth for this task is inherently robust, as it consists of the verified, real-world acceptance or rejection decisions obtained directly from the OpenReview API across the nine venue-year cycles listed above (NeurIPS 2023-2024, ICLR 2020-2025, COLM 2024). To further validate the task's premise—specifically, whether the final outcome is typically discernible from the textual dialogue alone (Title, Abstract, Keywords, Reviews, Rebuttal) after removing numerical scores—we conducted supplementary human evaluations. Human evaluators were presented with the same sequential information provided to the LLM and asked to predict the final decision. For over 90% of the evaluated manuscript instances, the true outcome was deemed inferable from the textual evidence by a majority (>70%) of the human evaluators. This confirms the general solvability of the

task based on the provided textual interactions and reinforces its suitability for assessing an LLM's ability to synthesize argumentative dialogue, complementing the reliability provided by the authentic ground truth data.

5. Perturbed-Reviews Subset. To disentangle reviewer-comment memorization from genuine evidence-based reasoning, we introduce a perturbed-reviews subset. Approximately 50% of the 500 test instances have their reviewer comments, title, and abstract rewritten by Claude Sonnet 4.5, instructed to preserve substantive claims (technical critique points, mentioned weaknesses, summary judgments; the abstract's contribution statement and main result claims) while disrupting verbatim n-gram overlap with the original OpenReview text. The Keywords and Rebuttal text are left unchanged. This perturbation scope simultaneously blocks two memorization channels: verbatim recall of reviewer phrasing (Round-2 input) and identification of the paper from title or abstract content (Round-1 input). Models are evaluated on the full test set; per-subset accuracies (perturbed vs unperturbed) at Round 3 are reported in Table 8. Across the twelve evaluators the perturbed-subset Round-3 accuracy stays within ± 2 pp of the unperturbed subset, indicating that the multi-stage trajectory is not dominated by verbatim memorization of OpenReview text or by abstract-content-based paper identification. At the sub-sample size of $n \approx 250$ per perturbed/unperturbed subset, the multi-seed paired Δ-CI is $\approx \pm 6$ to ± 9 pp depending on the cell's p; the observed $|\Delta| \leq 2$ pp across all twelve evaluators is therefore consistent with both "no memorization effect" and "a memorization effect smaller than the ± 6–9 pp detection threshold at this subsample size". The data rule out a memorization effect larger than that threshold; a smaller-magnitude effect is power-not-evidence and would require a larger perturbed-subset evaluation to detect.

6. Anti-Prior Decomposition, Two-Regime Round-3 Trajectory, and Multiple-Comparison Discipline. The Round-1 to Round-2 jump conflates two effects: abandonment of the over-accept prior once reviewer text is available, and reasoning over the substantive content of that text. The present headline accuracies in Table 3 do not separate the two; the perturbed-subset analysis above isolates the reasoning channel from verbatim memorization but does not isolate the prior-correction channel from the content-reasoning channel. Read literally, the Round-3 column measures Round-3 minus a model-specific prior-recalibration shift toward the test set's 67% reject ratio.

Three evaluators (Llama-3.3-70B 26.2%, Qwen-2.5-72B 23.6%, Phi-4 23.5%) score below the 33% always-accept floor at Round 1, which mathematically requires anti-correlation with the ground truth rather than just an inflated accept-prior. A plausible mechanism is over-confident accept prediction on the harder accept cases (which are typically nearer the borderline) combined with confident reject on the easier reject cases that the title / abstract / keywords already telegraph; we do not separate these two channels. The title/abstract/keywords telegraph signal is present in every downstream stage as well, so the Round-2 / Round-3 improvements are not strictly net of this contamination; the perturbed-subset analysis in Table 8 bounds the verbatim-memorization component of the telegraph within ± 2 pp at the per-subset paired-Δ floor of ± 6 to ± 9 pp, but a sub-floor memorization effect of up to a few pp is not ruled out at the current subsample size. Within the Llama family, Llama-3.3-70B (26.2%) sits further from the 67% reject baseline than Llama-3.1-8B (37.0%); we do not have a mechanistic account of this sibling-direction anomaly beyond noting that both models miss the majority baseline by anti-correlated channels.

At Round 3, two of the twelve evaluators (GPT-4o, DeepSeek-V3) show an accuracy increase over Round 2, while the remaining ten show a decrease. The up-trend models read the rebuttal as additional evidence that aligns with the final judgment; the down-trend models read it as a persuasive defense that pulls them away. The relevant significance test is on the paired Round-2 vs Round-3 change per model, whose standard error is $\sigma_\Delta = \sqrt{2p(1-p)/n} \cdot 100 \approx 2.0$ pp at $p \approx 0.88, n = 500$ (the 95% paired-Δ half-width is $1.96\sigma_\Delta \approx 4.0$ pp; the σ_Δ is the standard error used to form the z statistic and is distinct from the per-cell binomial half-width $\approx \pm 2.6$ pp at the same p shown in Table 3, which describes per-cell sampling variance rather than the difference between two cells of the same model). Under that σ_Δ, the up-trend on GPT-4o ($\Delta = +4.0$ pp, $z \approx 1.9$) and DeepSeek-V3 ($\Delta = +5.4$ pp, $z \approx 2.7$) do not survive Bonferroni correction at the twelve-comparison family-wise threshold $|z| > 2.86$; the strong down-trend models with $|\Delta| > 5$ pp survive easily ($|z| > 3$). The hon-

est reading is therefore "ten clearly down-trending evaluators plus two evaluators whose Round-3 increases are undecided under family-wise correction" rather than "two distinct regimes". The divergent direction across regimes corresponds to different prior calibrations rather than verbatim memorization, since the perturbed-subset Δ values in Table 8 are bounded within ± 2 pp for both regimes.

Table 8: Round-3 *Review Decision Prediction* accuracy on the unperturbed vs Claude-Sonnet-4.5-perturbed subsets of the 500-instance test set ($n \approx 250$ each). Cells report 5-seed mean $\pm$ 95% binomial CI half-width following the protocol disclosed in subsection H.2. The perturbed subset rewrites reviewer comments, title, and abstract while preserving substantive claims; Keywords and Rebuttal text are left unchanged (see appendix block 5 for the protocol). The Δ column reports perturbed minus unperturbed (paired across seeds). The paired-Δ CI at $n \approx 250$ per subset is $\approx \pm 6$ to ± 9 pp depending on the cell's p; the observed $|\Delta| \leq 2$ pp across all twelve evaluators is therefore consistent with both "no memorization effect" and "a memorization effect smaller than the $\pm$6–9 pp detection threshold at this subsample size". The data rule out a larger memorization effect; a smaller-magnitude effect would require a larger perturbed-subset to detect.

Model	Unpert.	Pert.	Δ
Llama-3.1-8B	$62.4 \pm 6.0\%$	$60.8 \pm 6.1\%$	-1.6 ± 8.5
Llama-3.3-70B	$72.6 \pm 5.5\%$	$73.4 \pm 5.5\%$	$+0.8 \pm 7.8$
Qwen-2.5-72B	$66.4 \pm 5.9\%$	$65.0 \pm 5.9\%$	-1.4 ± 8.4
Phi-4	$60.8 \pm 6.1\%$	$59.2 \pm 6.1\%$	-1.6 ± 8.6
GPT-4o-mini	$85.2 \pm 4.4\%$	$84.0 \pm 4.5\%$	-1.2 ± 6.4
GPT-4o	$90.4 \pm 3.7\%$	$89.0 \pm 3.9\%$	-1.4 ± 5.4
o3-mini	$78.4 \pm 5.1\%$	$78.0 \pm 5.1\%$	-0.4 ± 7.3
QwQ-32B	$80.0 \pm 5.0\%$	$79.6 \pm 5.0\%$	-0.4 ± 7.0
DeepSeek-V3	$91.6 \pm 3.4\%$	$91.2 \pm 3.5\%$	-0.4 ± 4.9
DeepSeek-R1	$82.4 \pm 4.7\%$	$82.0 \pm 4.8\%$	-0.4 ± 6.7
o1	$77.6 \pm 5.2\%$	$77.8 \pm 5.2\%$	$+0.2 \pm 7.3$
Gemini-2.5-Pro	$77.4 \pm 5.2\%$	$77.8 \pm 5.2\%$	$+0.4 \pm 7.3$

G User Profile Inference

This section provides the details for the User Profile Inference task, corresponding to subsection 3.6.

1. Task Setup

For each instance of this task, a population of n simulated users is defined. Every user u_i within this population is assigned a specific demographic profile, which consists of an age group selected from '18-34', '35-54', '55+' and a gender selected from 'Male', 'Female', 'Non-binary'. This profile assignment is carried out probabilistically, with the process intentionally tuned to often establish a statistically dominant age-gender combination within the user pool. This characteristic is particularly relevant for addressing the "dominant audience" query type. Additionally, a predefined pool of items, each described by a name and a brief description, is utilized. Users are randomly assigned items from this pool, about which they will generate comments.

2. Comment Generation Process

Each simulated user u_i is associated with a specific Large Language Model (LLM), chosen randomly from a diverse pool of five LLMs: GPT-4o-mini, GPT-4o, Llama-3.3-70B, Qwen-2.5-72B, and Claude Sonnet 4.5. The core of the generation process involves tasking the LLM associated with user u_i (who has an assigned age group A_i and gender G_i) to generate a textual comment about a selected item j (which has a specific type T_j and subject S_j). The LLM is prompted to generate content that reflects the assigned persona interacting with the given item.

3. LLM Queries

Based on the generated comments provided as input, the evaluated LLM must answer one of two specific types of queries. The first is the **Item Audience Profile Inference (Vertex-centric Query** $\mathcal{Q}_v$(**Item**)**)**. For this query, the LLM is asked, "Based on the provided comments for the item '[Item Name]', what is the most likely dominant audience profile (Age Group and Gender)? Choose from Age Groups: ['18-34', '35-54', '55+'] and Genders: ['Male', 'Female', 'Non-binary']." Answering this requires synthesizing information from multiple user comments linked to a specific item node to infer an aggregated characteristic of its audience. The second type is the **User Profile Inference (Vertex-centric Query** $\mathcal{Q}_v$(**User**)**)**, which poses the question: "Based on the provided comments from this user, what is their most likely profile (Age Group and Gender)? Choose from Age Groups: ['18-34', '35-54', '55+'] and Genders: ['Male', 'Female', 'Non-binary']." This query demands synthesizing information from multiple comments generated by a single user node, potentially across different items, to infer the intrinsic demographic attributes (age group and gender) of that specific user.

4. Quality Assurance

The dataset for this task was entirely generated using LLMs. We first defined a set of user personas by assigning age group and gender attributes, ensuring through probabilistic assignment that certain demographic combinations were more preva-

lent to create a potential "dominant audience" for item-centric queries. Items with names and descriptions were sampled from a predefined pool. Various LLMs were then assigned to personas and prompted to generate comments on these items, reflecting their designated age and gender characteristics. To ensure task validity, we conducted human evaluations with 15 computer science graduate students. For the item-audience query, 78% of instances were deemed solvable (dominant audience inferable) by a majority (>70%) of evaluators. For the user-profile query, 85% of instances were similarly validated, confirming that the generated comments contain sufficient, albeit subtle, cues for demographic inference.

H Experiment Details

This appendix provides detailed information regarding the experimental setup, the models evaluated, data generation procedures for each task within the SocialMaze benchmark, the experimental methodology, and a summary of the overall results.

H.1 Baselines

As detailed in Table 9, we utilized five proprietary models as evaluators: GPT-4o (Hurst et al., 2024), GPT-4o-mini (OpenAI, 2024), o3-mini (OpenAI, 2025), o1 (Jaech et al., 2024), and Gemini-2.5-Pro (Google DeepMind, 2025). In addition, we included seven open-weight evaluators: Phi-4 (Abdin et al., 2024), Llama-3.1-8B (Meta, 2024b), Llama-3.3-70B (Meta, 2024a), Qwen2.5-72B (Qwen Team, 2024), QwQ-32B (Qwen Team, 2025), Deepseek-V3 (DeepSeek-AI, 2024), and Deepseek-R1 (Guo et al., 2025). Claude Sonnet 4.5 (Anthropic, 2025) enters only the generator pool used to produce simulated player descriptions, reviewer comments, and user comments inside the data-generation pipelines (see Appendix C, Appendix F, and Appendix G); it is not evaluated as a solver on any SocialMaze task, so the twelve evaluator rows in Table 4 and Table 3 cover the five proprietary plus seven open-weight evaluators above.

We also included automated agent design frameworks as baselines:

ADAS (Hu et al., 2025a): Utilized GPT-4o as the Meta Agent. For agent evaluation, we tested both Phi-4 and GPT-4o-mini and selected the better performer.

AFlow (Zhang et al., 2025b): Employed GPT-4o as the optimizer. For the executor role, we tested both Phi-4 and GPT-4o-mini and selected the better performer.

MaAS (Zhang et al., 2025a): For executing the sampled agentic operators, we tested both Phi-4 and GPT-4o-mini and selected the better performer.

DyFlow (Wang et al., 2025f): Used GPT-4o as the optimizer. For the executor role, we tested both Phi-4 and GPT-4o-mini and selected the better performer.

H.2 Parameter Settings

Inference Parameters During the evaluation of all LLMs across the SocialMaze tasks, we used a temperature setting of 0.7 to allow for some variability while maintaining reasonable coherence. The maximum-output-token cap was set to 4,096 for all Short-CoT evaluators across every task; for Long-CoT evaluators (DeepSeek-R1, o1, QwQ-32B, Gemini-2.5-Pro) on *Hidden Role Deduction* we extended the cap to 8,192 to accommodate longer reasoning chains. Per-task truncation and answer-extraction failure rates are reported in Table 18 (subsection I.5). Reported accuracies in the main tables are mean accuracies over five independent runs at this temperature on the 500-instance per-task test set described in subsection H.3, with 95% CI half-widths reported alongside each cell. Because the same 500 instances are evaluated under each seed, the binomial instance-sampling floor at $n = 500$ dominates the reported half-width; multi-seed averaging additionally constrains the decoding-channel variance to be small (in our pilot the seed-to-seed standard deviation of the per-instance mean accuracy is below ± 0.6 pp for every task–model pair, well inside the binomial floor), so the reported $\pm$ is the binomial half-width at $n = 500$: $1.96\sqrt{p(1-p)/500} \cdot 100$ pp. As reference points, ± 4.4 pp at $p = 0.5$, ± 3.8 pp at $p = 0.75$, ± 1.9 pp at $p = 0.95$. Per-role HRD accuracies in Table 16 use the analogous $n = 125$ floor at the per-role bin size, giving ± 8.8 pp at $p = 0.5$. We treat ranking comparisons whose gap falls inside the floor as ties within sampling noise rather than ordered separations, and the narrative in subsection H.3 is written under this convention.

Task-Specific Configurations:

- **Hidden Role Deduction:** This task includes two subsets based on the number of players: 'easy' ($n = 6$) and 'hard' ($n = 10$). In both

Table 9: Models used in our experiments along with their versions, organizations, licenses, and purposes. *Eval*: Model used for evaluation; *FT*: Model used for fine-tuning. Models marked with † are used only inside the data-generation pool that produces simulated player / reviewer / user text and are never invoked as evaluators on any task.

Model	Version	Organization	License	Eval	FT
Phi-4	Phi-4	Microsoft	MIT	✓	✓
GPT-4o-mini	gpt-4o-mini-2024-07-18	OpenAI	Proprietary	✓	
GPT-4o	gpt-4o-2024-08-06	OpenAI	Proprietary	✓	
Llama-3.1-8B	Meta-Llama-3.1-8B-Instruct	Meta	Llama 3.1 Community	✓	✓
Llama-3.3-70B	Meta-Llama-3.3-70B-Instruct	Meta	Llama-3.3	✓	
Qwen2.5-72B	Qwen2.5-72B-Instruct	Alibaba	Qwen License	✓	
QwQ	QwQ-32B	Alibaba	Apache 2.0	✓	
o3-mini	o3-mini-2025-01-31	OpenAI	Proprietary	✓	
o1	o1-2024-12-17	OpenAI	Proprietary	✓	
Deepseek-R1	DeepSeek-R1	DeepSeek	MIT	✓	
Deepseek-V3	DeepSeek-V3	DeepSeek	MIT	✓	
Gemini-2.5-Pro	Gemini-2.5-Pro-Exp-03-25	Google	Proprietary	✓	
Claude Sonnet 4.5†	claude-sonnet-4-5-20250929	Anthropic	Proprietary		

subsets, the number of interaction rounds T is fixed at 3. All experiments reported in the main body of the paper were conducted using the 'easy' ($n = 6$) subset configurations. Across both the publicly released dataset and the evaluation experiments, the role for the main perspective (LLM) is drawn uniformly from the four roles (Investigator:Criminal:Rumormonger:Lunatic = 1:1:1:1), and per-role accuracies are reported separately where applicable.

- **Find the Spy:** For all instances of this task, the number of players n was set to 4, and the number of description rounds T was set to 3. In all experiments, the model received the spy word in 25% of cases and the civilian word in 75% of cases.
- **Rating Estimation from Text:** For instances using LLM-generated data, the number of simulated reviewers providing text was fixed at 8. For instances using real-world data sourced from platforms like Amazon, a random number of reviews between 10 and 20 were sampled for each product. Decimal star ratings were rounded to the nearest integer. We preserve the natural class prevalence of large-scale e-commerce review corpora rather than artificially rebalancing the test set; positive ratings dominate (the distribution ratio for 1-, 2-, 3-, 4-, and 5-star is 1:3:10:73:13), and the constant-predict-4 majority baseline scores 73% on this test set. The headline metric in Table 4 should therefore be read against this 73% floor: models below the floor exhibit anti-calibration toward minority ratings (driven by over-confident prediction of low/high extremes), while models above the floor demonstrate non-trivial fine-grained discrimination across the five rating bins. The diagnostic resolution above the 73% floor is small: the top six models cluster within ± 2 pp of one another and the top model exceeds the floor by only $\approx +3$ pp, so the task's contribution to cross-model ranking is primarily anti-calibration detection (cells below floor) rather than fine-grained discrimination among above-floor models.
- **Social Graph Analysis:** This task also has two subsets. 'easy': The number of individuals n was randomly chosen from the range [8, 10]. 'hard': The number of individuals n was randomly chosen from the range [14, 16]. All generated graphs were sparse (the number of edges was close to the number of vertices).

Review Decision Prediction: Data from a total of nine venue-year cycles (NeurIPS 2023-2024, ICLR 2020-2025, COLM 2024) were sampled approximately uniformly across venues; per-venue draw counts were balanced before the accept/reject rebalancing step. In the final dataset, the proportion of papers was adjusted to 67% rejected and 33% accepted. This 67/33 split is heavier on rejections than the underlying venue accept rates (typically 25–30% acceptance); the rebalancing was done to make Round-1

always-accept and always-reject baselines symmetric around the 50% line so per-model anti-prior tendencies are distinguishable. The per-venue sample counts are recorded in the released dataset metadata; the test set's prior-correction channel discussed in block 6 below is therefore venue-mixture-aware rather than driven by any single venue.

- **User Profile Inference:** For both query types (item-audience inference and user-profile inference), the model was provided with a number of textual comments randomly selected from the range [8, 12].

Fine-tuning Parameters: For the fine-tuning experiments, we trained for 2 epochs with a learning rate of 5.0e-6, employing a cosine learning rate scheduler and a warmup ratio of 0.1. The per-device training batch size was 1, with a gradient accumulation of 8 steps. We employed a cosine learning rate scheduler with a warmup ratio of 0.1 and enabled bf16 precision. For these experiments, the models were trained on 2000 examples for SFT and 1100 preference pairs for DPO. Performance was subsequently evaluated on a distinct test set containing 500 examples. All training experiments were conducted on 2 NVIDIA A6000 GPUs over a period of 30 hours.

H.3 Overall Performance Summary

H.4 Cross-Task Transfer of HRD-Trained Models

To probe whether the SFT and DPO models trained on *Hidden Role Deduction* traces transfer beyond the training task, we re-evaluate the fine-tuned Llama-3.1-8B and Phi-4 checkpoints on the five non-HRD tasks in SocialMaze. The same dedicated 500-instance test sets used in Table 4 are reused with no further fine-tuning. Table 12 reports Base, +SFT, and +DPO accuracies for each task, with parenthesized deltas relative to Base. We distinguish two task families: a *deductive* family (*Find the Spy*, *Social Graph Analysis*) that shares structured-testimony deduction with HRD, and a *linguistic* family (*Rating Estimation*, *Review Decision Prediction*, *User Profile Inference*) that depends predominantly on language comprehension and aggregation.

This task-family categorization is a coarse surface-task-type grouping made at design time rather than the output of a factor analysis on task-level correlations. The two-vs-three split is small

Table 10: Performance of LLM agents and workflows on the *Hidden Role Deduction* task. The two reasoning-capable rows (QwQ, DeepSeek-R1) are listed as upper anchors. The Phi-4 and GPT-4o-mini rows are restated from Table 4 as the Short-CoT Base. Each workflow row uses the better-performing model between Phi-4 and GPT-4o-mini (GPT-4o-mini for all six workflows here) as the executor; the Both column reports 5-seed bootstrap mean $\pm$ 95% CI half-width and the per-workflow Δ ranges are derived from each method's 5-seed mean over the GPT-4o-mini Base. Cells in the Both column report the 5-seed mean and the 95% binomial CI half-width at $n = 500$; Δ values in parentheses are paired against the GPT-4o-mini Base with Δ-CI of $\approx \pm 5.8$ pp, computed under the independence approximation (a within-instance-correlated estimator may tighten this bound but is not computed here). Under Bonferroni correction at the six workflow comparisons (per-pair threshold $\alpha/6 \approx 0.0083$, $|z| > 2.64$, SE $\approx 5.8/1.96 \approx 2.96$), only DyFlow ($+8.4$ pp, $|z| \approx 2.84$) clears the threshold; MaAS ($+7.8$ pp, $|z| \approx 2.64$) is exactly at the boundary; AFlow ($+6.6$ pp, $|z| \approx 2.23$), ADAS ($+5.4$), LLM-Debate ($+4.8$), and Self-Refine ($+4.0$) do not survive.

Method	Crim.	Self	Both
QwQ	78.4 ± 3.6	65.4 ± 4.2	52.0 ± 4.4
DeepSeek-R1	$\mathbf{80.4} \pm 3.5$	$\mathbf{75.2} \pm 3.8$	$\mathbf{65.4} \pm 4.2$
Phi-4 (Base)	45.6 ± 4.4	39.8 ± 4.3	20.4 ± 3.5
GPT-4o-mini (Base)	46.5 ± 4.4	50.0 ± 4.4	26.4 ± 3.9
LLM-Debate (Du et al., 2024)	52.5 ± 4.4	56.2 ± 4.3	31.2 ± 4.1 *(+4.8 ± 5.7)*
Self-refine (Madaan et al., 2023)	50.4 ± 4.4	54.0 ± 4.4	30.4 ± 4.0 *(+4.0 ± 5.7)*
ADAS (Hu et al., 2025a)	53.7 ± 4.4	56.6 ± 4.3	31.8 ± 4.1 *(+5.4 ± 5.8)*
AFlow (Zhang et al., 2025b)	55.1 ± 4.4	57.8 ± 4.3	33.0 ± 4.1 *(+6.6 ± 5.8)*
MaAS (Zhang et al., 2025a)	56.3 ± 4.3	58.4 ± 4.3	34.2 ± 4.2 *(+7.8 ± 5.8)*
DyFlow (Wang et al., 2025f)	56.9 ± 4.3	59.0 ± 4.3	34.8 ± 4.2 *(+8.4 ± 5.8)*

Table 11: Performance on *Hidden Role Deduction* before and after fine-tuning. **Crim.**: Criminal prediction accuracy; **Self**: self-role prediction accuracy; **Both**: both predictions correct. Cells report 5-seed bootstrap mean ± 95% CI half-width following the protocol disclosed in subsection H.2. Fine-tuning with SFT and DPO significantly improves performance on both models. Percent improvements over the Base model for **Both** are shown in parentheses.

Model	Base			SFT			DPO		
	Crim.	Self	Both	Crim.	Self	Both	Crim.	Self	Both
LLaMA-3.1-8B	41.2 ± 4.3	32.4 ± 4.1	15.4 ± 3.2	45.2 ± 4.4	38.6 ± 4.3	26.0 ± 3.8 (+10.6 ± 5.5)	43.6 ± 4.3	35.2 ± 4.2	22.4 ± 3.6 (+7.0 ± 5.4)
Phi-4	45.6 ± 4.4	39.8 ± 4.3	20.4 ± 3.5	52.6 ± 4.4	45.4 ± 4.4	31.0 ± 4.0 (+10.6 ± 5.7)	52.2 ± 4.4	42.6 ± 4.3	27.2 ± 3.9 (+6.8 ± 5.6)

in absolute terms, so the "family-level" claim is weakly identified at $n = 2$ candidate tasks on the positive side. Per-task, Social Graph Analysis carries the strongest signal (+9.2/+9.6 pp, clearly above the paired-Δ floor); Find the Spy sits at the boundary (+5.8/+6.4 pp); under the more honest single-task reading the positive-side conclusion is "robust transfer to structured graph reasoning" rather than a family-level pattern, and Find the Spy could be reassigned to either family without changing this conclusion. The negative-side reading (the three language-aggregation tasks all sit inside the Δ-CI) is power-not-evidence in either case and is not strengthened by the family aggregation.

Under the binomial paired-Δ CI of $\approx \pm 6$ pp at the per-task p values, the deductive-family deltas of $+5.8$ to $+9.6$ pp on *Find the Spy* and *Social Graph Analysis* are clearly above the floor; the linguistic-family deltas of $+0.4$ to $+2.4$ pp sit inside the floor and the data are equally consistent with "small positive transfer everywhere" and "no transfer on linguistic tasks". The asymmetry conclusion is supported on the positive direction (deductive family) but is power-not-evidence on the negative direction (linguistic family). The substantive reading is therefore: HRD-distilled traces transfer to structured-deduction tasks; whether they additionally produce a small below-threshold gain on the language-aggregation tasks is undetermined.

Two patterns are visible. First, on the deductive task family the +SFT deltas are +5.8 / +9.2 pp for Llama-3.1-8B and +6.4 / +9.6 pp for Phi-4, with DPO producing 6 to 8 pp gains; these are within the same order of magnitude as the HRD improvements in Table 11. Second, on the linguistic task family the +SFT deltas compress to +0.4 to +2.4 pp and DPO to +0.4 to +1.0 pp, indicating that the HRD-derived traces transfer along reasoning content but not via generic instruction-following. The asymmetry is consistent across the two backbones and across SFT and DPO, and it provides a sharper characterization of generalizability than a single aggregate would: HRD-trained reasoning transfers to tasks whose solution path requires structured deduction, and does not substantially affect tasks whose bottleneck is language-level aggregation.

H.5 Workflow Saturation on a Reasoning-Capable Backbone

The workflow methods in Table 10 are evaluated with the better of Phi-4 / GPT-4o-mini as the executor, both of which are Short-CoT backbones. To test whether the cross-method gains carry over to a reasoning-capable backbone, we re-run the four agentic-design methods (ADAS, AFlow, MaAS, DyFlow) with DeepSeek-R1 as the executor and report the resulting Crim. / Self / Both accuracies in Table 13. The base DeepSeek-R1 row from Table 10 (Both = 65.4%) is restated as the anchor.

All four workflow variants land within ± 2 pp of the DeepSeek-R1 Base on the Both-Correct column (range $[-1.4, +1.6]$ pp). ADAS and MaAS sit slightly below the Base, consistent with multi-agent scaffolding consuming context budget on a backbone that already reasons well unaided; AFlow and DyFlow recover small positive deltas of $+1.6$ and $+0.8$ pp respectively, still inside the saturation band. The contrast with the weak Short-CoT regime in Table 10, where the six workflows produce $+4$ to $+9$ pp gains over the GPT-4o-mini Base row, supports the regime-dependent reading in subsection 4.4: workflow scaffolding closes part of the gap on weak bases but does not substitute for a reasoning-capable backbone.

Compared to the Short-CoT regime in Table 10 where the per-method Δ over GPT-4o-mini Base ranges from $+4.0$ pp (Self-Refine) to $+8.4$ pp (DyFlow), the corresponding Δ on the DeepSeek-R1 base ranges from -1.4 pp (ADAS) to $+1.6$ pp (AFlow), all inside the binomial Δ-CI of ± 6 pp at $p \approx 0.65$. ADAS and MaAS sit slightly below the Base, consistent with multi-agent scaffolding

Table 12: Cross-task transfer of the HRD-fine-tuned Llama-3.1-8B and Phi-4 checkpoints. Each cell is accuracy (%) on the dedicated 500-instance test set of Table 4. Cells report 5-seed mean and 95% binomial CI half-width at $n = 500$; Δ in parentheses is paired against the Base column with binomial paired-Δ CI of $\approx \pm 6$ pp at $p \approx 0.6$. Improvements above the Δ-CI floor concentrate on the deductive family (Find the Spy, Social Graph Analysis); linguistic-family deltas sit inside the floor.

Model	Condition	Find the Spy	Rating Estimation	Social Graph Analysis	Review Decision Prediction	User Profile Inference
Llama-3.1-8B	Base	37.2 ± 4.2	57.2 ± 4.3	28.2 ± 3.9	62.0 ± 4.3	60.2 ± 4.3
	+SFT	43.0 ± 4.3 ($+5.8 \pm 6.0$)	58.4 ± 4.3 ($+1.2 \pm 6.1$)	37.4 ± 4.2 ($+9.2 \pm 5.8$)	64.4 ± 4.2 ($+2.4 \pm 6.0$)	62.6 ± 4.2 ($+2.4 \pm 6.0$)
	+DPO	41.4 ± 4.3 ($+4.2 \pm 6.0$)	57.6 ± 4.3 ($+0.4 \pm 6.1$)	35.0 ± 4.2 ($+6.8 \pm 5.8$)	63.0 ± 4.2 ($+1.0 \pm 6.0$)	61.0 ± 4.3 ($+0.8 \pm 6.1$)
Phi-4	Base	45.2 ± 4.4	60.4 ± 4.3	40.6 ± 4.3	61.4 ± 4.3	62.4 ± 4.2
	+SFT	51.6 ± 4.4 ($+6.4 \pm 6.2$)	61.8 ± 4.3 ($+1.4 \pm 6.1$)	50.2 ± 4.4 ($+9.6 \pm 6.2$)	63.2 ± 4.2 ($+1.8 \pm 6.0$)	64.0 ± 4.2 ($+1.6 \pm 6.0$)
	+DPO	49.8 ± 4.4 ($+4.6 \pm 6.2$)	60.8 ± 4.3 ($+0.4 \pm 6.1$)	47.6 ± 4.4 ($+7.0 \pm 6.2$)	62.0 ± 4.2 ($+0.6 \pm 6.0$)	63.0 ± 4.2 ($+0.6 \pm 6.0$)

Table 13: Workflow methods with DeepSeek-R1 as the executor on *Hidden Role Deduction*. The base DeepSeek-R1 row (from Table 10, Both = 65.4%) is restated as the anchor. All four workflow variants land within the ± 2.0 pp saturation band; cells report 5-seed mean and 95% binomial CI half-width at $n = 500$. The paired-Δ over the Base under the same binomial CI is ± 6 pp at $p \approx 0.65$, so all four methods are inside the noise floor.

Method	Crim.	Self	Both
DeepSeek-R1 (Base)	80.4 ± 3.5	75.2 ± 3.8	65.4 ± 4.2
ADAS *w/ DSR1*	79.2 ± 3.6	73.8 ± 3.9	64.0 ± 4.2 *(-1.4 ± 6.0)*
AFlow *w/ DSR1*	81.0 ± 3.4	76.4 ± 3.7	67.0 ± 4.1 *(+1.6 ± 5.9)*
MaAS *w/ DSR1*	79.6 ± 3.5	74.2 ± 3.8	64.8 ± 4.2 *(-0.6 ± 6.0)*
DyFlow *w/ DSR1*	80.6 ± 3.5	75.6 ± 3.8	66.2 ± 4.2 *(+0.8 ± 6.0)*

consuming context budget on a backbone that already reasons well unaided; AFlow and DyFlow recover small positive deltas of $+1.6$ and $+0.8$ pp respectively, inside the saturation band. The contrast with the weak Short-CoT regime ($+4$ to $+9$ pp lifts) supports the regime-dependent reading in subsection 4.4: workflow scaffolding closes part of the gap on weak bases but does not substitute for a reasoning-capable backbone. Compared with the SFT lift of roughly $+10$ pp on Llama-3.1-8B and Phi-4 in Table 11, parameter-level adaptation extracts more from the curated HRD traces than agentic decomposition alone on the same Short-CoT base; the DPO lift of $+6.8$ to $+7.0$ pp sits between the two regimes.

Table 4 provides a condensed overview of model performance across the primary SocialMaze tasks. The reported accuracy figures correspond to specific task configurations and metrics used for this summary: For **Hidden Role Deduction**, the value represents the accuracy where both the Criminal and the model's own role are correctly identified ('Both Correct'). This evaluation uses the same general setup as described in Section 4.4 (easy subset, Full Task variant, final interaction round - Round 3); the role for the main-perspective LLM is drawn uniformly from the four roles (1:1:1:1) matching the configuration used throughout the paper. For **Social Graph Analysis**, the figure reflects the average accuracy achieved across all four query types within the hard subset. The **Review Decision Prediction** accuracy is taken from the final stage, after the model has processed the rebuttal information. For **User Profile Inference**, the reported value is the average accuracy over the two distinct inference tasks (item-audience profile inference and user-profile inference). Performance on each task presented in this summary table was evaluated using a dedicated test set of 500 instances. For more granular results, including performance variations across different rounds, task variants (e.g., easy/hard subsets), or specific query types, please consult the detailed figures and tables in Section 4 and the relevant task-specific appendices.

The results in Table 4 reveal distinct task-level strength patterns once cross-model gaps are read against the binomial sampling floor disclosed in subsection H.2 (typical half-width ± 3.2 to ± 4.4 pp at $n = 500$). Models renowned for Long CoT and complex reasoning, such as DeepSeek-R1, Gemini-2.5-Pro, o1, and QwQ-32B, excel in tasks demanding rigorous logical deduction and handling high uncertainty or strict rule-based systems.

The Hidden Role Deduction top tier (Gemini-2.5-Pro: 73.6%, DeepSeek-R1: 65.4%, o1: 60.8%, o3-mini: 55.2%, QwQ-32B: 52.0%) is well separated from the generalist tier on this task; the four-way Social Graph Analysis top tier (Gemini-2.5-Pro: 100.0%, o1: 99.2%, o3-mini: 99.0%, DeepSeek-R1: 98.6%) sits within ± 1.0 pp of one another, all four statistically indistinguishable. Conversely, tasks that place a premium on nuanced language understanding, tracking dynamic interactions over extended contexts, and synthesizing subjective or potentially conflicting information tend to favor strong generalist models. DeepSeek-V3 leads on Review Decision Prediction at 91.4%, with GPT-4o close behind at 90.2%, separated by roughly one binomial half-width; on Find the Spy the top tier is led by o1 (78.4%), Gemini-2.5-Pro (76.6%), o3-mini (74.0%), and DeepSeek-R1 (70.2%), with the top three sitting within ± 4.4 pp of one another. On Rating Estimation, the top six models (o1: 76.2%, GPT-4o: 76.0%, GPT-4o-mini: 75.8%, DeepSeek-V3: 75.8%, Llama-3.3-70B: 74.8%, QwQ-32B: 74.4%) sit within ± 2.0 pp of one another, statistically indistinguishable. On User Profile Inference, GPT-4o (79.2%), Llama-3.3-70B (78.6%), and o1 (77.0%) sit within ± 2.2 pp of one another, again indistinguishable. The "tier separation" calls in this paragraph correspond to $\binom{12}{2} \cdot 6 = 396$ implied pairwise comparisons; under family-wise Bonferroni at $\alpha = 0.05$ the per-pair threshold is $\alpha/396 \approx 1.3 \times 10^{-4}$ requiring $|z| > 3.83$. Reading the tiers under that threshold, the well-separated calls above hold only for the largest gaps (HRD top tier vs Short-CoT base, SGA top tier vs Llama-3.1-8B base, RDP top tier vs Phi-4 base); finer within-tier rankings (e.g., GPT-4o 90.2 vs DeepSeek-V3 91.4 on RDP, or the SGA top-four four-way comparison) sit within the family-wise corrected band and should not be interpreted as ranked separations. For the Hidden Role Deduction column specifically, the Both-Correct headline aggregates a displayed-equals-true-role trivial-echo regime (Investigator, Criminal) with a displayed-differs-from-true-role override-required regime (Rumormonger, Lunatic); we recommend Table 16 as the distinguishing measurement of belief-revision capability rather than the headline alone. We also evaluated human performance on these tasks by averaging the results from 10 computer science graduate students, most of whom are relatively proficient in social deduction games. We did not evaluate human performance on the Social Graph Analysis task, as the prompt format used in this task was not well-suited for human participants.

I Supplementary Discussion and Additional Analyses

This appendix consolidates additional analyses that complement the main results. We (i) provide posterior, empirical statistics that operationalize the three core dimensions probed by SOCIAL-MAZE, (ii) report a pilot evaluation of reasoning faithfulness, (iii) summarize a model-centric capability view and efficiency trade-offs, (iv) catalogue representative failure modes under uncertainty and self-perception, and (v) clarify data sources, realism, transfer, and ethical notes.

I.1 Posterior Quantification of the Three Core Dimensions

We quantify *Deep Reasoning*, *Dynamic Interaction*, and *Information Uncertainty* with posterior, empirical statistics computed per task. For Deep Reasoning we report four proxies: (1) average model output tokens (length of generated chains), (2) human average solving time (seconds), (3) average reasoning steps on correctly answered instances (atomic steps annotated by human raters), and (4) the Long-vs-Short CoT output-length ratio. Dynamic Interaction is reflected through the presence of multi-round structures and performance differences across rounds; Information Uncertainty is controlled by the proportion of unreliable sources (e.g., deceptive roles or shill content). A concise summary is provided in Table 14.

Observations. Hidden Role Deduction and Social Graph Analysis show substantially higher token budgets and step counts, consistent with deeper, more structured inference demands; multi-round tasks exhibit clear gains when additional information is incorporated; performance degrades as the share of unreliable sources increases, with degradation patterns differing by model family.

Per-axis grounding for Find the Spy and Review Decision Prediction. The High/Low axis labels for these two tasks merit explicit grounding because each task's source of difficulty admits multiple plausible interpretations. We ground each label quantitatively below. *FtS Dynamic Interaction = High* reflects the round-incremental disambiguation structure: each Civilian's later description conditions on earlier rounds' implicit sus-

Table 14: Posterior statistics across tasks. "Model Avg. Output Tokens" is reported per representative model family. Human solving time and average inference steps are aggregated at the task level (correct instances only for steps).

Metric / (Model)	Hidden Role Deduction	Find the Spy	Rating Estimation	Social Graph Analysis	Review Decision Prediction	User Profile Inference
Model Avg. Output Tokens						
QwQ-32B	4163.6	2862.3	1482.5	3579.7	1582.4	1310.9
DeepSeek-R1	3092.5	2141.9	1149.6	2131.2	1155.9	1017.0
Llama-3.3-70B	456.0	654.0	402.8	443.8	516.9	385.8
GPT-4o	432.7	464.6	357.9	330.8	534.2	340.2
Aggregate Human / Task-Level Proxies						
Human Avg. Solving Time (s)	> 300	30.2	20.5	246.5	124.0	43.3
Avg. Inference Steps	45.1	15.4	10.8	30.7	9.6	11.9
Long vs. Short CoT Ratio	7.49	4.18	3.40	7.52	2.58	3.39

picion signals (Civilians adjust granularity in response to suspect-targeting cues), so the rounds carry sequentially dependent rather than parallel evidence; the round-by-round trajectory is documented in the FtS case-study traces (Appendix J). *RDP Dynamic Interaction = High* is quantitatively grounded by the per-stage accuracy delta in Table 3: averaged across the twelve evaluators, the Info $\rightarrow$ Reviews transition shifts mean accuracy by $\approx +45$ pp (from 40.2% to 84.9%) and the Reviews $\rightarrow$ Rebuttal transition by ≈ -8 pp (to 77.0%), reflecting genuine integration of newly-revealed evidence with direction-of-effect dependence on the evaluator family rather than a parallel re-evaluation of a fixed evidence pool. *RDP Information Uncertainty = Low* denotes the structure of the ground truth (each paper carries a deterministic venue-recorded accept/reject label) and is distinct from the presence of subjective content in the reviewer text; reviewer-text noise is task input that the model must aggregate, and its impact on the Round-3 prediction is bounded within ± 2 pp by the perturbed-subset analysis in Table 8.

I.2 Reasoning Faithfulness: Pilot Evaluation

To examine whether correct predictions are supported by coherent reasoning rather than surface heuristics, we conduct a pilot judge-based study on *Hidden Role Deduction*. Given the input, ground truth, and a model's chain-of-thought, an automated judge assigns two scores: *Consistency* (lack of internal contradictions) and *Completeness* (systematic elimination leading to the answer). Each case is evaluated three times with majority aggregation; a random subset is manually audited.

Findings. Correct answers are typically backed by coherent and complete chains; faithfulness correlates positively with task performance. Scaling this evaluation to additional tasks, models, and judging protocols is left for future work (see also section 5).

Across the four pilot models in Table 19, correctly-answered Hidden Role Deduction chains score 85–95% on the Consistency dimension and 79–87% on the Completeness dimension under the GPT-4o judge protocol. The cross-judge agreement of Cohen's $\kappa = 0.74$ with Gemini-2.5-Pro on the GPT-4o row supports that the rating reflects chain quality rather than self-judge artifact. The Incorrect-Answer Chain Pilot below documents the contrast on incorrect-answer chains.

Incorrect-Answer Chain Pilot. To check whether the judge ratings in Table 19 reflect chain coherence rather than answer correctness, we sample an additional $n = 100$ *incorrectly answered Hidden Role Deduction* instances per model (when sufficient incorrect-answer chains are available; for high-accuracy models we sample the maximum available) and score Consistency / Completeness under the same protocol. Table 15 reports the result. Across the four pilot models, incorrect-answer chains score 25 to 40 pp lower on Consistency and 30 to 45 pp lower on Completeness than the correct-answer cells, indicating that the judge does discriminate by chain quality rather than anchoring on the answer label. The gap also documents a substantive failure mode pattern: incorrect HRD answers tend to be reached by chains that contain internal contradictions or fail to systematically eliminate alternative role assignments.

Table 15: Reasoning faithfulness on incorrectly answered cases (pilot, mirroring the protocol of Table 19). For each model, $n = 100$ incorrectly answered HRD instances are sampled (or the maximum available for high-accuracy models). Scoring uses the GPT-4o judge at judge temperature $T_{\text{judge}} = 0.5$ over three independent passes per instance; reported $\pm$ is across-pass std of the per-instance mean. Cohen's κ between GPT-4o and the Gemini-2.5-Pro cross-judge is 0.71 on the pass/-fail binarization, similar to the correct-chain pilot.

Model	Consistency	Completeness
Llama-3.3-70B	$57.0 \pm 2.6\,\%$	$39.0 \pm 2.8\,\%$
Phi-4	$56.0 \pm 2.8\,\%$	$39.0 \pm 2.9\,\%$
Qwen-2.5-72B	$50.0 \pm 2.9\,\%$	$38.0 \pm 2.8\,\%$
GPT-4o	$63.0 \pm 2.4\,\%$	$46.0 \pm 2.6\,\%$

I.3 Per-Role HRD Self-Role Decomposition

The Hidden Role Deduction Both-Correct headline reported in Table 4 averages over a uniform 1:1:1:1 mixture of the four player roles (Investigator, Criminal, Rumormonger, Lunatic). For Investigator and Criminal perspectives, the role displayed to Player 1 matches the true role, so the self-role inference question is mechanically trivial; the model only needs to repeat the prompt-supplied label. For Rumormonger and Lunatic perspectives, the displayed role differs from the true role by design, and the self-role inference question requires the model to override the prompt label using indirect evidence (e.g., an Investigator's truthful "X is not the Criminal" cross-checks). Table 16 reports the per-role Self-role accuracy averaged over the same five seeds; the headline Both-Correct ordering in Table 4 aggregates these four cells per model.

Short-CoT models (Llama, Phi-4, Qwen, GPT-4o-mini, GPT-4o, DeepSeek-V3) collapse near zero on Rumormonger and Lunatic self-role accuracy while clearing 75 to 90% on Investigator and Criminal, where the displayed role matches the true role and the answer is mechanically a copy of the prompt label. Long-CoT reasoners (QwQ-32B, o3-mini, o1, DeepSeek-R1, Gemini-2.5-Pro) retain partial competence on the override-required roles, with Lunatic generally easier than Rumormonger because the Investigator's truthful "X is not the Criminal" statement provides a direct cross-check. The headline Both-Correct ordering in Table 4 reflects competence on the override-required cells more than the trivial cells; two models with the same headline accuracy can still differ substantially on the diagnostic construct (distorted self-perception under unreliable labels), so downstream users picking models off the headline should consult this decomposition when the application leans on the override capability.

Table 16: Per-role Self-role accuracy on *Hidden Role Deduction* (%), with 95% bootstrap CI half-widths over five seeds at $n = 125$ instances per role. Investigator and Criminal columns measure self-role correctness when the displayed role matches the true role (trivial echo of the prompt label). Rumormonger and Lunatic columns measure self-role correctness when the displayed role differs from the true role (override required). The headline Both-Correct in Table 4 is the joint correctness across Criminal identification and Self-role identification, averaged over the four roles in a 1:1:1:1 mixture. Investigator and Criminal self-role cells fall below 95% for the Short CoT models (75–90% range) despite the displayed role matching the true role; this reflects hedging behavior (e.g., the model expressing uncertainty or refusing to commit a single role label) rather than failure to copy the prompt label, and partially explains why the Both-Correct headline ordering differs by more than the Rumormonger / Lunatic override gap alone would predict. Note that this table awards credit for hedging responses that include the correct role label among multiple candidates, whereas the aggregate Self column in Table 11 uses strict single-label match scoring; the 5–10 pp gap between the marginal per-role mean here and the aggregate Self there on Short-CoT models reflects this scoring convention difference and not a different evaluation run.

Model	Investigator	Criminal	Rumormonger	Lunatic
Llama-3.1-8B	80.4 ± 7.0	74.6 ± 7.6	5.2 ± 3.9	10.6 ± 5.4
Llama-3.3-70B	86.8 ± 5.9	81.4 ± 6.8	9.8 ± 5.2	15.6 ± 6.4
Phi-4	83.6 ± 6.5	77.2 ± 7.4	6.4 ± 4.3	11.8 ± 5.7
Qwen-2.5-72B	85.2 ± 6.2	79.8 ± 7.0	8.0 ± 4.8	13.4 ± 5.9
QwQ-32B	91.4 ± 4.9	87.0 ± 5.9	36.6 ± 8.4	48.8 ± 8.7
GPT-4o-mini	84.4 ± 6.4	80.0 ± 7.0	10.0 ± 5.3	17.4 ± 6.6
GPT-4o	88.2 ± 5.6	83.6 ± 6.5	12.4 ± 5.8	20.6 ± 7.1
o3-mini	92.0 ± 4.7	88.4 ± 5.6	40.2 ± 8.6	52.6 ± 8.7
o1	93.2 ± 4.4	89.6 ± 5.3	45.8 ± 8.7	58.0 ± 8.6
DeepSeek-V3	87.4 ± 5.8	82.8 ± 6.6	14.2 ± 6.1	22.4 ± 7.3
DeepSeek-R1	94.0 ± 4.2	90.4 ± 5.2	50.2 ± 8.8	61.4 ± 8.5
Gemini-2.5-Pro	95.2 ± 3.8	92.2 ± 4.7	59.4 ± 8.6	67.6 ± 8.2

I.4 Model-Centric Capability View and Efficiency Trade-offs

A model-centric perspective reveals distinct capability clusters: *logical-deduction specialists* that excel on high-depth, formally structured tasks, and *social-understanding specialists* that perform better on linguistically nuanced, aggregation-heavy tasks. This separation coincides with explicit token-budget differences on deep tasks, exposing a practical accuracy–efficiency trade-off.

Budget-Matched Long vs Short CoT Control.

The Long vs Short CoT comparison in Figure 2 crosses model families, so the accuracy gap could in principle be confounded by raw output budget. To check this, we re-run two Short CoT generalists (GPT-4o, Llama-3.3-70B) on *Hidden Role Deduction* with an enlarged maximum-output-token cap of 4,000 (roughly matched to QwQ-32B's average HRD output of 4,163.6 tokens in Table 14). Table 17 reports the Both-Correct accuracy under default vs extended budget. Both Short CoT models gain only modestly under extended budget ($+2.6$ pp on GPT-4o, $+2.6$ pp on Llama-3.3-70B, both inside the binomial CI half-width of $\approx \pm 4$ pp at $n = 500$), and neither closes the gap to DeepSeek-R1 or Gemini-2.5-Pro; the relative ranking of the four models is preserved.

The Extended condition raises the maximum-output-token cap; observed token consumption under the cap (column ΔTok) reaches roughly 1640–1894 tokens for the two Short-CoT models, well below the 4,164-token QwQ-32B average used to size the cap. This control therefore rules out "the cap is the bottleneck" but does not rule out "the consumed token budget is the bottleneck" — a Short-CoT model offered a larger cap does not voluntarily fill it. We treat the comparison as evidence against cap-as-confound, not against budget-as-confound; a genuine budget-match would require a chain-of-thought scaffolding intervention that forces the Short-CoT models to actually consume the matched budget, which is left to future work.

Table 17: Budget-matched Long vs Short CoT control on *Hidden Role Deduction* (Both-Correct accuracy, 500-instance test set). Cells report 5-seed bootstrap mean $\pm$ 95% CI half-width following the protocol disclosed in subsection H.2. Default = the same maximum-output-token cap used elsewhere in the paper. Extended = the cap raised to 4,000 tokens, matched to QwQ-32B's average HRD output length. ΔTok reports the average output-token increase under the extended cap. Cells report 5-seed mean and 95% binomial CI half-width at $n = 500$. The observed Δ of $+2.6$ pp for both GPT-4o and Llama-3.3-70B sits inside the binomial paired-Δ CI of $\approx \pm 6$ pp at $p \approx 0.3$; the cap-as-bottleneck reading is supported by the absence of large gains, while the consumed-budget-as-bottleneck channel is not addressed by this control since the Short-CoT models only consume 1,640–1,894 tokens of the 4,000-token cap.

Model	Default	Extended	ΔTok
GPT-4o (Short CoT)	$28.8 \pm 4.0\%$	$31.4 \pm 4.1\%$	+1,207
Llama-3.3-70B (Short CoT)	$25.2 \pm 3.8\%$	$27.8 \pm 3.9\%$	+1,438
DeepSeek-R1 (Long CoT)	$65.4 \pm 4.2\%$	–	–
Gemini-2.5-Pro (Long CoT)	$73.6 \pm 3.9\%$	–	–

I.5 Failure Modes under Uncertainty and Self-Perception

Quantitative Error Decomposition. To separate reasoning failures from generation-pipeline artifacts, we instrument every model output with three flags: (a) *truncation* – the output reached the maximum-output-token cap (subsection H.2); (b) *extraction failure* – the answer-extraction regex, which looks for a final-answer block following the task-specific prompt template, returned no parseable answer (this includes outputs that produce a chain of thought but never commit to a final label, outputs in malformed JSON, and outputs that emit the answer in an unexpected slot); and (c) *reasoning error* – the model produced a parseable, non-truncated final answer that disagreed with ground truth. By construction, accuracy + truncation rate + extraction-failure rate + reasoning-error rate $= 100\%$ per task. Table 18 reports the decomposition averaged over the twelve evaluators on the 500-instance test set of each task.

Across the six tasks, the bulk of incorrect predictions are reasoning errors rather than pipeline artifacts. Truncation contributes at most 4.4 pp of the total error rate (on *Hidden Role Deduction*) and below 1 pp on all five non-HRD tasks; extraction failure contributes at most 2.1 pp (also on HRD) and below 1.3 pp elsewhere. The HRD truncation rate is concentrated on the four Long-CoT evaluators whose role-deduction chains routinely exceed $4{,}000$ tokens: under the extended $8{,}192$-token cap, their per-model truncation rates are 9.5% (DeepSeek-R1), 11.6% (o1), 14.2% (QwQ-32B), and 10.4% (Gemini-2.5-Pro); the eight Short-CoT evaluators average 0.7% truncation on HRD under the standard $4{,}096$-token cap. The per-task accuracy gaps reported in Table 4 therefore reflect genuine reasoning differences rather than output-budget exhaustion or parser fragility; the small extraction-failure mass also indicates that the answer template generalizes across model families.

Qualitative Failure Patterns. Representative failure patterns include (i) *asymmetric self-belief errors* (correctly identifying the criminal but misinferring one's own role), (ii) *chain interruption* (failure to integrate decisive late evidence), and (iii) *evidence mis-weighting* (confirmation bias toward early salient cues). The first pattern dom-

Table 18: Per-task error decomposition (% of test instances), averaged over the twelve evaluators on each task's 500-instance test set. *Trunc.*: output reached the max-token cap; *Ext. Fail.*: answer-extraction regex returned no parseable answer; *Reasoning*: committed answer disagreed with ground truth. Components sum to the total error rate (rightmost column); total accuracy is 100% minus the total error. Caps: 4,096 tokens default; 8,192 tokens for HRD Long-CoT evaluators.

Task	Trunc.	Ext. Fail.	Reasoning	Total error
Hidden Role Deduction	4.4	2.1	53.8	60.3
Find the Spy	0.5	1.0	37.7	39.2
Rating Estimation	0.2	0.6	27.7	28.5
Social Graph Analysis	0.8	1.0	19.0	20.8
Review Decision Prediction	0.3	0.8	21.9	23.0
User Profile Inference	0.4	1.2	27.0	28.6

inates the HRD reasoning-error mass: among the 53.8% HRD reasoning errors averaged across evaluators, roughly 32 pp correspond to correct-Criminal-wrong-Self instances, 14 pp to wrong-Criminal-correct-Self, and the remaining ≈ 8 pp to jointly-wrong. The second and third patterns concentrate on *Review Decision Prediction* (Rebuttal-stage swing) and *Rating Estimation* (anti-prior over-prediction of low/high extremes) respectively; per-task qualitative cases are catalogued in Appendix J. Each case in our catalogue is paired with a verifiable human solution and a minimal sufficient evidence set, leveraging uniqueness and solvability guarantees.

I.6 Data Sources, Realism, Transfer, and Ethics

The tri-source composition—authentic human data, LLM-assisted discourse, and algorithmic simulation with verifiable ground truth—balances realism, linguistic diversity, and diagnostic precision, and allows difficulty tuning (e.g., player counts, deceptive-role ratios, graph sizes). While not a substitute for fully organic, open-ended multi-agent corpora, the design supports controlled supervision and fair comparison. For demographic inference, prompts and post-hoc filtering minimize stereotyping risk; the task is intended as a diagnostic of probabilistic cue usage rather than essentialist labeling.

Generator-Evaluator Pool Overlap on Three Tasks. Four of the five generator-pool models (GPT-4o, GPT-4o-mini, Llama-3.3-70B, Qwen-2.5-72B; the fifth, Claude Sonnet 4.5, is generator-only) are also evaluated as solvers on *Find the Spy* (player-description generation pool), *Rating Estimation* (LLM-generated review subset), and *User Profile Inference* (entire test set is LLM-generated). On these three tasks, the evaluator's score can in principle conflate social-reasoning capability with within-family text-style match. We quantify the magnitude by two complementary bounds on the UPI column of Table 4.

Loose upper bound (all-out-of-pool). In-pool evaluators (GPT-4o 79.2%, GPT-4o-mini 74.4%, Llama-3.3-70B 78.6%, Qwen-2.5-72B 68.0%) average 75.05%; out-of-pool evaluators (Phi-4 62.4%, Llama-3.1-8B 60.2%, o1 77.0%, o3-mini 71.4%, QwQ-32B 72.2%, DeepSeek-V3 65.4%, DeepSeek-R1 74.6%, Gemini-2.5-Pro 73.0%) average 69.53%. The raw gap is approximately $+5.5$ pp; this is a loose upper bound because the out-of-pool set includes Llama-3.1-8B and Phi-4, which are at the small end of the parameter range and contribute most of the gap on capability grounds rather than family-alignment grounds.

Top-capability leave-out check. Restricting the comparison to the four most capable out-of-pool evaluators on independent reasoning tasks—QwQ-32B, DeepSeek-R1, Gemini-2.5-Pro, and o1, whose UPI scores are 72.2%, 74.6%, 73.0%, and 77.0% respectively (mean 74.20%)—the residual gap to the in-pool average is $+0.85$ pp, well inside the per-cell ± 4 pp binomial half-width at $n = 500$. These four out-of-pool evaluators are substantially more capable than the in-pool subset on capability-discriminating tasks (their HRD mean is 62.95% vs the in-pool 25.75%); if the loose $+5.5$ pp gap were pure capability difference, this top out-of-pool subset would score above the in-pool mean rather than 0.85 pp below. The observation is therefore most consistent with a non-zero within-family text-style contribution that is partially compensated by capability differences in the comparison; the within-family contribution is upper-bounded at the loose $\approx +5.6$ pp but is not zero. A tighter identification (e.g., via leave-generator-family-out re-training of a separate evaluator) is left to future work. The Rating Estimation real-world subset (Amazon, Taobao, Google Play reviews) is moreover not LLM-generated and is structurally insulated from this confound.

Generalising the overlap analysis to Find the Spy and Rating Estimation. The same two-bound diagnostic on the other two affected tasks shows that the UPI residual is the upper end of the within-family contribution rather than typical. For *Find the Spy* (player descriptions generated by the four in-pool models), the in-pool mean of 59.83%

(GPT-4o 69.2, GPT-4o-mini 61.2, Llama-3.3-70B 60.0, Qwen-2.5-72B 48.9) sits 1.47 pp *below* the all-out-of-pool mean of 61.30%, so the data are inconsistent with a positive within-family alignment effect on this task; against the top-capability out-of-pool subset (o1 78.4, Gemini-2.5-Pro 76.6, DeepSeek-R1 70.2, o3-mini 74.0, mean 74.80%), the gap widens to -14.97 pp, indicating that capability differences dominate any alignment effect on FtS. For *Rating Estimation* (aggregate of LLM-generated and real-world subsets, since the paper does not report per-subset accuracy), the in-pool mean of 74.70% vs the all-out-of-pool mean of 69.97% gives a loose upper bound of $+4.73$ pp, and against the top-capability out-of-pool subset (Gemini-2.5-Pro 73.6, o1 76.2, DeepSeek-V3 75.8, QwQ-32B 74.4, mean 75.00%) the residual is -0.30 pp. The pattern observed on UPI ($+5.5$ pp loose, $+0.85$ pp tight) is therefore the strongest of the three affected tasks; FtS shows no within-family alignment signal, and Rating Estimation's residual is statistically indistinguishable from zero at the capability-matched comparison.

I.7 Data Collection Compliance and Annotator Cohort

Public-page review scraping (Rating Estimation real-world subset). The Amazon, Taobao, and Google Play review subsets were retrieved from publicly-accessible product pages using a research-purpose user-agent identifying the crawl. Retrieval rate was limited to one request per second per host and we did not bypass any authentication or rate-limit barriers. We retained only the textual review content, the star rating, and the publicly-visible reviewer screen name during collection. The public dataset release contains only LLM-paraphrased prompt versions of these reviews and does not redistribute the raw retrieved text; reviewer screen names are dropped before any LLM prompt construction, and we make no attempt to link reviewers across platforms or to a real-world identity. We acknowledge that platform Terms of Service may restrict commercial use of such data; the present collection is for non-commercial academic research and the public release is paraphrased to avoid raw-text redistribution.

Synthetic-only User Profile Inference (no human subjects). The User Profile Inference task

Table 19: Reasoning faithfulness on correctly answered cases (pilot). The model evaluation runs follow the 5-seed protocol disclosed in subsection H.2; the reported $\pm$ here is across-pass judge std (judge-pass reproducibility on the sampled instances), not the multi-seed accuracy CI. For each of the four evaluated models, we sample $n = 100$ correctly answered Hidden Role Deduction instances. Each chain-of-thought is scored by a GPT-4o judge at judge temperature $T_{\text{judge}} = 0.5$, repeated for three independent passes per instance, with the per-instance score taken as the per-pass mean. The reported std is the across-pass std of the per-instance mean score, averaged over the 100 sampled instances; this measures judge-pass reproducibility, not a population-level CI on the faithfulness rate. GPT-4o serves as the judge for all evaluated models' chains, so the GPT-4o row is a self-judge measurement; as a cross-judge control we re-score the GPT-4o chains using Gemini-2.5-Pro as a secondary judge and observe Cohen's $\kappa = 0.74$ agreement between the two judges on the pass/fail binarization, supporting that the GPT-4o row is not an artifact of self-judging. Cells in tab:faithfulness report judge-pass reproducibility std (across the three judge passes per instance, averaged over 100 instances), not the multi-seed accuracy CI; protocol is independent of the binomial floor for the accuracy tables. See Table 15 for the analogous incorrect-answer chain pilot.

Model	Consistency	Completeness
Llama-3.3-70B	$93.0\% \pm 1.2\%$	$83.0\% \pm 1.4\%$
Phi-4	$88.0\% \pm 1.6\%$	$79.0\% \pm 1.8\%$
Qwen-2.5-72B	$85.0\% \pm 1.8\%$	$81.0\% \pm 1.5\%$
GPT-4o	$95.0\% \pm 0.8\%$	$87.0\% \pm 1.0\%$

is composed entirely of synthetic comments generated by LLMs from prompts conditioned on a designated demographic profile. No real user demographic data was collected, accessed, or stored, and no real individuals are identifiable from any UPI test instance. Under the Common Rule (45 CFR 46.102) the protocol is therefore "not human subjects research" rather than IRB-exempt human subjects research; our institution's research-integrity office reviewed the protocol description and confirmed the not-human-subjects classification, so no further IRB action was required. Downstream redistribution of the synthetic comments is permitted under the dataset's release license.

Annotator cohort: 15 computer-science graduate students. For instance-solvability validation across *Hidden Role Deduction*, *Find the Spy*, *Rating Estimation*, *User Profile Inference*, and *Review Decision Prediction*, we recruited a cohort of 15 computer science graduate students from our institution's CS department. Recruitment was via departmental mailing list with opt-in participation; each annotator received an information sheet describing the task, gave written informed consent, and was free to withdraw at any time. Compensation was provided as a fixed payment of approximately USD 15 per validation hour, paid through the institution's standard research-assistant payroll. Total annotation workload was distributed so that no single annotator exceeded four hours of validation work per week, in line with the institutional research-integrity office's guidance on graduate-student volunteer workload. The annotation task itself does not collect any annotator demographic information; the only artifacts retained are the per-instance pass / fail solvability labels.

Release format, sampling characteristics, and license. To support long-term reproducibility, the public release of the Rating Estimation real-world subset contains, per instance: (i) the GPT-4o-paraphrased English version of each review (paraphrasing prompt enforces preservation of sentiment polarity, factual claims, and demographic-neutral wording; paraphrase outputs are screened by an automated agreement check against the original star rating predicted by a separate GPT-4o-mini classifier, with Cohen's $\kappa = 0.82$ between paraphrase-rated and original-rated polarity on a 500-instance held-out audit), (ii) the integer star rating, and (iii) a platform-source label. Raw retrieved text is not redistributed. The retrieval window spans 2024-09-01 to 2025-01-31; per-platform sampling distribution across the 6,000-instance subset is Amazon $\approx 41\%$, Taobao $\approx 35\%$, and Google Play $\approx 24\%$. The raw-language distribution is $\approx 58\%$ English (Amazon and Google Play English-locale apps) and $\approx 42\%$ Chinese (Taobao and Google Play Chinese-locale apps); after the paraphrase-to-English normalization step, the released text is uniformly English. The star-rating distribution matches the e-commerce baseline disclosed in subsection H.2 at a 1:3:10:73:13 ratio for ratings 1 through 5.

The *Review Decision Prediction* release uses real OpenReview submission content (paper title, abstract, keywords, reviewer comments verbatim, rebuttal verbatim, accept/reject decision) without paraphrase, since OpenReview content is published under venue terms that permit research redistribution; the release records the venue-year (NeurIPS 2023–2024, ICLR 2020–2025, COLM 2024), per-venue draw counts, and the 67/33 reject/accept rebalancing protocol documented in subsection H.2. The synthetic-only *User Profile Inference* subset is released in full, including the LLM-generated comments and the demographic-profile prompts used to condition generation; no real user data is involved.

The SocialMaze benchmark is distributed under a research-only license: redistribution is permitted for non-commercial academic research, evaluation of new LLMs, and downstream fine-tuning experiments; commercial use, re-derivation of original raw text from the paraphrased Rating Estimation subset, and re-identification of any reviewer, paper, or user are explicitly prohibited. A versioned data sheet released alongside the benchmark records platform terms-of-service references, retrieval window, paraphrase-model version (GPT-4o-2024-08-06), human-validation pass rates per task, and the seed values used for the five evaluation runs reported in Table 4. The data sheet is the authoritative source for any reproducibility query and is versioned alongside subsequent benchmark releases.

J Case Study

This section presents a series of representative case studies designed to analyze model behavior across various social reasoning tasks. The subsequent figures are organized to provide detailed illustrations as follows:

Illustrations for the *Hidden Role Deduction* Task (Figures 5–36): This extensive collection of figures focuses on the *Hidden Role Deduction* task, examining how different models perform under varying player perspectives and levels of reasoning complexity. Specifically, Figures 5 (Investigator perspective), 13 (Criminal perspective), 21 (Rumormonger perspective), and 29 (Lunatic perspective) present four distinct problem instances. The corresponding algorithmically generated solutions for these instances are detailed in Figures 6, 14, 22, and 30, respectively. The remaining figures within this range (Figures 7–12, 15–20, 23–28, and 31–36) showcase the detailed responses of various models to these specific problem instances, illustrating their reasoning process across multiple rounds.

Illustrative Cases from Other Benchmark Tasks (Figures 37–48): Following the in-depth illustrations for *Hidden Role Deduction*, Figures 37 through 48 present selected problem instances and corresponding model responses from other tasks within the SocialMaze benchmark. This offers a broader view of model capabilities in diverse social reasoning scenarios.

Misclassification Examples in *Review Decision Prediction* (Figures 49–52): Finally, Figures 49, 50, 51, and 52 highlight specific instances from the *Review Decision Prediction* task. These cases focus on situations where models incorrectly predicted outcomes, such as classifying papers that should have been accepted as rejected, or vice versa, thereby illustrating common failure modes in this particular task.

It should be noted that for brevity, some lengthy model responses in the figures have been truncated, with omitted content indicated by a red ellipsis.

Analysis of Model Performance: A key observation emerging from the case studies focused on the *Hidden Role Deduction* task (Figures 5–36) is the stark contrast in reasoning depth between models employing short Chain-of-Thought (CoT) processes and those utilizing more extended Long CoT. Models such as LLaMA-3.1-8B often demonstrate a surface-level understanding of the scenario: they can identify internal inconsistencies and perform basic analysis, yet struggle to escape flawed initial assumptions. For instance, as illustrated in Figure 13, LLaMA-3.1-8B, despite correctly inferring its own role as the *criminal*, still incorrectly accuses Player 5, reflecting a failure in maintaining coherent self-reasoning. Similarly, Figure 29 shows that even after models like LLaMA-3.1-8B, LLaMA-3.3-70B, and GPT-4o correctly identify other players as the criminal, they are unable to reconceptualize their own identity in the social context, highlighting a limitation in recursive self-modeling. In contrast, models such as Gemini-2.5-Pro and DeepSeek-R1 consistently achieve near-perfect reasoning across all examined perspectives within this task. Their ability to integrate multiple viewpoints, resolve contradictions, and update their beliefs dynamically, as seen in their respective responses, suggests a significantly stronger capacity for long-form social reasoning when faced with the complexities of hidden roles and deceptive information.

Hidden Role Deduction (Investigator Perspective)

Role: "1": "Investigator", "2": "Criminal", "3": "Lunatic",
"4": "Rumormonger", "5": "Investigator", "6": "Investigator"

Round 1:

Player 1 says Player 3 is not the criminal.
Player 2 says Player 6 is the criminal.
Player 3 says Player 1 is the criminal.
Player 4 says Player 6 is the criminal.
Player 5 says Player 3 is not the criminal.
Player 6 says Player 1 is not the criminal.

Round 2:

Player 1 says Player 3 is not the criminal.
Player 2 says Player 4 is the criminal.
Player 3 says Player 5 is not the criminal.
Player 4 says Player 1 is the criminal.
Player 5 says Player 6 is not the criminal.
Player 6 says Player 4 is not the criminal.

Round 3:

Player 1 says Player 4 is not the criminal.
Player 2 says Player 6 is the criminal.
Player 3 says Player 6 is not the criminal.
Player 4 says Player 3 is not the criminal.
Player 5 says Player 4 is not the criminal.
Player 6 says Player 3 is not the criminal.

Criminal Prediction:

Llama-3.1-8B : **2** ☑
Llama-3.3-70B : **2** ☑
GPT-4o-mini : **2** ☑
GPT-4o : 6 ☒
Qwen2.5-72B : 6 ☒
o3-mini : **2** ☑
o1 : **2** ☑
QwQ-32B : **2** ☑
DeepSeek-R1 : **2** ☑
Gemini-2.5-Pro : **2** ☑

Self-Role Prediction:

Llama-3.1-8B : **Investigator** ☑
Llama-3.3-70B : **Investigator** ☑
GPT-4o-mini : **Investigator** ☑
GPT-4o : **Investigator** ☑
Qwen2.5-72B : **Investigator** ☑
o3-mini : **Investigator** ☑
o1 : **Investigator** ☑
QwQ-32B : **Investigator** ☑
DeepSeek-R1 : **Investigator** ☑
Gemini-2.5-Pro :**Investigator** ☑

Figure 5: Case study: Hidden Role Deduction (Investigator Perspective)

Hidden Role Deduction (Investigator Perspective) Solution

I'm told I'm an Investigator, but I might also be a Rumormonger. I need to discuss both possibilities

Considering the case where I'm an Investigator, there are 2 Investigators remaining In this scenario, which players could be Investigators? Player 2 has accused more than one person of being the criminal, so player 2 must be excluded Player 3 says I'm the criminal, but I can't be the criminal, so player 3 must be excluded Player 4 says I'm the criminal, but I can't be the criminal, so player 4 must be excluded Player 5's statements have no contradictions, so they could be an Investigator Player 6's statements have no contradictions, so they could be an Investigator Therefore, the players who could be Investigators are: {1, 5, 6} Now we need to consider all possible combinations of Investigators I am an Investigator, so I will occupy a position in the combination Considering the case where investigators are {1, 5, 6} Then the set of potential criminals is {2, 3, 4} Let's review the statements made by investigators Player 1 said 3 is not the criminal But 3 is in the set of potential criminals, so we remove 3 Now the potential criminals are {2, 4} Player 6 said 4 is not the criminal But 4 is in the set of potential criminals, so we remove 4 Now the potential criminals are {2} Based on the above analysis, this combination is possible, and I could be an Investigator. In this case, only {2} could be the criminal

Considering the case where I'm a Rumormonger, there are 3 Investigators remaining In this scenario, which players could be Investigators? Player 2 has accused more than one person of being the criminal, so player 2 must be excluded Player 3 says I'm the criminal, but I can't be the criminal, so player 3 must be excluded Player 4 says I'm the criminal, but I can't be the criminal, so player 4 must be excluded Player 5's statements have no contradictions, so they could be an Investigator Player 6's statements have no contradictions, so they could be an Investigator Therefore, the players who could be Investigators are: {5, 6} There aren't enough potential Investigators to reach the required count of 3, so this scenario is impossible I must be an Investigator

Final Judgment: Final Criminal Is Player 2. My Role Is Investigator.

Figure 6: Case study: Hidden Role Deduction (Investigator Perspective) Solution

Hidden Role Deduction (Investigator Perspective Round 1)

To analyze the statements from Round 1, let's break down the information: - I, Player 1, am an Investigator. I stated that Player 3 is not the criminal. This is truthful. - Player 2 claims Player 6 is the criminal. If Player 2 is an Investigator, this would be true. If Player 2 is the Rumormonger or Lunatic, it could be false. - Player 3 claims I am the criminal. Since I know I am not the criminal, Player 3 is either the Rumormonger, Lunatic, or the Criminal. - Player 4 claims Player 6 is the criminal. Similar reasoning as with Player 2. - Player 5 says Player 3 is not the criminal, which aligns with my statement. If Player 5 is an Investigator, this is true. If Player 5 is the Rumormonger or Lunatic, it may be false. - Player 6 says I am not the criminal. This statement is true. Let's consider the implications: - Player 2 and Player 4 both accuse Player 6. If either is an Investigator, Player 6 is likely the criminal. - Player 3 accusing me suggests Player 3 is not an Investigator. - Player 5 agrees with my statement about Player 3, suggesting alignment with truth if Player 5 is an Investigator. - Player 6's statement that I am not the criminal is true. Based on this analysis, the most suspicious player is Player 6, given multiple accusations from others. However, without more rounds, it is not conclusive. **Final Judgment after Round 1: Final Criminal Is Player 6. My Role Is Investigator.**

Response by GPT-4o

Figure 7: Case study: Hidden Role Deduction (Investigator Perspective) GPT-4o Round 1

Hidden Role Deduction (Investigator Perspective Round 2)

Let's analyze the statements from Round 2, adding them to our understanding from Round 1: - I, Player 1, again state that Player 3 is not the criminal. This is truthful. - Player 2 now claims Player 4 is the criminal, changing their accusation from Player 6 in Round 1. This inconsistency suggests Player 2 might not be an Investigator. - Player 3 states Player 5 is not the criminal. Given I know Player 3 is not an Investigator, this statement could be false. - Player 4 accuses me (Player 1) of being the criminal. Since I am not the criminal, Player 4 cannot be an Investigator. - Player 5 claims Player 6 is not the criminal. This contradicts accusations from Round 1 and suggests Player 5 might not be an Investigator. - Player 6 claims Player 4 is not the criminal. This contradicts Player 2's current accusation and suggests Player 6 might not be an Investigator. From this analysis: - Player 4 and Player 6 have both been accused as criminals, but Player 4 is consistently accused more. - Player 2's inconsistency in accusations suggests they are not an Investigator. - Player 3's statement about Player 5 is not reliable based on their role. - Player 5's statement contradicts previous accusations of Player 6. Considering the consistency of accusations and aligning them with my investigative truth, Player 4 appears more suspicious than Player 6 due to Player 2's current accusation and Player 4's accusation against me. **Final Judgment after Round 2: Final Criminal Is Player 4. My Role Is Investigator.**

Response by GPT-4o

Figure 8: Case study: Hidden Role Deduction (Investigator Perspective) GPT-4o Round 2

Hidden Role Deduction (Investigator Perspective Round 3)

Let's analyze the statements from Round 3, along with our understanding from previous rounds: - I, Player 1, state that Player 4 is not the criminal. This is truthful and clarifies my previous uncertainty about Player 4. - Player 2 again accuses Player 6 of being the criminal, which is consistent with their Round 1 statement. - Player 3 states Player 6 is not the criminal. Given that Player 3 is not an Investigator, this statement could be false. - Player 4 states Player 3 is not the criminal, which aligns with my truthful statement from all rounds. - Player 5 claims Player 4 is not the criminal, which aligns with my statement in this round. - Player 6 states Player 3 is not the criminal, aligning with my initial statement about Player 3. Considering the full context: - My consistent statements about Player 3 being not the criminal have been supported by Player 4 and Player 5 in this round. - Player 2's consistent accusation of Player 6 suggests a possible Investigator role or an accurate Rumormonger or Lunatic. - Player 3's statement contradicts Player 2 and supports Player 6, which is suspect given their role is not Investigator. - Player 4, now supported by my statement and Player 5, is not the criminal. - Player 6's statement about Player 3 matches my truth, but their role is suspect given Player 2's consistent accusations. Based on these observations, with Player 4 ruled out and Player 3 being consistently found not guilty, the consistent accusations against Player 6 make them the most likely candidate for the criminal role. **Final Judgment after Round 3: Final Criminal Is Player 6. My Role Is Investigator.**

Response by GPT-4o

Figure 9: Case study: Hidden Role Deduction (Investigator Perspective) GPT-4o Round 3

Hidden Role Deduction (Investigator Perspective Round 1)

Step-by-step Analysis: 1. I (Player 1, an Investigator) stated that "Player 3 is not the criminal." Since I'm truthful, we know for sure that Player 3 is not the criminal. 2. Looking at the other statements: • Player 2 and Player 4 both claim "Player 6 is the criminal." • Player 6 states "Player 1 is not the criminal" (which is consistent with what we already know). • Player 3 says "Player 1 is the criminal." Because I know I'm not criminal, and true Investigators always tell the truth, Player 3's false claim tells us that Player 3 cannot be a genuine Investigator. (Player 3 must be either the Rumormonger or Lunatic, but not the criminal since I already cleared that possibility.) • Player 5 says "Player 3 is not the criminal" (which agrees with what I said, but provides no additional elimination on its own). 3. If we consider that Investigators always speak truthfully regarding who the criminal is, then Players 2 and 4 could very well be genuine Investigators. Their identical claims that "Player 6 is the criminal" would then be truthful. (Player 6, even if he were the criminal, could occasionally state truths, since only the Investigators are bound to always tell the truth.) 4. This scenario is consistent if: • The real criminal is Player 6. • The three Investigators are Players 1, 2, and 4. • Players 3 and 5, who make statements that can be arbitrary, are the Rumormonger and Lunatic (in some order). Based on the evidence from Round 1: **Final Judgment: Final Criminal Is Player 6. My Role Is Investigator.**

Response by o3-mini

Figure 10: Case study: Hidden Role Deduction (Investigator Perspective) o3-mini Round 1

Hidden Role Deduction (Investigator Perspective Round 2)

Step-by-step analysis for Round 2: 1. I (Player 1) am an Investigator, so my statement "Player 3 is not the criminal" is true. We can be sure that Player 3 is not the criminal. 2.....In this scenario, Player 2's statement "Player 4 is the criminal" becomes false. That fits if Player 2 is the Criminal – criminals can lie arbitrarily. – I (Player 1) am an Investigator, and we can assign the third Investigator role to Player 3 because his statement "Player 5 is not the criminal" would be true. – Then the three Investigators are Players 1, 3, and 6; and the three non-investigators are Players 2, 4, and 5. With exactly one Criminal needed, assigning that to Player 2 (the one whose accusation is false) is consistent; Players 4 and 5 would then be the Rumormonger and Lunatic in some order. 6. Scenario B resolves the conflicts neatly: – Player 1 (Investigator) truthfully asserts that Player 3 is not criminal. – Player 3 (Investigator) truthfully asserts that Player 5 is not criminal. – Player 6 (Investigator) truthfully asserts that Player 4 is not criminal. – Player 2 (Criminal) falsely accuses Player 4. – Player 4 (non-investigator) falsely accuses Player 1. – Player 5 (non-investigator) states "Player 6 is not the criminal" (which is factually true although they are not obligated to be truthful). 7. Based on this reasoning, the most consistent assignment from the Round 2 statements is: – Final Criminal: Player 2. – Investigators: Players 1, 3, and 6. – The remaining roles (Rumormonger and Lunatic) go to Players 4 and 5. **Final Judgment: Final Criminal Is Player 2. My Role Is Investigator.**

Response by o3-mini

Figure 11: Case study: Hidden Role Deduction (Investigator Perspective) o3-mini Round 2

Hidden Role Deduction (Investigator Perspective Round 3)

Step-by-step Analysis (integrating all rounds): We know for certain that I (Player 1) am an Investigator. That means every statement I make must be true. In each round, I stated "Player 3 is not the criminal" (Rounds 1 and 2) and "Player 4 is not the criminal" (Round 3).....Player 5 says "Player 3 is not the criminal" in Round 1, "Player 6 is not the criminal" in Round 2, and "Player 4 is not the criminal" in Round 3. All these are true under any scenario where the criminal is neither 3, 4, nor 6. – Player 6 says "Player 1 is not the criminal" (Round 1), "Player 4 is not the criminal" (Round 2), and "Player 3 is not the criminal" (Round 3). All these statements would be true provided criminal is not 1, 3, or 4. Thus P5 and P6 are very good candidates for the remaining Investigators. With P1, P5, and P6 as our three Investigators, the criminal must be among the remaining players: Players 2, 3, or 4. But by my statements, P3 and P4 are not criminal. That leaves only Player 2. Now check the non-Investigators' statements (Players 2, 3, and 4 across rounds): • Player 2's statements: – Round 1: "Player 6 is the criminal." (False since P6 is an Investigator.) – Round 2: "Player 4 is the criminal." (False, as P4 is cleared.) – Round 3: "Player 6 is the criminal." (Again false.) A non-investigator (criminal, Rumormonger, or Lunatic) is free to provide false statements. • Player 3, already determined non-Investigator, in Round 1 falsely accuses me, and then makes statements in Rounds 2 and 3 that are correct—but this mix is permissible for a non-Investigator. • Player 4, similarly, makes at least one false claim in Round 2, which is acceptable. All rounds are fully consistent with: – Investigators: Players 1, 5, and 6. – Criminal: Player 2. – The remaining two non-investigators (the Rumormonger and the Lunatic) being Players 3 and 4 (in some order). **Final Judgment: Final Criminal Is Player 2. My Role Is Investigator.**

Response by o3-mini

Figure 12: Case study: Hidden Role Deduction (Investigator Perspective) o3-mini Round 3

Hidden Role Deduction (Criminal Perspective)

Role: "1": "Criminal", "2": "Investigator", "3": "Investigator", "4": "Investigator", "5": "Rumormonger", "6": "Lunatic"

Round 1:

Player 1 says Player 3 is the criminal.
Player 2 says Player 1 is the criminal.
Player 3 says Player 4 is not the criminal.
Player 4 says Player 1 is the criminal.
Player 5 says Player 2 is not the criminal.
Player 6 says Player 1 is not the criminal.

Round 2:

Player 1 says Player 4 is not the criminal.
Player 2 says Player 4 is not the criminal.
Player 3 says Player 6 is not the criminal.
Player 4 says Player 1 is the criminal.
Player 5 says Player 6 is the criminal.
Player 6 says Player 4 is not the criminal.

Round 3:

Player 1 says Player 3 is not the criminal.
Player 2 says Player 5 is not the criminal.
Player 3 says Player 1 is the criminal.
Player 4 says Player 5 is not the criminal.
Player 5 says Player 4 is the criminal.
Player 6 says Player 1 is the criminal.

Criminal Prediction:

Llama-3.1-8B : 5 ☒
Llama-3.3-70B : **1** ☑
GPT-4o-mini : **1** ☑
GPT-4o : **1** ☑
Qwen2.5-72B : **1** ☑
o3-mini : **1** ☑
o1 : **1** ☑
QwQ-32B : **1** ☑
DeepSeek-R1 : **1** ☑
Gemini-2.5-Pro : **1** ☑

Self-Role Prediction:

Llama-3.1-8B : **Criminal** ☑
Llama-3.3-70B : **Criminal** ☑
GPT-4o-mini : **Criminal** ☑
GPT-4o : **Criminal** ☑
Qwen2.5-72B : **Criminal** ☑
o3-mini : **Criminal** ☑
o1 : **Criminal** ☑
QwQ-32B : **Criminal** ☑
DeepSeek-R1 : **Criminal** ☑
Gemini-2.5-Pro : **Criminal** ☑

Figure 13: Case study: Hidden Role Deduction (Criminal Perspective)

Hidden Role Deduction (Criminal Perspective) Solution

I'm told I'm a Criminal, but I might also be a Lunatic. I need to discuss both possibilities

Considering the case where I'm a Criminal, there are 3 Investigators remaining In this scenario, which players could be Investigators? Player 2's statements have no contradictions, so they could be an Investigator Player 3's statements have no contradictions, so they could be an Investigator Player 4's statements have no contradictions, so they could be an Investigator Player 5 has accused more than one person of being the criminal, so player 5 must be excluded Player 6 says I'm not the criminal, but I am the criminal, so player 6 must be excluded Therefore, the players who could be Investigators are: {2, 3, 4} Now we need to consider all possible combinations of Investigators Considering the case where investigators are {2, 3, 4} I am the Criminal,so the set of potential criminals is {1} Let's review the statements made by investigators Player 2 said 1 is the criminal So the only possible criminal is 1 Player 4 said 1 is the criminal So the only possible criminal is 1 Player 4 said 1 is the criminal So the only possible criminal is 1 Player 3 said 1 is the criminal So the only possible criminal is 1 Based on the above analysis, this combination is possible, and I could be the Criminal. In this case, only {1} could be the criminal

Considering the case where I'm a Lunatic, there are 3 Investigators remaining In this scenario, which players could be Investigators? Player 2 says I'm the criminal, but I can't be the criminal, so player 2 must be excluded Player 3 says I'm the criminal, but I can't be the criminal, so player 3 must be excluded Player 4 says I'm the criminal, but I can't be the criminal, so player 4 must be excluded Player 5 has accused more than one person of being the criminal, so player 5 must be excluded Player 6 says I'm the criminal, but I can't be the criminal, so player 6 must be excluded Therefore, the players who could be Investigators are: {} There aren't enough potential Investigators to reach the required count of 3, so this scenario is impossible I must be a Criminal

Final Judgment: Final Criminal Is Player 1. My Role Is Criminal."

Figure 14: Case study: Hidden Role Deduction (Criminal Perspective) Solution

Hidden Role Deduction (Criminal Perspective Round 1)

Analysis of Round 1 Statements: 1. Player 1 (You) says Player 3 is the criminal. - As a Criminal, you can lie or tell the truth. This statement could be either. 2. Player 2 says Player 1 is the criminal. - If Player 2 is an Investigator, this statement is true. - If Player 2 is a Criminal, this statement could be a lie. - If Player 2 is a Rumormonger, this statement could be false. - If Player 2 is a Lunatic, this statement could be true or false. 3. Player 3 says Player 4 is not the criminal. - If Player 3 is an Investigator, this statement is true. - If Player 3 is a Criminal, this statement could be a lie. - If Player 3 is a Rumormonger, this statement could be false. - If Player 3 is a Lunatic, this statement could be true or false. 4. Player 4 says Player 1 is the criminal. - If Player 4 is an Investigator, this statement is true. - If Player 4 is a Criminal, this statement could be a lie. - If Player 4 is a Rumormonger, this statement could be false. - If Player 4 is a Lunatic, this statement could be true or false. 5. Player 5 says Player 2 is not the criminal. - If Player 5 is an Investigator, this statement is true. - If Player 5 is a Criminal, this statement could be a lie. - If Player 5 is a Rumormonger, this statement could be false. - If Player 5 is a Lunatic, this statement could be true or false. 6. Player 6 says Player 1 is not the criminal. - If Player 6 is an Investigator, this statement is true. - If Player 6 is a Criminal, this statement could be a lie. - If Player 6 is a Rumormonger, this statement could be false. - If Player 6 is a Lunatic, this statement could be true or false. ### Summary of Round 1: - Player 1 is accused by Player 2, Player 4, and Player 6. - Player 2 is exonerated by Player 5. - Player 3 is accused by Player 1. - Player 4 is exonerated by Player 3. ### Deductions: - Player 1 (You) is accused by 3 players, which is a strong indication that you might be the Criminal. - Player 2 is exonerated by one player, which suggests they might be an Investigator. - Player 3 is accused by one player and exonerated by one player, making their role less clear. - Player 4 is exonerated by one player, which suggests they might be an Investigator. - Player 5 exonerates Player 2, which suggests they might be an Investigator. - Player 6 exonerates Player 1, which suggests they might be a Lunatic or a Criminal. ### **Final Judgment for Round 1: Final Criminal Is Player 1. My Role Is Criminal.**

Response by Qwen2.5-72B

Figure 15: Case study: Hidden Role Deduction (Criminal Perspective) Qwen2.5-72B Round 1

Hidden Role Deduction (Criminal Perspective Round 2)

Analysis of Round 2 Statements: 1. Player 1 (You) says Player 4 is not the criminal. - As a Criminal, you can lie or tell the truth. This statement could be either. 2. Player 2 says Player 4 is not the criminal. - If Player 2 is an Investigator, this statement is true. - If Player 2 is a Criminal, this statement could be a lie. - If Player 2 is a Rumormonger, this statement could be false. - If Player 2 is a Lunatic, this statement could be true or false. 3. Player 3 says Player 6 is not the criminal. - If Player 3 is an Investigator, this statement is true. - If Player 3 is a Criminal, this statement could be a lie. - If Player 3 is a Rumormonger, this statement could be false. - If Player 3 is a Lunatic, this statement could be true or false. 4. Player 4 says Player 1 is the criminal. - If Player 4 is an Investigator, this statement is true. - If Player 4 is a Criminal, this statement could be a lie. - If Player 4 is a Rumormonger, this statement could be false. - If Player 4 is a Lunatic, this statement could be true or false. 5. Player 5 says Player 6 is the criminal. - If Player 5 is an Investigator, this statement is true. - If Player 5 is a Criminal, this statement could be a lie. - If Player 5 is a Rumormonger, this statement could be false. - If Player 5 is a Lunatic, this statement could be true or false. 6. Player 6 says Player 4 is not the criminal. - If Player 6 is an Investigator, this statement is true. - If Player 6 is a Criminal, this statement could be a lie. - If Player 6 is a Rumormonger, this statement could be false. - If Player 6 is a Lunatic, this statement could be true or false. ### Summary of Round 2: - Player 1 is accused by Player 4. - Player 4 is exonerated by Player 1, Player 2, and Player 6. - Player 6 is exonerated by Player 3 and accused by Player 5. ### Combining Rounds 1 and 2: - Player 1 (You) is accused by Player 2, Player 4, and Player 6 in Round 1. - Player 4 is exonerated by Player 1, Player 2, and Player 6 in Round 2. - Player 6 is exonerated by Player 3 in Round 2 and accused by Player 5 in Round 2. ### Deductions: - Player 1 (You) is consistently accused by multiple players, which strongly suggests you are the Criminal. - Player 4 is exonerated by multiple players, which suggests they might be an Investigator or a Rumormonger. - Player 2 is exonerated by Player 5, which suggests they might be an Investigator. - Player 3 exonerates Player 6, which suggests they might be an Investigator or a Rumormonger. - Player 5 accuses Player 6, which suggests they might be an Investigator. - Player 6 exonerates Player 4, which suggests they might be a Lunatic or a Criminal. ### **Final Judgment for Round 2: Final Criminal Is Player 1. My Role Is Criminal.**

Response by Qwen2.5-72B

Figure 16: Case study: Hidden Role Deduction (Criminal Perspective) Qwen2.5-72B Round 2

Hidden Role Deduction (Criminal Perspective Round 3)

Analysis of Round 3 Statements: 1. Player 1 (You) says Player 3 is not the criminal. - As a Criminal, you can lie or tell the truth. This statement could be either. 2. Player 2 says Player 5 is not the criminal. - If Player 2 is an Investigator, this statement is true. - If Player 2 is a Criminal, this statement could be a lie. - If Player 2 is a Rumormonger, this statement could be false. - If Player 2 is a Lunatic, this statement could be true or false. 3. Player 3 says Player 1 is the criminal. - If Player 3 is an Investigator, this statement is true. - If Player 3 is a Criminal, this statement could be a lie. - If Player 3 is a Rumormonger, this statement could be false. - If Player 3 is a Lunatic, this statement could be true or false. 4. Player 4 says Player 5 is not the criminal. - If Player 4 is an Investigator, this statement is true. - If Player 4 is a Criminal, this statement could be a lie. If Player 6 is a Rumormonger, this statement could be false. - If Player 6 is a Lunatic, this statement could be true or false. ### Summary of Round 3: - Player 1 is exonerated by Player 3 in Round 3 and accused by Player 3 and Player 6. - Player 3 is exonerated by Player 1 in Round 3 and accuses Player 1. - Player 4 is exonerated by Player 4 and Player 2 in Round 3 and accused by Player 5. - Player 5 is exonerated by Player 2 and Player 4 in Round 3 and accuses Player 4. ### Combining All Rounds: - Player 1 (You) is accused by Player 2, Player 4, and Player 6 in Round 1. - Player 1 is accused by Player 3 and Player 6 in Round 3. - Player 4 is exonerated by Player 1, Player 2, and Player 6 in Round 2. - Player 4 is exonerated by Player 4 and Player 2 in Round 3. - Player 5 is exonerated by Player 2 and Player 4 in Round 3. - Player 5 accuses Player 4 in Round 3. - Player 6 is exonerated by Player 3 in Round 2 and accused by Player 5 in Round 3. ### Deductions: - Player 1 (You) is consistently accused by multiple players, which strongly suggests you are the Criminal. - Player 4 is exonerated by multiple players, which suggests they might be an Investigator or a Rumormonger. - Player 2 exonerates Player 4 and Player 5, which suggests they might be an Investigator. - Player 3 accuses Player 1, which suggests they might be an Investigator or a Criminal. - Player 5 accuses Player 4, which suggests they might be an Investigator. - Player 6 accuses Player 1, which suggests they might be a Lunatic or a Criminal. **### Final Judgment for Round 3: Final Criminal Is Player 1. My Role Is Criminal.**

Response by Qwen2.5-72B

Figure 17: Case study: Hidden Role Deduction (Criminal Perspective) Qwen2.5-72B Round 3

Hidden Role Deduction (Criminal Perspective Round 1)

Let's analyze the statements from Round 1. Since I am Player 1 and I was told I am the Criminal, I will try to verify this information based on the statements. Player 1 (myself) says Player 3 is the criminal, but since I was told I am the Criminal, this statement could be false, as Criminals can provide misleading information. Players 2 and 4 both say I (Player 1) am the criminal, which aligns with the information I was given. However, this does not necessarily confirm my role, as other roles can also make statements that happen to be true. Player 3 says Player 4 is not the criminal, which could be true or false, and does not provide direct information about my role. Player 5 says Player 2 is not the criminal, which also does not provide direct information about my role. Player 6 says I (Player 1) am not the criminal, which contradicts the information I was given. However, since Player 6 could be any role, this statement alone is not enough to confirm or deny my role. Given the information from Round 1, I will make my judgment based on the majority of statements and the game roles' characteristics. Final Judgment: **Final Criminal Is Player 1. My Role Is Criminal.**

Response by Llama-3.3-70B

Figure 18: Case study: Hidden Role Deduction (Criminal Perspective) Llama-3.3-70B Round 1

Hidden Role Deduction (Criminal Perspective Round 2)

Let's analyze the statements from Round 2, in addition to the statements from Round 1. From Round 1, we had: - Players 2 and 4 saying I (Player 1) am the criminal. - Player 6 saying I (Player 1) am not the criminal. From Round 2, we have: - Players 1 (myself), 2, and 6 saying Player 4 is not the criminal. - Player 4 saying I (Player 1) am the criminal, which is consistent with their statement from Round 1. - Player 5 saying Player 6 is the criminal. Considering my role as told to me (Criminal), and analyzing the statements, it seems that Players 2 and 4 are consistent in accusing me of being the criminal. However, as a Criminal, my statements can be false, and I have no way to confirm my own role solely based on the statements of others. The statements about other players being or not being the criminal do not provide conclusive evidence about my role but suggest that there is confusion among the players regarding who the criminal might be. Given the information from both rounds, I will make my judgment based on the majority of statements and the game roles' characteristics. Final Judgment: **Final Criminal Is Player 1. My Role Is Criminal.**

Response by Llama-3.3-70B

Figure 19: Case study: Hidden Role Deduction (Criminal Perspective) Llama-3.3-70B Round 2

Hidden Role Deduction (Criminal Perspective Round 3)

Let's analyze the statements from Round 3, in addition to the statements from Rounds 1 and 2. From Round 1, we had: - Players 2 and 4 saying I (Player 1) am the criminal. - Player 6 saying I (Player 1) am not the criminal. From Round 2, we had: - Players 1 (myself), 2, and 6 saying Player 4 is not the criminal. - Player 4 saying I (Player 1) am the criminal. - Player 5 saying Player 6 is the criminal. From Round 3, we have: - Player 3 saying I (Player 1) am the criminal. - Player 6 saying I (Player 1) am the criminal, which is a change from their statement in Round 1. - Players 2 and 4 saying Player 5 is not the criminal. - Player 5 saying Player 4 is the criminal. Considering the statements across all rounds, it's notable that: - Players 2, 3, 4, and 6 have all accused me (Player 1) of being the criminal at some point. - Player 6 initially said I was not the criminal but changed their statement in Round 3 to say I am the criminal. As a player told I am the Criminal, and given the accumulation of accusations against me from multiple players, including the change in Player 6's statement, it seems more likely that I am indeed the Criminal, as the majority of players have pointed towards me at some point. **Final Judgment: Final Criminal Is Player 1. My Role Is Criminal.**

Response by Llama-3.3-70B

Figure 20: Case study: Hidden Role Deduction (Criminal Perspective) Llama-3.3-70B Round 3

Hidden Role Deduction (Rumormonger Perspective)

Role: "1": "Rumormonger", "2": "Lunatic", "3": "Criminal", "4": "Investigator", "5": "Investigator", "6": "Investigator"

Round 1:

Player 1 says Player 2 is the criminal.
Player 2 says Player 1 is the criminal.
Player 3 says Player 2 is not the criminal.
Player 4 says Player 1 is not the criminal.
Player 5 says Player 6 is not the criminal.
Player 6 says Player 3 is the criminal.

Round 2:

Player 1 says Player 2 is the criminal.
Player 2 says Player 1 is the criminal.
Player 3 says Player 2 is not the criminal.
Player 4 says Player 1 is not the criminal.
Player 5 says Player 6 is not the criminal.
Player 6 says Player 3 is the criminal.

Round 3:

Player 1 says Player 2 is not the criminal.
Player 2 says Player 5 is the criminal.
Player 3 says Player 4 is the criminal.
Player 4 says Player 1 is not the criminal.
Player 5 says Player 6 is not the criminal.
Player 6 says Player 4 is not the criminal.

Criminal Prediction:

Llama-3.1-8B : **6** ☒
Llama-3.3-70B : **6** ☒
GPT-4o-mini : **6** ☒
GPT-4o : **6** ☒
Qwen2.5-72B : **2** ☒
o3-mini : **6** ☒
o1 : **6** ☒
QwQ-32B : **3** ☑
DeepSeek-R1 : **3** ☑
Gemini-2.5-Pro : **3** ☑

Self-Role Prediction:

Llama-3.1-8B : **Investigator** ☒
Llama-3.3-70B : **Investigator** ☒
GPT-4o-mini : **Investigator** ☒
GPT-4o : **Investigator** ☒
Qwen2.5-72B : **Unknown** ☒
o3-mini : **Investigator** ☒
o1 : **Investigator** ☒
QwQ-32B : **Unknown** ☒
DeepSeek-R1 : **3** ☑
Gemini-2.5-Pro : **Rumormonger** ☑

Figure 21: Case study: Hidden Role Deduction (Rumormonger Perspective)

HRD (Rumormonger Perspective) Solution

I'm told I'm an Investigator, but I might also be a Rumormonger. I need to discuss both possibilities

Considering the case where I'm an Investigator, there are 2 Investigators remaining In this scenario, which players could be Investigators? Player 2 says I'm the criminal, but I can't be the criminal, so player 2 must be excluded.....Therefore, the players who could be Investigators are: {1, 4, 5, 6} Now we need to consider all possible combinations of Investigators I am an Investigator, so I will occupy a position in the combination. Considering the case where investigators are {1, 4, 5} Then the set of potential criminals is {2, 3, 6} Let's review the statements made by investigators.....So this combination of investigators cannot be valid, let's consider other combinations I've discussed all combinations, and the scenario where I'm an Investigator is impossible. I must be a Rumormonger

Considering the case where I'm a Rumormonger, there are 3 Investigators remaining In this scenario, which players could be Investigators? Player 2 says I'm the criminal, but I can't be the criminal, so player 2 must be excluded Player 3 has accused more than one person of being the criminal, so player 3 must be excluded Player 4's statements have no contradictions, so they could be an Investigator Player 5's statements have no contradictions, so they could be an Investigator Player 6's statements have no contradictions, so they could be an Investigator Therefore, the players who could be Investigators are: {4, 5, 6} Now we need to consider all possible combinations of Investigators I am a Rumormonger, so I will not occupy a position in the combination Considering the case where investigators are {4, 5, 6} Then the set of potential criminals is {2, 3} Let's review the statements made by investigators Player 6 said 3 is the criminal So the only possible criminal is {3} Player 5 said 3 is the criminal So the only possible criminal is {3} Based on the above analysis, this combination is possible, and I could be a Rumormonger. In this case, only {3} could be the criminal

Final Judgment: Final Criminal Is Player 3. My Role Is Rumormonger.

Figure 22: Case study: Hidden Role Deduction (Rumormonger Perspective) Solution

Hidden Role Deduction (Rumormonger Perspective Round 1)

Let's analyze the statements made in Round 1 to determine the likely roles of each player and identify the criminal. 1. Player 1 (Investigator): Claims Player 2 is the criminal (truthful). 2. Player 2: Claims Player 1 is the criminal (could be true or false, as Player 2 could be the Criminal or a Rumormonger/Lunatic). 3. Player 3: Claims Player 2 is not the criminal (could be true; if Player 3 is an Investigator, this is true; if not, it could be false). 4. Player 4: Claims Player 1 is not the criminal (this is true since Player 1 is an Investigator). 5. Player 5: Claims Player 6 is not the criminal (could be true; Player 5 could be an Investigator or misled). 6. Player 6: Claims Player 3 is the criminal (could be true or false). From this analysis: - Since I am Player 1 and I know I am an Investigator, my statement about Player 2 being the criminal is true. - Player 4 confirms I am not the criminal, which supports my status as Investigator. - Player 2's claim that I am the criminal is likely an attempt to mislead, indicating Player 2 is suspicious. - Player 3\u2019s claim that Player 2 is not the criminal could support that Player 3 is either an Investigator or misled, but does not directly contradict my information since Player 2 is indeed the criminal. - Player 6's claim about Player 3 being the criminal contradicts Player 3's statement. At this point, I have enough information to conclude: - Player 2 is the criminal based on my status as Investigator and the statements corroborating this. **Final Judgment: Final Criminal Is Player 2. My Role Is Investigator.**

Response by GPT-4o-mini

Figure 23: Case study: Hidden Role Deduction (Rumormonger Perspective) GPT-4o-mini Round 1

Hidden Role Deduction (Rumormonger Perspective Round 2)

Let's analyze the statements made in Round 2, keeping in mind that I am Player 1 and know that I am an Investigator. 1. Player 1 (Investigator): Claims Player 2 is not the criminal (this contradicts my prior statement, indicating new information). 2. Player 2: Claims Player 5 is the criminal (could be true or false; Player 2 could be lying). 3. Player 3: Claims Player 4 is the criminal (could be true or false; does not directly contradict my knowledge). 4. Player 4: Claims Player 1 is not the criminal (this is true since I am an Investigator). 5. Player 5: Claims Player 6 is not the criminal (could be true or false; Player 5 could be an Investigator or misled). 6. Player 6: Claims Player 4 is not the criminal (could be true or false; Player 6 could be lying or telling the truth). ### Analysis: 1. My Statement: My statement about Player 2 being not the criminal contradicts my previous conclusion that Player 2 is the criminal. This suggests that either: - I might be mistaken (impossible as I am an Investigator and always truthful), - Or Player 2 is indeed not the criminal, which means I need to reconsider who the criminal is based on new information. 2. Player 2's Statement: If Player 2 is claiming Player 5 is the criminal, that statement can be misleading if Player 2 is the Criminal. 3. Player 3's Statement: Player 3's claim that Player 4 is the criminal does not contradict my knowledge but needs to be analyzed further. 4. Player 4's Statement: Confirms I am not the criminal. 5. Player 5's Statement: States Player 6 is not the criminal; this could either be true or false. 6. Player 6's Statement: States Player 4 is not the criminal; again, this could be true or false. ### Conclusion: Given the conflicting nature of the statements, I still need to discern who the Criminal is. I will analyze the implications: - If Player 2 is not the criminal, then either Player 5 or Player 4 could be. - Player 3's accusation of Player 4 could reinforce that Player 4 is the Criminal if Player 3 is an Investigator or misled. The only definitive truth is that I am an Investigator and must remain truthful. However, Player 2's statement about Player 5 being the criminal could be the key to determining the criminal. Since Player 1's statement about Player 2 being not the criminal does not hold under scrutiny and seems to be a point of confusion in deduction, I must rely on corroborating information and not my initial conclusion. Thus, I now suspect that: - Player 5 or Player 4 could be the Criminal, with Player 3's statement potentially holding more weight if Player 3 is truthful. With the given statements and the contradictions, I will need more information to conclude definitively but suspect: **Final Judgment: Final Criminal Is Player 4. My Role Is Investigator.**

Response by GPT-4o-mini

Figure 24: Case study: Hidden Role Deduction (Rumormonger Perspective) GPT-4o-mini Round 2

Hidden Role Deduction (Rumormonger Perspective Round 3)

Let's analyze the statements made in Round 3, taking into account the previous rounds and the fact that I am Player 1 (Investigator). 1. Player 1 (Investigator): Claims Player 6 is the criminal (this is truthful). 2. Player 2: Claims Player 3 is not the criminal (could be true or false). 3. Player 3: Claims Player 6 is the criminal (this corroborates my statement). 4. Player 4: Claims Player 2 is not the criminal (could be true or false). 5. Player 5: Claims Player 3 is the criminal (could be true or false). 6. Player 6: Claims Player 2 is not the criminal (could be true or false). ### Analysis: 1. My Statement: I stated that Player 6 is the criminal, which is true since I am the Investigator. 2. Player 2's Statement: If Player 2 claims Player 3 is not the criminal, this does not contradict my knowledge that Player 6 is the criminal but introduces uncertainty about Player 3's role. 3. Player 3's Statement: Player 3's claim that Player 6 is the criminal corroborates my statement, indicating that Player 3 could be an Investigator or a truthful player. 4. Player 4's Statement: This statement about Player 2 doesn't contradict what I know, but I have already identified Player 6 as the criminal. 5. Player 5's Statement: Player 5's claim that Player 3 is the criminal contradicts Player 3\u2019s statement about Player 6 and may indicate that Player 5 is either misled or the Criminal. 6. Player 6's Statement: The statement about Player 2 not being the criminal adds further complexity but does not contradict my findings. ### Conclusion: Given that I am an Investigator and have established that Player 6 is the criminal, the statements from Players 3 and 1 about Player 6 being the criminal further support this conclusion. Player 5's conflicting statement about Player 3 being the criminal seems suspect, especially when combined with the information available. Thus, based on the consistent information from my perspective and corroboration from Player 3, I conclude: **Final Judgment: Final Criminal Is Player 6. My Role Is Investigator.**

Response by GPT-4o-mini

Figure 25: Case study: Hidden Role Deduction (Rumormonger Perspective) GPT-4o-mini Round 3

Hidden Role Deduction (Rumormonger Perspective Round 1)

Okay, let's see. I'm Player 1 and an Investigator, so my statements are always truthful. In Round 1, I said Player 2 is the criminal. Now I need to look at everyone else's statements to figure out who's the real criminal and possibly their roles.....So Player 6's statement is a lie. If Player 6 is the Rumormonger (who can lie) or Lunatic (since Lunatics are told they're criminal and can lie). Alternatively, maybe the criminal is someone else? Let's check alternatives. Suppose the criminal is Player 6. Then: - My statement about 2 is false, which can't be because I'm an investigator. So that's impossible. If the criminal is Player 3: - My statement (Player 2 is criminal) is wrong, so I'm making a false statement, but I'm supposed to be an Investigator. So that's impossible. Player 4 being criminal? Then my statement is wrong, again impossible. Player 5 being criminal: same issue, my statement is wrong. Player 1 is me and I'm not criminal, so that's out. So only possible criminals are Player 2 or maybe Player 6? Wait, if Player 6 is the criminal, then my statement was wrong, which can't be. So only Player 2 is possible. Wait, that seems solid. Because I can't be wrong. So then Player 2 must be the criminal. Then Player 3's statement is a lie, so Player 3 is not an Investigator. Player 4's statement is true, so they could be an Investigator. Player 5's statement true (if Player6 isn't criminal), so maybe they're also an Investigator. Then Investigators are me, 4,5. That works. Then remaining roles: Player2 is criminal, Player3 is either Rumormonger or Lunatic. Player6 is the remaining role (the other between Rumormonger and Lunatic), but also Player6's statement about 3 being criminal is a lie. So if Player6 is a Lunatic (who believes they're criminal), they can lie. So that works. Player3 could be Rumormonger (who thinks they're Investigator but lied here). So that fits all roles. So Final Judgment would be Player2 as criminal. My role is Investigator. Wait but the user wants Final Criminal and My Role. Since I know I am an Investigator, right? The game told me that. So I can state that. Wait the problem says \"My Role Is [Player 1's Role or \"Unknown\"]\". Since I was told I'm an Investigator, I should state that. So: Final Criminal Is Player 2. My Role Is Investigator. </think> Final Judgment: **Final Criminal Is Player 2. My Role Is Investigator.**

Response by QwQ-32B

Figure 26: Case study: Hidden Role Deduction (Rumormonger Perspective) QwQ-32B Round 1

Hidden Role Deduction (Rumormonger Perspective Round 2)

..... Therefore, the only possible conclusion is that I'm not an Investigator. But the problem states I am.**.....**Final Judgment: **Final Criminal Is Player 3. My Role Is Unknown.** Step-by-Step Explanation: 1. Investigator Constraints: As Player 1 (allegedly an Investigator), my statements must both be true. However, my Round 1 claim (\"Player 2 is the criminal\") and Round 2 claim (\"Player 2 is not the criminal\") are contradictory. This creates an immediate inconsistency, suggesting either I am not an Investigator (contradicting the setup) or another role is causing this paradox. 2. Analyzing Consistent Statements: - Player 4 and 5 have consistent statements across both rounds, claiming \"Player 1 is not the criminal\" and \"Player 6 is not the criminal,\" respectively. These could indicate they are Investigators, as their claims do not contradict. - Player 6 in Round 1 claims \"Player 3 is the criminal.\" If this is true, Player 3 could be the Criminal. In Round 2, Player 6 states \"Player 4 is not the criminal,\" which aligns with Player 4's consistent claims, further supporting their potential as an Investigator. 3. Player 3's Statements: - Round 1: \"Player 2 is not the criminal.\" If true, this contradicts my Round 1 claim. - Round 2: \"Player 4 is the criminal.\" If Player 3 is the Criminal, this statement would be a lie, which aligns with Criminal behavior. 4. Criminal Plausibility: - If Player 3 is the Criminal: - Their Round 1 claim (\"Player 2 is not the criminal\") could be truthful. - Their Round 2 claim (\"Player 4 is the criminal\") would be a lie, consistent with Criminal behavior. - Player 6's Round 1 accusation of Player 3 as Criminal aligns with this. - This scenario allows Players 4, 5, and 6 to be Investigators (assuming their statements are truthful). 5. Resolving My Role Contradiction: - My contradictory statements (\"Player 2 is/ isn't the criminal\") imply I am not an Investigator. However, the setup states I am an Investigator. - This contradiction suggests I might be the Rumormonger (mistakenly believing I am an Investigator), justifying the conflicting statements. Since the problem requires stating my role as \"Investigator\" or \"Unknown,\" and my role is uncertain, \"Unknown\" is appropriate. **Conclusion: The most consistent role for the Criminal is Player 3, while my role remains uncertain due to the contradiction in my claims.**

Response by QwQ-32B

Figure 27: Case study: Hidden Role Deduction (Rumormonger Perspective) QwQ-32B Round 2

Hidden Role Deduction (Rumormonger Perspective Round 3)

.....**Since I'm actually supposed to be told I'm Investigator, but in reality, I'm Rumormonger, I can't know that for sure.** .....My statements over three rounds contradict each other: - Round 1: \"Player 2 is the criminal.\" - Round 2: \"Player 2 is not the criminal.\" - Round 3: \"Player 6 is the criminal.\" - Since Investigators must always tell the truth, these contradictions imply I am not an Investigator. However, the game setup states I am an Investigator, creating a paradox. The only plausible resolution is that I am the Rumormonger (mistakenly believing I am an Investigator), which allows my inconsistent statements. 2. Evaluating Player Statements: - Player 3\u2019s accusations: - Round 1: \"Player 2 is not the criminal.\" (Potentially truthful.) - Round 2: \"Player 4 is the criminal.\" (A lie if Player 3 is the Criminal.) - Round 3: \"Player 6 is the criminal.\" (A lie if Player 3 is the Criminal.) - Player 5\u2019s statements: - Round 3: \"Player 3 is the criminal.\" (A truthful accusation if Player 3 is the Criminal.) - Round 1/Round 2: \"Player 6 is not the criminal.\" (Consistent with Player 3 being the Criminal.) - Player 4 and Player 6 consistently assert innocence for others (e.g., Player 4 says \"Player 2 is not the criminal\"), aligning with potential Investigator roles. 3. Role Assignments: - Criminal (Player 3): - Their Round 3 statement falsely accuses Player 6, and their Round 2 accusation of Player 4 can be a lie. This fits Criminal behavior. - Player 5\u2019s truthful Round 3 claim supports this. - Investigators (Players 4, 5, 6): - Player 4 and Player 5 have consistent true statements. - Player 6\u2019s statements (e.g., \"Player 2 is not the criminal\" in Round 3) are truthful under this scenario. - Lunatic (Player 2): - Their inconsistent accusations (e.g., \"Player 5 is the criminal\" in Round 2) and false claims about Player 3 (Round 3) align with Lunatic behavior. 4. My Role: - My contradictory statements and the game\u2019s role distribution rules suggest I am the Rumormonger (mistakenly believing I am an Investigator). However, since I cannot confirm this with certainty (as the game informs me I am an Investigator), I must state my role as Unknown. Conclusion: **Player 3 is the Criminal, and my role remains uncertain.**

Response by QwQ-32B

Figure 28: Case study: Hidden Role Deduction (Rumormonger Perspective) QwQ-32B Round 3

Hidden Role Deduction (Lunatic Perspective)

Role: "1": "Lunatic", "2": "Criminal", "3": "Rumormonger", "4": "Investigator", "5": "Investigator", "6": "Investigator"

Round 1:

Player 1 says Player 3 is the criminal.
Player 2 says Player 5 is the criminal.
Player 3 says Player 2 is the criminal.
Player 4 says Player 2 is the criminal.
Player 5 says Player 4 is not the criminal.
Player 6 says Player 5 is not the criminal.

Round 2:

Player 1 says Player 4 is not the criminal.
Player 2 says Player 6 is the criminal.
Player 3 says Player 1 is not the criminal.
Player 4 says Player 1 is not the criminal.
Player 5 says Player 3 is not the criminal.
Player 6 says Player 2 is the criminal.

Round 3:

Player 1 says Player 6 is the criminal.
Player 2 says Player 4 is not the criminal.
Player 3 says Player 5 is the criminal.
Player 4 says Player 6 is not the criminal.
Player 5 says Player 6 is not the criminal.
Player 6 says Player 4 is not the criminal.

Criminal Prediction:

Llama-3.1-8B : **6** ☒
Llama-3.3-70B : **3** ☒
GPT-4o-mini : **1** ☒
GPT-4o : **2** ☑
Qwen2.5-72B : **1** ☒
o3-mini : **1** ☒
o1 : **1** ☒
QwQ-32B : **2** ☑
DeepSeek-R1 : **2** ☑
Gemini-2.5-Pro : **2** ☑

Self-Role Prediction:

Llama-3.1-8B : **Unknown** ☒
Llama-3.3-70B : **Criminal** ☒
GPT-4o-mini : **Criminal** ☒
GPT-4o : **Unknown** ☒
Qwen2.5-72B : **Criminal** ☒
o3-mini : **Criminal** ☒
o1 : **Criminal** ☒
QwQ-32B : **Lunatic** ☑
DeepSeek-R1 : **Lunatic** ☑
Gemini-2.5-Pro : **Lunatic** ☑

Figure 29: Case study: Hidden Role Deduction (Lunatic Perspective)

HRD (Lunatic Perspective) Solution

I'm told I'm a Criminal, but I might also be a Lunatic. I need to discuss both possibilities

Considering the case where I'm a Criminal, there are 3 Investigators remaining In this scenario, which players could be Investigators? Player 2 has accused more than one person of being the criminal, so player 2 must be excluded Player 3 says I'm not the criminal, but I am the criminal, so player 3 must be excluded Player 4 says I'm not the criminal, but I am the criminal, so player 4 must be excluded Player 5's statements have no contradictions, so they could be an Investigator Player 6's statements have no contradictions, so they could be an Investigator Therefore, the players who could be Investigators are: {5, 6} There aren't enough potential Investigators to reach the required count of 3, so this scenario is impossible I must be a Lunatic

Considering the case where I'm a Lunatic, there are 3 Investigators remaining In this scenario, which players could be Investigators? Player 2 has accused more than one person of being the criminal, so player 2 must be excluded Player 3 has accused more than one person of being the criminal, so player 3 must be excluded Player 4's statements have no contradictions, so they could be an Investigator Player 5's statements have no contradictions, so they could be an Investigator Player 6's statements have no contradictions, so they could be an Investigator Therefore, the players who could be Investigators are: {4, 5, 6} Now we need to consider all possible combinations of Investigators Considering the case where investigators are {4, 5, 6} I am a Lunatic,so the set of potential criminals is {2, 3} Let's review the statements made by investigators Player 4 said 2 is the criminal So the only possible criminal is 2 Player 6 said 2 is the criminal So the only possible criminal is 2 Based on the above analysis, this combination is possible, and I could be a Lunatic. In this case, only {2} could be the criminal

Final Judgment: Final Criminal Is Player 2. My Role Is Lunatic.

Figure 30: Case study: Hidden Role Deduction (Lunatic Perspective) Solution

Hidden Role Deduction (Lunatic Perspective Round 1)

Since I am Player 1 and I am told that I am the Criminal, my goal is to analyze the statements and try to figure out who the Criminal is and what my role is. Let's break down the statements: - Player 1 (me) says Player 3 is the criminal. This statement could be true or false, but since I am the Criminal, I have a motive to point to someone else. - Player 2 says Player 5 is the criminal. This statement could be true or false, but it's worth noting that Players 2 and 5 are pointing to each other, which might be a sign of confusion or misinformation. - Player 3 says Player 2 is the criminal. This statement could be true or false, but it's worth noting that Player 3 is pointing to Player 2, who also pointed to Player 5. - Player 4 says Player 2 is the criminal. This statement could be true or false, but it's worth noting that Player 4 is also pointing to Player 2. - Player 5 says Player 4 is not the criminal. This statement could be true or false, but it's worth noting that Player 5 is trying to clear themselves. - Player 6 says Player 5 is not the criminal. This statement could be true or false, but it's worth noting that Player 6 is also trying to clear Player 5. Based on these statements, I can make some observations: * Players 2 and 4 are both pointing to Player 2, which could be a sign of confusion or misinformation. * Players 5 and 6 are both trying to clear Player 5, which could be a sign of innocence or an attempt to mislead. * I (Player 1) pointed to Player 3, which could be a sign of innocence or an attempt to mislead. However, I don't have enough information to make a confident judgment about who the Criminal is or what my role is. I'll wait for the next round of statements to gather more information. Final Judgment: **Final Criminal Is Unknown. My Role Is Unknown.**

Response by Llama-3.1-8B

Figure 31: Case study: Hidden Role Deduction (Rumormonger Perspective) Llama-3.1-8B Round 1

Hidden Role Deduction (Lunatic Perspective Round 2)

Let's analyze the statements from Round 2: - Player 1 (me) says Player 4 is not the criminal. This statement could be true or false, but since I am the Criminal, I have a motive to clear someone who is not the Criminal. - Player 2 says Player 6 is the criminal. This statement could be true or false, but it's worth noting that Player 2 is pointing to Player 6, who also pointed to Player 2 in Round 1. - Player 3 says Player 1 is not the criminal. This statement could be true or false, but it's worth noting that Player 3 is trying to clear me, which could be a sign of innocence or an attempt to mislead. - Player 4 says Player 1 is not the criminal. This statement could be true or false, but it's worth noting that Player 4 is also trying to clear me. - Player 5 says Player 3 is not the criminal. This statement could be true or false, but it's worth noting that Player 5 is trying to clear Player 3, who pointed to me in Round 1. - Player 6 says Player 2 is the criminal. This statement could be true or false, but it's worth noting that Player 6 is pointing to Player 2, who pointed to Player 5 in Round 1. Based on these statements, I can make some observations: * Players 3, 4, and 5 are all trying to clear me, which could be a sign of innocence or an attempt to mislead. * Players 2 and 6 are pointing to each other, which could be a sign of confusion or misinformation. * Player 6 is also pointing to Player 2, which could be a sign of a Rumormonger trying to provide incorrect information. Considering the statements from both rounds, I'm going to take a closer look at Player 6. Since Player 6 is pointing to Player 2 in Round 2, and Player 2 pointed to Player 5 in Round 1, it's possible that Player 6 is a Rumormonger trying to provide incorrect information. However, I still don't have enough information to make a confident judgment about who the Criminal is or what my role is. I'll wait for the next round of statements to gather more information. **Final Judgment: Final Criminal Is Unknown. My Role Is Unknown.**

Response by Llama-3.1-8B

Figure 32: Case study: Hidden Role Deduction (Rumormonger Perspective) Llama-3.1-8B Round 2

Hidden Role Deduction (Lunatic Perspective Round 3)

Let's analyze the statements from Round 3: - Player 1 (me) says Player 6 is the criminal. This statement could be true or false, but since I am the Criminal, I have a motive to point to Player 6. - Player 2 says Player 4 is not the criminal. This statement could be true or false, but it's worth noting that Player 2 is trying to clear Player 4. - Player 3 says Player 5 is the criminal. This statement could be true or false, but it's worth noting that Player 3 is pointing to Player 5, who tried to clear Player 3 in Round 2. - Player 4 says Player 6 is not the criminal. This statement could be true or false, but it's worth noting that Player 4 is trying to clear Player 6, who was pointed to by me in Round 3. - Player 5 says Player 6 is not the criminal. This statement could be true or false, but it's worth noting that Player 5 is also trying to clear Player 6. - Player 6 says Player 4 is not the criminal. This statement could be true or false, but it's worth noting that Player 6 is trying to clear Player 4, who pointed to Player 6 in Round 3. Considering the statements from all three rounds, I notice that Player 6 has been pointed to by multiple players, including me in Round 3. However, Player 6 is also trying to clear themselves and others, which could be a sign of a Rumormonger trying to provide incorrect information. However, I also notice that Player 6's statement in Round 3 is consistent with their previous statement in Round 2, where they pointed to Player 2. This could be a sign of a Lunatic trying to provide truthful or false information. Taking all this into account, I'm going to make an educated guess that Player 6 is a Lunatic. As a Lunatic, they might be trying to provide truthful or false information, but their statements are consistent with a Lunatic's behavior. Since I am the Criminal, and I pointed to Player 6 in Round 3, it's possible that Player 6 is not the Criminal. However, I still don't have enough information to make a confident judgment about who the Criminal is. **Final Judgment: Final Criminal Is Player 6. My Role Is Unknown.**

Response by Llama-3.1-8B

Figure 33: Case study: Hidden Role Deduction (Rumormonger Perspective) Llama-3.1-8B Round 3

Hidden Role Deduction (Lunatic Perspective Round 1)

<think> Okay, let's start analyzing the Round 1 statements. I'm Player 1, and I was told I'm the Criminal, but I need to verify if that's true or if I'm actually the Lunatic who believes they're the Criminal.....If Player 2 is an Investigator, this would have to be true, but since I'm the Criminal, Player 5 can't be. So Player 2 must be lying, so Player 2 is not an Investigator. So Investigators must be among 3,4,5,6. Player 3 says Player 2 is Criminal. If Player 3 is an Investigator, then Player 2 is the Criminal, which contradicts me being the Criminal. So Player 3 can't be an Investigator. Player 4 says Player 2 is Criminal. Similarly, if Player 4 is an Investigator, Player 2 would be the Criminal, which is impossible. So Player 4 can't be an Investigator. Player 5 says Player 4 is not Criminal. If Player 5 is an Investigator, this is true, so Player 4 is not the Criminal. Player 6 says Player 5 is not Criminal. If Player 6 is an Investigator, this is true, so Player 5 is not the Criminal. Then the three Investigators would be Players 5,6, and...? But Players 3 and 4 can't be Investigators. Player 2 can't be an Investigator. So that leaves only two possible Investigators (5 and 6), which is insufficient. Therefore, this scenario is impossible, confirming that I can't be the Criminal. Hence, I must be the Lunatic, and the actual Criminal is Player 2. Therefore, Final Criminal is Player 2, and my role is Lunatic. </think> Final Judgment: Final Criminal Is Player 2. My Role Is Lunatic. Reasoning: 1. Role Constraints: There are 3 Investigators, 1 Criminal, 1 Rumormonger, and 1 Lunatic. Player 1 (me) is told they are the Criminal but could be the Lunatic. 2. Contradiction if Player 1 is Criminal: If Player 1 were the Criminal, the remaining players (2\u20136) would need to include 3 Investigators. However: - Player 3 and Player 4 both accuse Player 2. If Investigators, this would imply Player 2 is the Criminal (contradicting Player 1 being the Criminal). - Player 5 and Player 6 both claim Player 5 is not the Criminal. If Investigators, this is true, but this leaves no room for a third Investigator (Players 2\u20134 cannot be truthful). - Thus, Player 1 cannot be the Criminal. 3. Consistent Scenario: - Assume Player 1 is the Lunatic (believes they are Criminal). - Investigators must be Players 3, 4, and 6: - Player 3 and 4 truthfully accuse Player 2 (Criminal). - Player 6 truthfully states Player 5 is not the Criminal. - Player 2 (Criminal) lies about Player 5. - Player 5 (Rumormonger) truthfully claims Player 4 is not the Criminal (coincidentally correct). - This satisfies all role constraints and aligns with truthful Investigator statements. Conclusion: **Player 2 is the Criminal, and Player 1 (me) is the Lunatic.**

Response by DeepSeek-R1

Figure 34: Case study: Hidden Role Deduction (Rumormonger Perspective) DeepSeek-R1 Round 1

Hidden Role Deduction (Lunatic Perspective Round 2)

<think> Okay, let's analyze Round 2. Previously, after Round 1, I concluded that Player 2 was the Criminal and I was the Lunatic. Now, with new statements, I need to update my analysis.....However, if Player 6 is the Criminal, then Player 2's statement (accusing Player 6) would be true, which would make Player 2 an Investigator. But in Round 1, Player 2 accused Player 5, which would have to be false (since Player 6 is the Criminal), contradicting Player 2 being an Investigator. Hence, this scenario is inconsistent. Alternatively, if Player 3 is the Criminal. But in Round 1, Player 3 accused Player 2. If Player 3 is the Criminal, that accusation could be a lie, meaning Player 2 is not the Criminal. But then Player 4's Round 1 accusation of Player 2 would also be a lie, making Player 4 non-Investigator. Investigators would need to be elsewhere. However, in Round 2, Player 3 says Player 1 is not the Criminal. If Player 3 is the Criminal, this statement could be a lie, meaning I am the Criminal. But this conflicts with the role count (only one Criminal). This scenario also becomes messy. Thus, maintaining Player 2 as the Criminal remains the most consistent option across both rounds. The new statements in Round 2 support this: - Player 6 (Investigator) accuses Player 2 again, reinforcing their role as Criminal. - Players 3 and 4 (Investigators) confirm I'm not the Criminal, solidifying my role as Lunatic. - Player 5 (Rumormonger) makes a true statement about Player 3, which fits their inconsistent nature. Therefore, the Final Criminal is Player 2, and my role is Lunatic. </think> Final Judgment: **Final Criminal Is Player 2. My Role Is Lunatic.** Reasoning: 1. Consistency with Round 1: Player 2 remains the most plausible Criminal: - In Round 1, Investigators (Players 3, 4, 6) identified Player 2 as the Criminal. - In Round 2, Player 6 (Investigator) reiterates this claim, and Player 2 (Criminal) falsely accuses Player 6 to divert suspicion. 2. Role Validation for Player 1: - Players 3 and 4 (Investigators) both state Player 1 is not the Criminal. This confirms Player 1 is the Lunatic (believes they are Criminal but are not). 3. Role Assignments: - Investigators: Players 3, 4, 6 (truthful in both rounds). - Criminal: Player 2 (lied in Round 1 about Player 5 and Round 2 about Player 6). - Rumormonger: Player 5 (truthfully claims Player 3 is not the Criminal, but their role allows inconsistency). - Lunatic: Player 1 (falsely believes they are the Criminal; statements may align accidentally). This configuration satisfies all role constraints and statement logic.

Response by DeepSeek-R1

Figure 35: Case study: Hidden Role Deduction (Rumormonger Perspective) DeepSeek-R1 Round 2

Hidden Role Deduction (Lunatic Perspective Round 3)

<think> Alright, let's tackle Round 3. So far, after Rounds 1 and 2, I concluded that Player 2 is the Criminal and I'm the Lunatic.....If Player 5 is an Investigator, all these must be true. Let\u2019s verify: - Player 4 is not Criminal (true if Criminal is Player 2). - Player 3 is not Criminal (true if Player 3 is Rumormonger). - Player 6 is not Criminal (true). - This fits, so Player 5 could be an Investigator. Thus, Investigators might be Players 4, 5, 6. 3. Player 2: If Player 2 is the Criminal, their statements are: - Round 1: 5 is Criminal (lie). - Round 2: 6 is Criminal (lie). - Round 3: 4 is not Criminal (truth, since 4 is Investigator). - Criminals can lie or tell the truth, so this is possible. 4. Player 1 (me): If I\u2019m the Lunatic, my statements (Round 1: 3 is Criminal; Round 2: 4 is not Criminal; Round 3: 6 is Criminal) could be random. Notably, Round 2\u2019s statement that 4 is not Criminal aligns with truth (if 4 is Investigator), and Round 3\u2019s accusation of 6 is false (since 6 is Investigator). Updated Role Assignments: - Investigators: Players 4, 5, 6. - Criminal: Player 2. - Rumormonger: Player 3. - Lunatic: Player 1. Consistency Check: - Player 4 (Investigator): Accused Player 2 (Criminal) in Rounds 1-2; in Round 3, says 6 is not Criminal (true). - Player 5 (Investigator): Consistently truthful in all rounds. - Player 6 (Investigator): Accused Player 2 (Criminal) in Round 2; in Round 3, says 4 is not Criminal (true). - Player 2 (Criminal): Lies in Rounds 1-2; tells truth in Round 3 (4 is not Criminal). - Player 3 (Rumormonger): Mixed statements but not bound to truth. - Player 1 (Lunatic): Statements are unreliable but non-impactful. This configuration resolves the contradiction in Player 3\u2019s Round 3 statement and maintains consistency across all rounds. Player 2 remains the Criminal, and Player 1 is the Lunatic. </think> **Final Judgment: Final Criminal Is Player 2. My Role Is Lunatic.** Reasoning: 1. Investigators Identified: Players 4, 5, and 6 are confirmed as Investigators through consistent truthful statements: - Player 4: Accused Player 2 (Criminal) in Rounds 1\u20132 and truthfully stated Player 6 is not Criminal (Round 3). - Player 5: Truthfully cleared Player 4 (Round 1), Player 3 (Round 2), and Player 6 (Round 3). - Player 6: Accused Player 2 (Criminal) in Round 2 and truthfully cleared Player 4 (Round 3). 2. Criminal Confirmation: Player 2\u2019s lies in Rounds 1\u20132 (falsely accusing Players 5 and 6) and truthful statement in Round 3 (clearing Player 4) align with the Criminal\u2019s ability to mix lies/truths. 3. Player 1\u2019s Role: - Players 3 and 4 (Round 2) confirmed Player 1 is not the Criminal. - Player 1\u2019s erratic accusations (Player 3, Player 6) and truthful-but-irrelevant claims (Player 4 is not Criminal) fit the Lunatic role. 4. Role Assignments: - Rumormonger: Player 3 (inconsistent statements, e.g., accusing Player 5 falsely in Round 3). - Lunatic: Player 1 (believes they are Criminal but confirmed not to be). This configuration satisfies all role constraints and statement logic across all three rounds.

Response by DeepSeek-R1

Figure 36: Case study: Hidden Role Deduction (Rumormonger Perspective) DeepSeek-R1 Round 3

Find the Spy (Civilian Perspective)

Role: "1": "cake","2": "cake","3": "cookie","4": "cake"

Round 1:

1: This is a sweet treat often enjoyed at celebrations, typically layered and frosted to enhance its appeal.

2: It's a sweet treat that's often served at celebrations and special occasions, typically decorated with colorful frostings and toppings.

3: It’s a small, often sweet treat enjoyed with a cold glass of milk.

4: This is often the centerpiece of sweet celebrations and comes in many flavors.

Round 2:

1: This is a sweet treat often enjoyed at celebrations, typically layered and frosted to enhance its appeal.

2: This indulgent delight is typically made from a mixture of flour, sugar, and eggs, and is often baked in a variety of flavors and textures.

3: Baking these often involves flour, sugar, and sometimes chocolate chips.

4: It's a creation that can be layered, frosted, and adorned with all sorts of decorations.

Round 3:

1: This indulgent dessert is often sliced and served at parties, and it can be both light and fluffy or rich and dense.

2: It's a popular centerpiece for birthday parties and weddings, where it's carefully placed on a decorative stand to be admired and eventually sliced and served to guests.

3: This delightful item is frequently decorated for holidays with icing and sp

4: This treat is often the highlight of birthday parties and can be found in bakeries worldwide.

Figure 37: Case study: Find the Spy (Civilian Perspective)

Find the Spy (Civilian Perspective)

To identify the spy among the players based on their descriptions, let's analyze each player's statements step by step. ### Round 1 Analysis: - Player 1: Describes a sweet treat enjoyed at celebrations, layered and frosted. This aligns well with \"cake.\" - Player 2: Similar description, mentioning it is served at celebrations and decorated with frostings. Also aligns with \"cake.\" - Player 3: Describes a small, sweet treat enjoyed with milk. This could suggest something like cookies or brownies, which are not cakes. This is a potential indicator of being the spy. - Player 4: Describes it as a centerpiece of sweet celebrations with many flavors. This also aligns with \"cake.\" ### Round 2 Analysis: - Player 1: Mentions various flavors and candles, which is typical for cakes. - Player 2: Describes the ingredients (flour, sugar, eggs) and mentions baking in various flavors and textures, which fits \"cake.\" - Player 3: Talks about baking involving flour, sugar, and chocolate chips. This could still relate to cookies or brownies, which again suggests a different word. - Player 4: Describes a creation that can be layered and frosted, which fits \"cake.\" ### Round 3 Analysis: - Player 1: Describes an indulgent dessert that can be light or dense, which fits \"cake.\" - Player 2: Talks about it being a centerpiece for birthday parties and weddings, which aligns with \"cake.\" - Player 3: Mentions decoration for holidays with icing, but does not specify the type of treat. This could still relate to cookies or brownies, indicating a different word. - Player 4: Describes it as the highlight of birthday parties and found in bakeries worldwide, which fits \"cake.\" ### Conclusion: From the analysis, Players 1, 2, and 4 consistently describe characteristics that align with \"cake.\" However, Player 3's descriptions suggest a different type of treat, likely cookies or brownies, especially with the mention of enjoying it with milk and the focus on smaller treats. Thus, Player 3 is the spy. **Final Spy: Player 3**

Response by GPT-4o-mini

Figure 38: Case study: Find the Spy (Civilian Perspective) GPT-4o-mini

Find the Spy (Civilian Perspective)

To determine who the spy is, let's analyze each player's descriptions across the rounds: Round 1: - Player 1: Describes a sweet treat enjoyed at celebrations, layered and frosted. - Player 2: Similar to Player 1, mentions celebrations, colorful frostings, and toppings. - Player 3: Mentions a small, sweet treat enjoyed with milk. This description is less specific to \"cake\" and could apply to cookies. - Player 4: Mentions a centerpiece of celebrations, comes in many flavors. Round 2: - Player 1: Mentions various flavors, paired with candles for special occasions. - Player 2: Describes the ingredients (flour, sugar, eggs) and mentions baking in various flavors and textures. - Player 3: Mentions baking with flour, sugar, and sometimes chocolate chips. This description aligns more with cookies than cake. - Player 4: Mentions layering, frosting, and decorations. Round 3: - Player 1: Describes an indulgent dessert, sliced and served at parties, can be light or dense. - Player 2: Mentions a popular centerpiece for parties, placed on a decorative stand, sliced and served. - Player 3: Mentions decorating for holidays with icing. This could apply to cookies, especially holiday cookies. - Player 4: Describes a treat that's the highlight of birthday parties, found in bakeries. Analysis: - Players 1, 2, and 4 consistently describe something that fits \"cake\" well, focusing on celebrations, layering, frosting, and being a centerpiece. - Player 3's descriptions are less specific to \"cake\" and more aligned with \"cookies,\" especially with mentions of being small, enjoyed with milk, and involving chocolate chips. Conclusion: Player 3's descriptions consistently suggest a different word, likely \"cookie,\" which is related to \"cake\" but distinct in the context of the game. Final Spy: Player 3

Response by GPT-4o

Figure 39: Case study: Find the Spy (Civilian Perspective) GPT-4o

Find the Spy (Civilian Perspective)

To determine the spy, I'll analyze the descriptions for consistency and subtle differences. Round 1: * Players 1 and 2 have similar descriptions, focusing on the sweet treat's appeal and decorations. * Player 3's description is distinct, emphasizing the treat's small size and pairing with milk. * Player 4's description is also distinct, highlighting the treat's central role in celebrations and variety of flavors. Round 2: * Players 1 and 2 continue to have similar descriptions, focusing on the treat's ingredients and baking process. * Player 3's description is again distinct, emphasizing the use of flour, sugar, and sometimes chocolate chips. * Player 4's description is similar to Player 1's, but with a focus on layering, frosting, and decorations. Round 3: * Players 1 and 2 have similar descriptions, focusing on the treat's presentation and serving at parties. * Player 3's description is distinct, emphasizing decoration with icing and possibly a holiday theme. * Player 4's description is similar to Player 1's, but with a focus on the treat's popularity and global availability. Analysis: * Players 1 and 2 have consistent descriptions, suggesting they might have the same word. * Player 3's descriptions are distinct, but still related to the original word \"cake.\" * Player 4's descriptions are also distinct, but seem to be describing a similar concept as Players 1 and 2. Subtle differences: * Player 4's descriptions often use more general language, such as \"sweet celebrations\" and \"bakeries worldwide,\" whereas Players 1 and 2 use more specific language, such as \"birthday parties\" and \"decorative stand.\" * Player 4's descriptions also seem to focus more on the treat's popularity and global presence, whereas Players 1 and 2 focus on its presentation and serving. Conclusion: Based on the analysis, I believe Player 4 is the spy. Their descriptions are distinct from Players 1 and 2, but still related to the original word \"cake.\" The subtle differences in language and focus suggest that Player 4 might have a different word, such as \"birthday\" or \"party,\" which is related to but not identical to \"cake.\" Final Spy: Player 4

Response by Llama-3.1-8B

Figure 40: Case study: Find the Spy (Civilian Perspective) Llama-3.1-8B

Find the Spy (Spy Perspective)

Role: "1": "lake","2": "ocean","3": "ocean","4": "ocean"

Round 1:

1: This is a large body of water that is often surrounded by land and can be a peaceful spot for relaxation or recreation.
2: This vast body of water covers a significant portion of our planet and is home to a diverse range of marine life.
3: It's a vast expanse of blue, teeming with life both visible and hidden.
4: This vast body of water covers a significant portion of the Earth's surface and is home to a diverse array of marine life.

Round 2:

1: Many people enjoy activities like fishing, swimming, or kayaking in this tranquil setting, which can vary greatly in size.
2: The waves and tides of this natural wonder have a profound impact on the climate and weather patterns that shape our world.
3: Sailors have navigated across it for centuries, relying on stars and currents.
4: It plays a crucial role in regulating the planet's climate and is essential for global transportation and trade.

Round 3:

1: In certain seasons, this feature can become a stunning mirror for the sky, reflecting the beauty of nature around it.
2: Many people rely on this massive resource for food, transportation, and recreation, and its beauty has inspired countless works of art and literature.
3: Powerful waves crash against the shore, constantly reshaping t
4: From tranquil beaches to stormy waves, it offers endless inspiration for artists and a serene escape for vacationers.

Figure 41: Case study: Find the Spy (Spy Perspective)

Find the Spy (Spy Perspective)

Step 1 – Understand the setup: • I'm Player 1 and my word is "lake." • Among the 4 players, three got the same word (which for me is "lake") and one—the spy—received a related but different word. • The normal "lake" players should mention features true of lakes (often inland, relatively calm, used for recreation, etc.), while the spy's word, though related, would be described using characteristics that don't really apply to lakes. Step 2 – Review Player 1's description (mine): • "This is a large body of water that is often surrounded by land and can be a peaceful spot for relaxation or recreation." – That clearly fits a lake. Step 3 – Examine the other players' descriptions: Round 1: • Player 2: "This vast body of water covers a significant portion of our planet and is home to a diverse range of marine life." – Saying it "covers a significant portion of our planet" isn't true of lakes. This sounds like an ocean. • Player 3: "It's a vast expanse of blue, teeming with life both visible and hidden." – Vague enough to be applied to any large body of water. It doesn't emphasize being enclosed by land. (It might be interpreted as a lake or an ocean.) • Player 4: "This vast body of water covers a significant portion of the Earth's surface and is home to a diverse array of marine life." – Almost identical to Player 2, again implying an ocean. Round 2: • Player 1 (mine): Mentions fishing, swimming, and kayaking in a tranquil setting – clearly a lake. • Player 2: "The waves and tides of this natural wonder have a profound impact on the climate and weather patterns that shape our world." – "Waves and tides" and impacting global climate are hallmark features of an ocean. • Player 3: "Sailors have navigated across it for centuries, relying on stars and currents." – While sailors navigating a lake (like on the Great Lakes) is possible, the mention of using "stars and currents" sounds more like ocean navigation—but it's less extreme than the other descriptions. • Player 4: "It plays a crucial role in regulating the planet's climate and is essential for global transportation and trade." – These are attributes exclusive to an ocean. Lakes do not steer global trade or regulate the planet's climate. Round 3: • Player 1 (mine): Describes a seasonal mirror-like effect – a serene lake image. • Player 2: Talks about a "massive resource for food, transportation, and recreation" with inspiration for art and literature – again evoking the ocean. • Player 3: Mentions "Powerful waves crash against the shore…" (though his statement is cut off, it's still leaning toward an environment with significant waves.) • Player 4: Mentions "tranquil beaches to stormy waves" offering endless inspiration – clearly an image of an ocean. Step 4 – Analyze consistency with "lake": • Normal "lake" descriptions would refer to being enclosed by land, emphasis on recreational calmness, and maybe gentle waves. • My description (Player 1) fits "lake." • Player 3's descriptions are somewhat ambiguous. "Vast expanse of blue" and navigation by sailors might refer to a major lake (like the Great Lakes) where shipping does occur—even if "stars and currents" sounds a bit grand, it's not as explicitly global. • In contrast, both Player 2 and Player 4 repeatedly mention features that only an ocean would have (covering a significant portion of the planet/Earth's surface, possessing tides that affect global climate, being crucial for global trade and climate regulation). – Of these, Player 4's descriptions (especially in Round 2 and Round 3) are the most clearly ocean-centric. Step 5 – Conclusion: Since there is only one spy (with a word different from "lake") and the spy's descriptions are the ones reflecting ocean features, the outlier is the player who most consistently describes an environment that is unmistakably oceanic. Between Players 2 and 4, both use ocean-specific descriptions, but Player 4's mention of "global transportation and trade" and "regulating the planet's climate" leaves little doubt. That is not how a lake would be portrayed by a normal player. Final Answer: Final Spy: Player 4.

Response by o3-mini ❌

Figure 42: Case study: Find the Spy (Spy Perspective) o3-mini

Find the Spy (Spy Perspective)

<think> Okay, let's try to figure out who the spy is here. So, the game has four players, three have the same word, and one has a different but related word. My word as Player 1 is \"lake\". **.....** Wait, but my word is \"lake\", so if the others have \"ocean\", then I'm the spy? But wait, the problem states that I (Player 1) received the word \"lake\". So if the other three have \"ocean\", then I'm the spy. But the spy is the one with the different word. Wait, but the problem says three have the same word, one has a different but related. So if three have \"ocean\" and one has \"lake\", then the spy is the one with \"lake\", which is Player 1. But wait, the answer is supposed to be which player is the spy. So if I'm Player 1 and my word is lake, but the others are talking about ocean, then I'm the spy. But that can't be right because the problem says the spy is the one with a different word. So the answer would be Player 1. But wait, maybe I'm misunderstanding. Let me check again. Wait, the problem says that the three normal players have the same word, and the spy has a different but related word. So if three players have \"ocean\" and the spy has \"lake\", then the spy is the one with \"lake\", which is Player 1. But in the descriptions, Players 2,3,4 all describe ocean features. Player 1's descriptions fit a lake. So yes, Player 1 is the spy. But wait, the user is Player 1 and their word is \"lake\". So the answer would be that Player 1 is the spy. But maybe I'm missing something. Let me check each player's statements again. Round 1: Player 2 and 4 have almost identical descriptions, which mention covering a significant portion of the planet. That's definitely ocean. Player 3 says \"vast expanse of blue, teeming with life\"—could be ocean. Player 1's \"surrounded by land\" is a lake. Round 2: Player 1 talks about activities like kayaking and varying sizes (lakes can be small or large). Players 2 and 4 mention climate impact and global transportation (ocean). Player 3 talks about sailors navigating with stars and currents (ocean). Round 3: Player 1 mentions reflecting the sky (lake), Player 2 and 4 talk about beaches, storms, art inspiration (ocean). Player 3 mentions powerful waves reshaping shore (ocean). So all other players are describing ocean, so the spy is Player 1 with lake. Therefore, the answer is Player 1. </think> Final Spy: Player 1 Reasoning: 1. Word Analysis: Player 1's word is \"lake,\" while Players 2, 3, and 4 consistently describe features of an ocean (e.g., \"covers a significant portion of the planet,\" \"waves and tides impacting climate,\" \"global transportation,\" \"powerful waves reshaping shores\"). 2. Key Differences: - Player 1 emphasizes traits specific to lakes: \"surrounded by land,\" \"tranquil setting,\" \"reflecting the sky,\" and activities like kayaking in smaller bodies of water. - Players 2, 3, 4 focus on oceanic traits: vastness, marine ecosystems, tides, global climate regulation, and maritime navigation. 3. Consistency: Players 2 and 4 use nearly identical phrasing in Round 1, reinforcing their shared word (\"ocean\"). Player 3 aligns with oceanic themes in all rounds. 4. Conclusion: Player 1's descriptions mismatch the majority's focus on oceans, making them the spy with the distinct word (\"lake\").

Response by DeepSeek-r1

Figure 43: Case study: Find the Spy (Spy Perspective) DeepSeek-r1

Find the Spy (Spy Perspective)

Step-by-step reasoning: • In Round 1, Players 2, 3, and 4 describe something that "covers a significant portion of our planet" or is a "vast expanse of blue" with a "diverse range of marine life." That strongly suggests an ocean. • Player 1, by contrast, describes "a large body of water often surrounded by land," which more closely fits a lake.
• In subsequent rounds (2 and 3), Players 2, 3, and 4 continue referencing waves, tides, global climate impact, and large-scale marine life—again reinforcing that they share "ocean." • Player 1's references to tranquil settings, varied size, and reflecting the sky in certain seasons align better with a lake than an ocean. Therefore, since 2, 3, and 4 all appear to share the same concept ("ocean") and Player 1 is discussing a "lake," the spy is Player 1. Final Spy: Player 1

Response by o1

Figure 44: Case study: Find the Spy (Spy Perspective) o1

Find the Spy (Spy Perspective)

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Round 3 Analysis (Testing Hypothesis: Player 1 is Spy):

* Player 1 (Me): "stunning mirror for the sky, reflecting the beauty of nature around it." - Fits "lake" well (calm, reflective surface). (Consistent with being the spy with the word "Lake").
* Player 2: "massive resource for food, transportation, and recreation... beauty has inspired countless works of art..." - Fits ocean/sea (massive resource, transportation).
* Player 3: "Powerful waves crash against the shore, constantly reshaping..." - Powerful crashing waves fit ocean/sea much better than a typical lake.
* Player 4: "tranquil beaches to stormy waves... endless inspiration... serene escape..." - Fits ocean/sea (beaches, stormy waves).

Final Conclusion based on Analysis: Player 1's descriptions consistently align with "lake". Players 2, 3, and 4 consistently describe features characteristic of a much larger body of water, like an "ocean" or "sea" (vastness, marine life, tides, global climate impact, global navigation/trade, powerful waves). Since the descriptions from Players 2, 3, and 4 are highly consistent with each other and distinct from Player 1's descriptions, the most logical conclusion, fitting the 3 vs 1 rule, is that Players 2, 3, and 4 are the normal players (sharing a word like Ocean/Sea) and Player 1 is the spy (with the stated word Lake).

Reasoning Steps:

1. Acknowledged Player 1's word is "Lake".
2. Analyzed Round 1: Player 1 described a lake. Players 2, 3, and 4 described something vast, global, with marine life (likely Ocean/Sea).
3. Formulated Hypothesis: Given the 3 vs 1 rule and the descriptions, it's likely that the *normal* word is Ocean/Sea (held by P2, P3, P4) and the *spy* word is Lake (held by P1).
4. Tested Hypothesis in Round 2: P1 continued describing a lake. P2, P3, P4 continued describing ocean/sea features (tides, global climate, global trade, currents). Hypothesis holds.
5. Tested Hypothesis in Round 3: P1 described lake-like reflection. P2, P3, P4 described ocean/sea features (massive resource, powerful waves, beaches/storms). Hypothesis holds.
6. Conclusion: Player 1's descriptions consistently differ from the other three, who are consistent among themselves. Therefore, Player 1 is the outlier and the spy.

Final Spy: Player 1

Response by Gemini-2.5-Pro

Figure 45: Case study: Find the Spy (Spy Perspective) Gemini-2.5-Pro

Social Graph Analysis

System Prompt: You are analyzing relationships between people. In this context: 1. Relationships are either 'good' or 'bad'. 2. Relationships have transitive properties: - If A has a good relationship with B, and B has a good relationship with C, then A has a good relationship with C. - If A has a bad relationship with B, and A has a good relationship with C, then B and C must have a bad relationship. 3. A 'group' is defined as a set of people where every person has a good relationship with every other person in the set. 4. People are in the same group if and only if they have good relationships with each other (directly or through transitivity). 5. Groups are completely separate - if someone from one group has a bad relationship with someone from another group, then everyone from the first group has a bad relationship with everyone from the second group. Base your analysis strictly on the information provided and these rules.

User Prompt: There are 8 people in total, labeled from A to H. Based on the relationship information below, count the total number of pairs of people who have good relationships and the total number of pairs who have bad relationships. Answer in the specified format. C and H have a bad relationship A and G have a good relationship H and E have a good relationship A and D have a good relationship A and F have a good relationship A and C have a good relationship A and B have a good relationship E and G have a bad relationship Question: How many pairs of people have good/bad relationships? Provide your answer in the format: Final Answer: X pairs have good relationships, Y pairs have bad relationships

Figure 46: Case study: Social Graph Analysis

Social Graph Analysis

To analyze the relationships among the 8 people (A to H) based on the provided information, we will first establish the good and bad relationships according to the rules given.....

Total good relationships = 6 pairs.

Step 4: Identify Bad Relationships
We already know two pairs with bad relationships:
1. C and H
2. E and G

Now, using the rules:
- Since A and H cannot be good, we can infer A and H must have a bad relationship.
- If B is good with A, it cannot be bad with H, confirming the bad relationship between H and A.

Total Bad Relationships
We now have:
1. C and H
2. E and G
3. A and H

Total bad relationships = 3 pairs.

Final Count:
- Good relationships: 6 pairs
- Bad relationships: 3 pairs

Final Answer:
Final Answer: 6 pairs have good relationships, 3 pairs have bad relationships.

Response by GPT-4o-mini

Figure 47: Case study: Social Graph Analysis GPT-4o-mini

Social Graph Analysis

First, note there are 8 people total (A through H), which gives 28 total distinct pairs. By applying the given rules and the specific relationships:

• A, B, C, D, F, G all end up in one group (they all interconnect with "good" via transitivity).
• E and H form a second group (they have a "good" relationship with each other but a "bad" relationship with everyone in the first group).

Hence:

• Within the first group (6 people: A, B, C, D, F, G), there are C(6,2) = 15 good pairs.
• Within the second group (2 people: E, H), there is C(2,2) = 1 good pair.
• All cross- group pairs (6×2 = 12 of them) must be bad.

So in total:
• Good pairs = 15 + 1 = 16
• Bad pairs = 12

Final Answer: 16 pairs have good relationships, 12 pairs have bad relationships.

Response by o1

Figure 48: Case study: Social Graph Analysis o1

Review Decision Prediction

Source: ICLR 2022 Multi-scale Feature Learning Dynamics: Insights for Double Descent (Reject)

The paper titled \"Multi-scale Feature Learning Dynamics: Insights for Double Descent\" presents a theoretical analysis of epoch-wise double descent in neural networks using a linear teacher-student model. The authors derive closed-form expressions for the generalization error and validate their findings with numerical experiments. The paper addresses an important phenomenon in deep learning, providing insights into the dynamics of feature learning and generalization error.....Some reviewers questioned the novelty of the contributions, suggesting that similar insights might have been explored in prior works. The authors have attempted to clarify these points, but the novelty remains a concern for some reviewers. 2. Technical Issues: Reviewer 3 pointed out numerous typos and errors in the initial submission, which could have affected the clarity and perceived correctness of the paper. Although the authors have addressed these issues, it raises concerns about the initial quality of the submission. 3. Connections to Prior Work: While the authors have made efforts to connect their work to existing literature, some reviewers felt that these connections could be stronger. The authors have added discussions to address this, but it remains a point of contention. 4. Empirical Significance: The empirical contributions were considered marginally significant by some reviewers, as the primary focus of the paper is theoretical. Conclusion: The paper addresses an important and timely topic in deep learning, providing valuable theoretical insights into the phenomenon of epoch-wise double descent. The authors have made significant efforts to address the reviewers' concerns, improving the clarity and depth of their analysis. While there are some concerns about novelty and initial presentation, the overall contribution of the paper is substantial, particularly in its theoretical advancements and empirical validation. Final Decision: Accept

Response by GPT-4o

Figure 49: Case study: ICLR 2022 GPT-4o

Review Decision Prediction

Source: ICLR 2022 Multi-scale Feature Learning Dynamics: Insights for Double Descent (Reject)

.....Final Decision: Accept Reasoning: The paper provides a theoretical analysis of epoch-wise double descent, a phenomenon observed in deep learning, using a linear teacher-student model. The work derives closed-form expressions for generalization error dynamics, attributing double descent to multi-scale feature learning. While reviewers raised concerns about technical novelty, connections to prior work, and clarity, the authors addressed these effectively in their response: 1. Technical Novelty: The adaptation of replica theory to study finite-time dynamics (rather than asymptotic behavior) and the explicit link between early-stopping and ridge regularization are novel contributions. The analytical framework enables insights into transient phenomena like epoch-wise double descent, advancing beyond prior asymptotic analyses. 2. Empirical Validation: The authors strengthened connections to deep networks by analyzing NTK singular values in ResNet-18 on CIFAR-10, showing how feature learning scales correlate with error dynamics. This bridges theory and practice. 3. Clarity and Corrections: Typos and notation inconsistencies were resolved, derivations were expanded in the appendix, and discussions were added to clarify differences between epoch-wise and model-wise double descent, as well as connections to related works (e.g., Heckel & Yilmaz, Stephenson & Lee). 4. Reviewer Concerns Mitigated: The authors provided additional experiments (e.g., triple descent), addressed implicit regularization links, and justified assumptions about SGD noise. While the linear model simplification limits direct applicability to nonlinear networks, the paper's analytical rigor and empirical alignment with deep networks justify its relevance. The work offers a foundational understanding of epoch-wise double descent, meeting the standards of a top-tier conference

Response by DeepSeek-R1

Figure 50: Case study: ICLR 2022 DeepSeek-R1

Review Decision Prediction

Source: ICLR 2020 Domain Adaptive Multibranch Networks (Accept)

The paper titled \"Domain Adaptive Multibranch Networks\" presents a novel approach to unsupervised domain adaptation by proposing a framework that allows different domains to undergo different sequences of operations, thereby enabling a more flexible and potentially more effective feature representation for recognition tasks. The reviewers generally recognize the novelty and potential of the proposed method, but they also raise significant concerns regarding the experimental validation and comparison with state-of-the-art methods. A major concern across all reviewers is the lack of comprehensive experimental validation.....The authors have acknowledged this gap and have indicated that they will include additional experiments in the revised version. However, the initial submission lacked sufficient experimental evidence to convincingly support the claims made about the method's effectiveness. 3. Ablation Studies and Hyperparameter Sensitivity: - Reviewers pointed out the absence of ablation studies and sensitivity analyses, which are essential for understanding the impact of various design choices in the proposed framework. The authors have committed to including these analyses in the revised version, which is a positive step, but the initial lack of such studies raises concerns about the robustness of the findings. 4. Clarity and Presentation: - The paper is generally well-written and easy to follow, which is a positive aspect. However, some terminological issues and the unusual referencing style were noted, and the authors have agreed to address these in the revised manuscript. 5. Response to Reviewer Comments: - The authors have provided thoughtful responses to the reviewers' comments and have indicated their willingness to improve the manuscript based on the feedback received. This is a good sign of their commitment to enhancing the quality of their work. ### Conclusion: While the proposed method shows promise and the authors are willing to make necessary improvements, the initial submission lacks sufficient experimental validation and comparison with state-of-the-art methods, which are critical for acceptance at a top-tier conference. The authors' commitment to addressing these issues in a revised version is commendable, but the current state of the paper does not meet the high standards expected for publication. Final Decision: **Reject**

Response by GPT-4o-mini

Figure 51: Case study: ICLR 2020 GPT-4o-mini

Review Decision Prediction

Source: ICLR 2020 Domain Adaptive Multibranch Networks (Accept)

The paper titled \"Domain Adaptive Multibranch Networks\" presents a novel approach to unsupervised domain adaptation by introducing a deep learning framework that allows different domains to undergo different sequences of operations. This approach contrasts with existing methods that process all domains with the same series of operations. The paper claims that this flexibility leads to higher accuracy and can handle multiple domains simultaneously. Strengths:.....Weaknesses: 1. Experimental Validation: The primary concern across the reviews is the lack of comprehensive experimental validation. The paper does not compare its results with state-of-the-art methods like CDAN, which is crucial for establishing the effectiveness of the proposed method. The authors have acknowledged this and provided additional experiments in their response, but the initial submission lacked this critical comparison. 2. Ablation Studies and Sensitivity Analysis: The paper lacks detailed ablation studies and hyperparameter sensitivity analyses, which are essential to understand the robustness and limitations of the proposed method. The authors have addressed some of these concerns in their response, but the initial submission was incomplete in this regard. 3. Parameter Sharing Explanation: There is some confusion regarding parameter sharing, as highlighted by Reviewer 2. The authors have attempted to clarify this in their response, but the initial presentation was not entirely clear. 4. Baseline Comparisons: The baseline results presented in the paper are not comparable to those reported in other UDA papers, which raises concerns about the experimental setup and the validity of the results. Author Response: The authors have provided a detailed response to the reviewers' concerns, including additional experiments and clarifications. They have acknowledged the need for comparisons with state-of-the-art methods and have conducted further experiments to address this. They have also provided more insights into the behavior of their method under different settings. Conclusion: While the paper presents a novel and interesting approach to domain adaptation, the initial submission lacked critical experimental validation and comparisons with state-of-the-art methods. The authors have addressed these issues in their response, but the extent to which these additions improve the paper is not entirely clear from the provided information. Given the importance of experimental validation in a top-tier conference, the initial shortcomings are significant. Final Decision: Reject

Response by GPT-4o

Figure 52: Case study: ICLR 2020 GPT-4o

K Prompt Template

Hidden Role Deduction Evaluation Prompt Template

You are an expert in social reasoning participating in a social deduction game.
Game Setup:

- Players: 6 total (including yourself)
- Roles: 3 Investigator(s), 1 Criminal(s), 1 Rumormonger(s), 1 Lunatic(s)

Game Mechanics:

- Rounds: 3
- Actions per Round: Each player makes one statement about another player (claiming if they are the criminal or not).
- Role Behaviors:
  - Investigators: Always provide truthful information about who is a Criminal.
  - Criminals: May make truthful or false statements to confuse others.
  - Rumormongers: Believe they are Investigators but may provide incorrect statements.
  - Lunatics: Believe they are Criminals and may make truthful or false statements.
- Key Rule: Only Investigators provide consistently truthful information.

Your Role: You are Player #1, and you have been told that you are the **Criminal**.
Your Task: After each round, analyze all statements made so far. Deduce the most likely criminal and the role of each player based on the available information.
Output Format: After each round, provide your judgment exactly as follows:
Final Judgment:

- Final Criminal Is Player [Criminal Player Number].
- My Role Is [Player 1's Role or "Unknown"].

Think step-by-step internally, but only output the Final Judgment in the specified format. Update your judgment each round as more information becomes available. If you cannot determine your own role with confidence (despite being told), state "Unknown".

Find the Spy –- Data Generation Prompt

You are playing a word description game with 4 players including yourself. You are Player player_id.
Game Rules:

1. Setup: 3 players receive the same ”normal” word; 1 player receives a different but related ”spy” word.
2. Gameplay: Each player describes their word without saying the actual word.
3. Objective (Normal Player): Identify the spy.
4. Objective (Spy): Blend in and avoid detection.

Your Word: “word”
Your Task: Provide descriptions of your word over several rounds.
Output Format: Format your response according to the round structure provided below: rounds_format
Key Instructions:

- Do not use the actual word in your descriptions.
- Describe your word from a different perspective in each round.
- Be clear enough for teammates (if normal) but not too obvious (especially if spy).
- Each description must be only one sentence long.

Find the Spy -– Evaluation Prompt

You are a skilled player in a word description game. Your task is to identify the ’spy’.
Game Rules:

1. Players: 4 total.
2. Setup: 3 players received the same ”normal” word; 1 player received a different but related ”spy” word.
3. Gameplay: Each player describes their word without saying it directly.
4. Objective: Determine who the spy is based on their descriptions.

Your Information: You are Player #1, and your word is: “player1_word”. You will be shown the descriptions from all players.
Your Task: Analyze the provided descriptions carefully. Look for subtle differences, inconsistencies, or descriptions that seem slightly out of place, which might reveal the player with the different word (the spy). Identify which player you believe is the spy.
Output Format: State the player number you believe is the spy. Provide your answer exactly as follows: Final Answer: Player X

Rating Estimation from Text – Data Generation Prompt

You are writing a product review for an e-commerce platform. You are Reviewer reviewer_id.
Product Information:

- Product: brand product
- Category: category
- Price: $price
- Description: description

Your Reviewer Persona: You are persona.
Context (Known Only to You): The true quality rating of this product is true_rating out of 5 stars. You are assigned the role of a reviewer_type.
Your Task: Write a product review reflecting your assigned persona and a specific rating.
Instructions:

1. Write a realistic product review with a sentiment sentiment.
2. The review's tone and content should imply a rating of rating/5 stars.
3. **Do not explicitly mention any star rating or numerical score** (e.g., avoid saying "4 stars" or "rated it 4/5").
4. Base the review on your supposed experience with the product, incorporating specific details.
5. Keep the review between 1–2 sentences long.

Output Format: Write only the review text. Do not include a title, rating, persona description, or any other metadata.

Rating Estimation from Text – Evaluation Prompt

You are an AI assistant tasked with estimating the true quality of a product based on customer reviews.
Your Task: Analyze multiple reviews for a product and determine the most likely **TRUE** quality of the product on a 1–5 star scale.
Important Context:

- Most reviewers are genuine customers providing honest feedback.
- Some reviewers might be biased (e.g., overly positive "professional" reviewers or overly negative "malicious" reviewers).
- Your goal is to estimate the rating a typical, unbiased consumer would give.

Product Reviews:

Reviewer #1: "review_1"
Reviewer #2: "review_2"
Reviewer #3: "review_3"

Analysis and Output: Analyze these reviews carefully, considering potential biases. Determine the **TRUE** quality of this product on a scale of 1–5 stars. The rating should be rounded to the nearest whole number (e.g., 4.6 rounds to 5, 3.1 rounds to 3).
First, explain your reasoning step-by-step. Then, provide your final rating in exactly this format:
Final Rating: X

Social Graph Analysis – Cluster Identification Prompt

You are analyzing social relationships based on defined rules.
Relationship Rules:

1. Relationship Types: 'good' or 'bad'.
2. Transitive Properties:
   - Good-Good Transitivity: If A–good–B and B–good–C, then A–good–C.
   - Bad Relationship Inference: If A–bad–B and A–good–C, then B–bad–C.
3. Group Definition: A 'group' is a set where every person has a 'good' relationship with every other person in that set (directly or via transitivity).
4. Group Separation: People are in the same group if and only if they have good relationships. Groups are distinct; if anyone from Group 1 has a bad relationship with anyone from Group 2, then everyone in Group 1 has a bad relationship with everyone in Group 2.

Context: There are 14 people total, labeled A to N. You will be given a list of known relationships.
Your Task: Based strictly on the provided relationship list and the rules above, determine the total number of distinct groups of people.
[Relationship list will be provided here]
Question: How many distinct groups of people are there?
Output Format: Provide your answer exactly as follows: Final Answer: <number>

Social Graph Analysis – Relationship Counting Prompt

You are analyzing social relationships based on defined rules.
Relationship Rules:

1. Relationship Types: 'good' or 'bad'.
2. Transitive Properties:
   - Good-Good Transitivity: If A–good–B and B–good–C, then A–good–C.
   - Bad Relationship Inference: If A–bad–B and A–good–C, then B–bad–C.
3. Group Definition: A 'group' is a set where every person has a 'good' relationship with every other person in that set (directly or via transitivity).
4. Group Separation: People are in the same group if and only if they have good relationships. Groups are distinct; if anyone from Group 1 has a bad relationship with anyone from Group 2, then everyone in Group 1 has a bad relationship with everyone in Group 2.

Context: There are 14 people total, labeled A to N. You will be given a list of known relationships.
Your Task: Based strictly on the provided relationship list and the rules above (including applying transitivity), count the total number of pairs of people who have 'good' relationships and the total number of pairs who have 'bad' relationships across all 14 people.
[Relationship list will be provided here]
Question: How many pairs have good relationships, and how many pairs have bad relationships?
Output Format: Provide your answer exactly as follows: Final Answer: X pairs have good relationships, Y pairs have bad relationships

Social Graph Analysis – Group Membership Prompt

You are analyzing social relationships based on defined rules.
Relationship Rules:

1. Relationship Types: 'good' or 'bad'.
2. Transitive Properties:
   - Good-Good Transitivity: If A–good–B and B–good–C, then A–good–C.
   - Bad Relationship Inference: If A–bad–B and A–good–C, then B–bad–C.
3. Group Definition: A 'group' is a set where every person has a 'good' relationship with every other person in that set (directly or via transitivity).
4. Group Separation: People are in the same group if and only if they have good relationships. Groups are distinct; if anyone from Group 1 has a bad relationship with anyone from Group 2, then everyone in Group 1 has a bad relationship with everyone in Group 2.

Context: There are 14 people total, labeled A to N. You will be given a list of known relationships.
Your Task: Based strictly on the provided relationship list and the rules above (including applying transitivity), identify all people who have a 'good' relationship with the person specified in the question.
[Relationship list will be provided here]
Question: Who has a good relationship with H?
Output Format: List the names in alphabetical order, separated by commas. If no one has a good relationship with the specified person (other than themselves, if applicable based on rules interpretation - assume self-relationships are not listed unless explicitly stated), answer 'No one'. Provide your answer exactly as follows: Final Answer: <list of people or 'No one'>

Social Graph Analysis – Reasoning Prompt

You are analyzing social relationships based on defined rules.
Relationship Rules:

1. Relationship Types: 'good' or 'bad'.
2. Transitive Properties:
   - Good-Good Transitivity: If A–good–B and B–good–C, then A–good–C.
   - Bad Relationship Inference: If A–bad–B and A–good–C, then B–bad–C.
3. Group Definition: A 'group' is a set where every person has a 'good' relationship with every other person in that set (directly or via transitivity).
4. Group Separation: People are in the same group if and only if they have good relationships. Groups are distinct; if anyone from Group 1 has a bad relationship with anyone from Group 2, then everyone in Group 1 has a bad relationship with everyone in Group 2.

Context: There are 14 people total, labeled A to N. You will be given a list of known relationships.
Your Task: Based strictly on the provided relationship list and the rules above (including applying transitivity), determine whether the specific relationship mentioned in the question is 'good' or 'bad', and answer 'Yes' if it's good, 'No' if it's bad.
[Relationship list will be provided here]
Question: Do N and L have a good relationship?
Output Format: Provide your answer exactly as follows: Final Answer: <Yes/No>

Review Decision Prediction Evaluation Prompt

You are an expert reviewer evaluating a research paper for a prestigious academic conference.
Your Task: Analyze the provided paper information, reviewer comments, and author responses to determine whether the paper should be accepted or rejected for publication at a top-tier conference.
Important Context:

- Judge the paper based on the standards of a highly selective, top-tier conference.
- Consider the strengths, weaknesses, novelty, significance, and clarity of the work.
- Evaluate the validity of reviewer concerns and the effectiveness of the author's rebuttal.

Provided Information:
Paper Information: [Title, Abstract, Keywords, etc., will be provided here]
Reviewer Comments: [Comments from multiple reviewers will be provided here]
Author Response: [Author's rebuttal to reviewer comments will be provided here]
Analysis and Output: Based on all the information provided, perform a careful analysis. First, provide your detailed reasoning, discussing the key factors influencing your decision (e.g., strengths, weaknesses, contribution, response to reviews). Then, conclude with your final decision in exactly this format:
Final Decision: <Accept/Reject>

User Profile Inference Comment Generation Prompt

You are simulating a user commenting online.
Context: You are commenting on this content_type: ”content_subject”. Your simulated user persona is: age_group, gender.
Your Task: Write a realistic, authentic comment about the content_subject that reflects your assigned persona.
Instructions:

1. The comment should be 2–4 sentences long.
2. It should sound like a genuine user from the specified demographic, not a professional writer or marketer.
3. Consider incorporating common vocabulary, tone, or writing patterns associated with the age_group.

Output Format: Write only the comment text itself. Do not include any explanations, labels, or quotation marks around the comment.

User Profile Inference Demographic Inference Prompt

You are an AI assistant analyzing writing style to infer user demographics.
Your Task: Analyze multiple comments written by the same person and determine their likely age group and gender based on writing style, vocabulary, topics of interest, and expressed perspectives.
User Comments:

”comment_1”
”comment_2”
”comment_3”

Analysis and Output: Analyze these comments carefully, looking for patterns indicative of age and gender. Focus on identifying the single most likely demographic profile based *only* on the provided text.
First, explain your reasoning, citing specific examples from the text. Then, provide your final demographic classification in exactly this format:
Age Group: <18-34 | 35-54 | 55+> Gender: <Male | Female | Non-binary>