The Stackelberg Speaker: Optimizing Persuasive Communication in Social Deduction Games

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Abstract

Large language model (LLM) agents have shown remarkable progress in social deduction games (SDGs). However, existing approaches primarily focus on information processing and strategy selection, overlooking the significance of persuasive communication in influencing other players' beliefs and responses. In SDGs, success depends not only on making correct deductions but also on convincing others to respond in alignment with one's intent. To address this limitation, we formalize turn-based dialogue in SDGs as a Stackelberg competition, where the current player acts as the leader who strategically influences the follower's response. Building on this theoretical foundation, we propose a reinforcement learning framework that trains agents to optimize utterances for persuasive impact. Through comprehensive experiments across four diverse social deduction benchmarks, we demonstrate that our agents significantly outperform baselines. This work represents a significant step toward developing AI agents capable of strategic social influence, with implications extending to scenarios requiring persuasive communication. Our code and data are available at `https://3dagentworld.github.io/leader_follower`.

1 Introduction

Large language model (LLM) agents have demonstrated remarkable capabilities across diverse domains, from computer desktop interactions (Nayak et al., 2025; Wang and Liu, 2025; Wang et al., 2025) to game environments like StarCraft (Ma et al., 2024; Shao et al., 2024a) and Minecraft (Wang et al., 2024a; Fu et al., 2025; Chai et al., 2025). These successes showcase the potential of LLMs in sequential decision-making and complex reasoning tasks. However, most existing applications involve agents interacting with deterministic, rule-based environments where feedback follows consistent patterns and information is inherently truthful. In contrast, real-world human interactions involve uncertainty, deception, and strategic communication, presenting different challenges for AI agents.

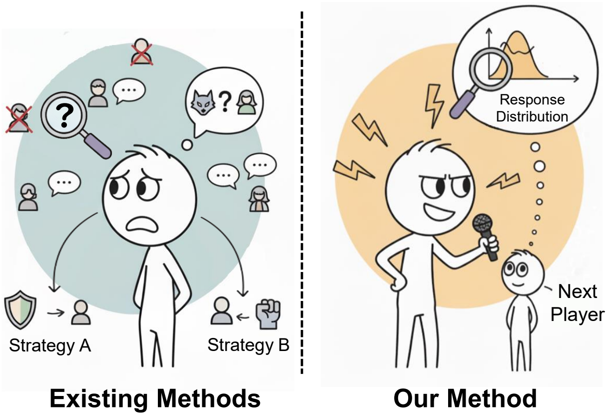

Figure 1: **Methodological paradigms.** Existing methods primarily focus on processing environmental information (such as identifying other players' roles) and selecting strategies based on this information. In contrast, our method measures the next player's response distribution and optimizes utterances specifically for persuasive impact on subsequent player responses.

Social deduction games (SDGs) such as Werewolf (Zhang et al., 2025c; Xu et al., 2023, 2024; Wu et al., 2024), Avalon (Light et al., 2023; Wang et al., 2023; Shi et al., 2023; Lan et al., 2024), and ONUW (Jin et al., 2024; Lai et al., 2023) provide ideal testbeds for developing agents that can handle these complexities. Recent work on LLM agents for SDGs has made notable progress. Approaches include using prompt engineering to perform reflection (Lan et al., 2024; Wang et al., 2024c), generating code for enhanced deduction (Light et al., 2025) and reinforcement learning (RL) for strategy selection (Xu et al., 2024; Jin et al., 2024; Xu et al., 2025). However, these methods largely adapt techniques from general task domains without fully leveraging the unique persuasive dynamics of social games. They typically concentrate on deducing

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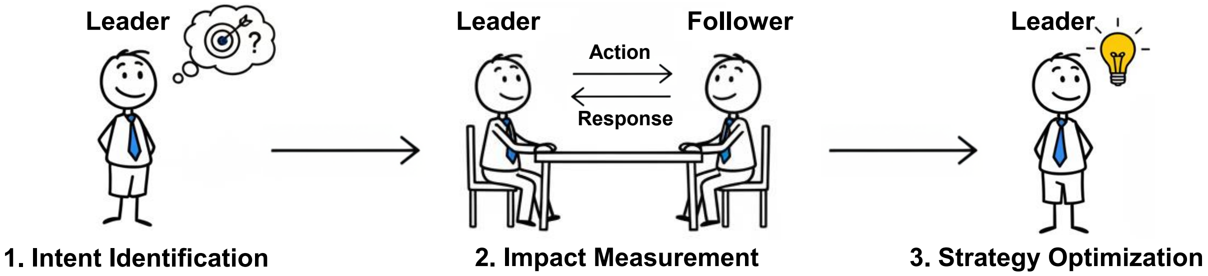

Figure 2: **Stackelberg optimization process.** First, the leader identifies its strategic intent by analyzing the current situation. Then, the leader measures the follower's response distribution to different leader actions. Finally, the leader optimizes its strategy to maximize its utility given the follower's response distribution.

other players' roles and making strategic choices, neglecting the critical ability to influence other players' beliefs and responses through persuasive communication.

The core challenge in SDGs extends beyond processing complex information and selecting optimal strategies. Success fundamentally depends on persuasive communication, which is the ability to shape how other players think and response. In Werewolf, for instance, a villager must not only identify werewolves but craft utterances that convince other players to vote accordingly. This persuasive dimension, central to both gameplay success and real-world human interaction, remains largely unaddressed in current research.

As shown in Figure 1, we address this gap by explicitly modeling and optimizing persuasive communication in SDGs. We formalize turn-based dialogue as a Stackelberg competition, a sequential game where one player (the leader) takes an action first, while the other player (the follower) responds accordingly. Figure 2 illustrates the key insight that in a Stackelberg competition, if the leader sufficiently understands how the follower will response, they can maximize their utility subject to the follower's response distribution as a constraint. In our context, at each turn in our collected self-play dataset, the current player acts as the leader who optimizes their utterances by measuring the next player's response distribution.

Building on this theoretical foundation, we propose an RL framework for training persuasive agents. Our method fine-tunes an LLM on our collected self-play dataset to refine base utterances into persuasive ones. The persuasive impact is measured by calculating how much an utterance shifts the probability distribution of the follower's responses toward desired outcomes. Since our Stackelberg optimization requires comparing different utterances based on their potential to elicit desired follower responses, we use GRPO (Shao et al., 2024b) to fine-tune the LLM, which computes relative advantages without requiring an explicit critic model. Through this approach, our agents learn to craft utterances that maximize persuasive impact.

We validate our approach through extensive experiments across three SDGs: Werewolf, Avalon, and ONUW. To further assess generalizability, we also extend our evaluation to a social simulation environment: Sotopia. Results demonstrate that our agents significantly outperform baseline methods by effectively guiding conversations and influencing other players' behaviors. The improvements are evident both in scenarios requiring trust-building and coordination as well as in deceptive roles.

Our contributions can be summarized as follows:

- We formulate turn-based dialogue in SDGs as a Stackelberg competition, providing a theoretical foundation for analyzing and optimizing persuasive communication.
- We propose a training framework that optimizes utterances to influence subsequent players' responses, enabling agents to proactively guide conversational flow.
- We demonstrate effectiveness and generalizability through comprehensive experiments on three SDGs and Sotopia, showing that our agents achieve superior performance.

2 Related Work

2.1 Social Deduction Game Agents

Social deduction games (SDGs) are multiplayer games where players are assigned hidden roles and must use communication, deduction, and deception to achieve their objectives. Early works on SDG agents (Osawa et al., 2014; Wang and

Kaneko, 2018) often rely on rule-based systems or predefined communication templates, limiting their adaptability and expressive power. More recently, LLMs have become the backbone of agents that can engage in free-form dialogue. Some works have demonstrated the effectiveness of prompt-based methods. For instance, Xu et al. (2023) develop Werewolf agents using information retrieval and experience reflection, ReCon (Wang et al., 2024c) prompts agents to play Avalon by reasoning from both their own and their opponents' perspectives, and Strategist (Light et al., 2025) generates strategies as code and uses tree search for selection.

To address the limited exploration of purely prompt-based agents, researchers have begun integrating reinforcement learning (RL). Wu et al. (2024) train a Thinker module to select an action from a predefined action space. Similarly, SLA (Xu et al., 2024) learns a policy to select from a set of candidate actions generated by an LLM, and LSPO (Xu et al., 2025) defines a finite strategy space by clustering and trains a policy to select among them. These methods typically reduce the rich space of natural language communication to classification problems. They learn to select from limited candidates rather than optimizing utterances in the natural language domain. Our work diverges by using RL to refine utterances directly within the continuous space of natural language, enabling more nuanced and flexible persuasive communication.

2.2 Reinforcement Learning for LLMs

Reinforcement Learning (RL) has been widely used to align LLMs with specific objectives. Methods like PPO (Ouyang et al., 2022) and DPO (Rafailov et al., 2023) optimize policies using reward models or preference pairs, proving effective in alignment (Liang et al., 2024) and sequential decision-making (Szot et al., 2024). To reduce reliance on expensive human annotation or separate critic models, GRPO (Shao et al., 2024b) leverages reward distributions within training batches to compute relative advantages. We employ GRPO to train agents to refine their communication, allowing them to learn persuasive strategies efficiently without explicit preference data.

2.3 Game-Theoretic Models of Communication

SDGs are often modeled as extensive-form Bayesian games, with traditional approaches like DeepRole (Serrino et al., 2019) and Cicero (Bakhtin et al., 2022) seeking equilibrium solutions. However, computing global equilibria in free-form language spaces is computationally intractable and often necessitates simplifying language into finite actions. We address these limitations by adopting the Stackelberg competition model, treating each turn as a leader-follower interaction. This local optimization captures the dynamics of persuasion and influence in real-time dialogue while remaining computationally feasible for complex language-based games.

3 Method

3.1 Preliminary

The Stackelberg competition is a strategic game model where one player (the leader) takes an action first, while the other player (the follower) responds accordingly. This sequential structure creates an information advantage that the leader can exploit through strategic foresight. In real-world scenarios, the follower's response may not be deterministic due to bounded rationality, incomplete information, or inherent randomness in decision-making. To handle this uncertainty, the leader must work with probabilistic response distributions. If the leader sufficiently understands how the follower will respond to different actions, they can maximize their utility by selecting actions that optimize their expected outcomes given the follower's response distribution as a constraint.

In turn-based dialogue scenarios like SDGs, this framework naturally applies where the current player serves as the leader who can influence subsequent conversation flow through strategic communication. Therefore, we model the interaction between consecutive players as a two-player Stackelberg competition, where the current player acts as the leader, and the next player acts as the follower. We provide further analysis for this in Appendix B.

During training, each speaking turn constitutes a training instance. As shown in Figure 3, our training framework involves three key steps: (1) **Intent Identification**: the leader identifies their strategic intent based on the current situation. (2) **Impact Measurement**: the leader measures the potential impact of different utterances on the follower's response. (3) **Strategy Optimization**: the leader optimizes their strategy to maximize expected utility given the follower's response distribution.

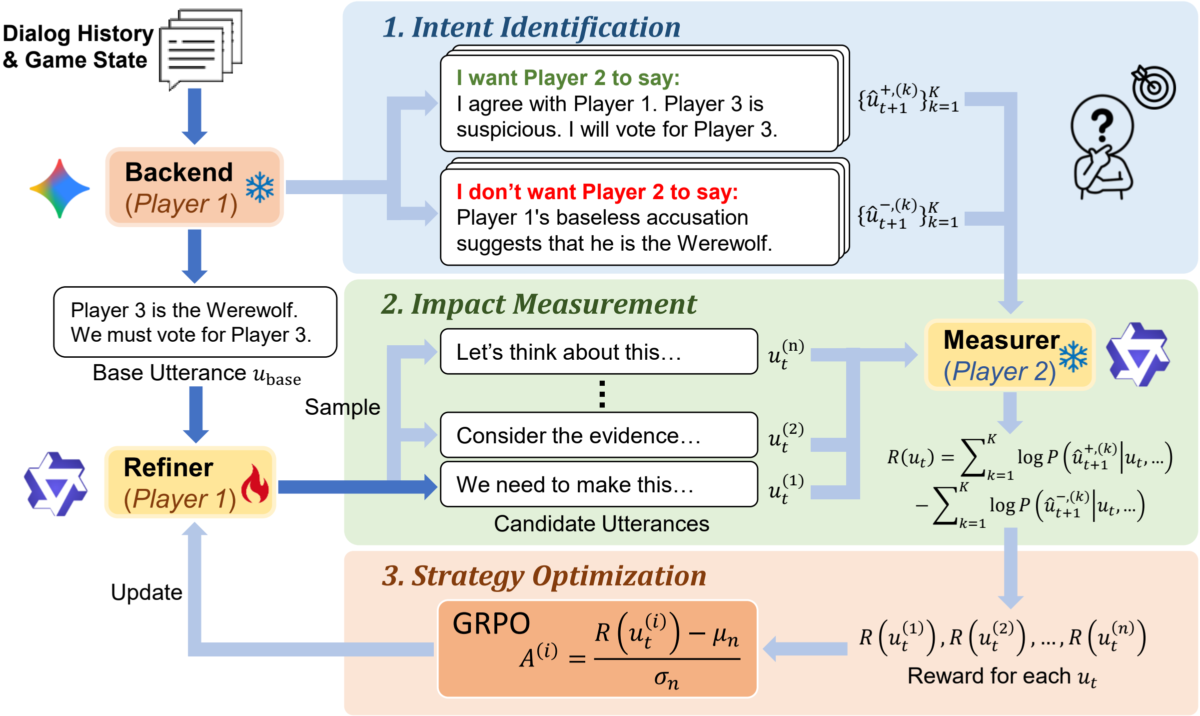

Figure 3: **The training framework of our agent.** Dark blue arrows indicate the inference pipeline, while light blue arrows represent additional processes during training. In this instance, Player 1 acts as the leader while Player 2 acts as the follower. The backend LLM identifies desired and undesired target responses, then generates a base utterance u_{base}. The Refiner enhances u_{base} for maximum persuasive impact. The Measurer computes rewards by measuring how different refined utterances u_t affect the probabilities of generating $\hat{u}_{t+1}^{+}$ and $\hat{u}_{t+1}^{-}$. Multiple utterances u_t are sampled for group relative advantage calculation during training, while only one is generated during inference. The backend uses an API-based LLM, while the Refiner and Measurer are two copies of the same open-source LLM, with the Measurer's parameters frozen.

3.2 Intent Identification

We formalize an SDG as a multi-agent sequential game with a set of players, where each player p is assigned a hidden role r at initialization. The game proceeds through several rounds, with each round consisting of a discussion phase and an action phase (e.g., voting, elimination).

During the discussion phase, players take turns making utterances. For player p_t speaking at turn t, their utterance generation depends on four key inputs: the game rules $\mathcal{R}$ that specify game mechanics and win conditions; the current game state G_t that includes publicly observable information such as eliminated players, revealed roles, and voting outcomes; the dialogue history $D_t = \{u_1, u_2, \ldots, u_{t-1}\}$ that contains all previous utterances; and their hidden role r_t.

At turn t, the current player p_t acts as the leader, while the next player p_{t+1} acts as the follower. Given the current context $(\mathcal{R}, G_t, D_t, r_t)$, the leader first identifies its persuasive intent: a set of K desired responses $\{\hat{u}_{t+1}^{+,(k)}\}_{k=1}^{K}$ that would be advantageous if spoken by p_{t+1}, and a set of K undesired responses $\{\hat{u}_{t+1}^{-,(k)}\}_{k=1}^{K}$ that would be disadvantageous. Here, we set $K = 3$. We employ the agent's backend LLM to analyze the situation and identify these response sets:

$$(\{\hat{u}_{t+1}^{+,(k)}\}_{k=1}^{K}, \{\hat{u}_{t+1}^{-,(k)}\}_{k=1}^{K}) = f_{\text{identify}}(\mathcal{R}, G_t, D_t, r_t). \quad (1)$$

3.3 Impact Measurement

Modern API-based LLMs (e.g., GPT-5, Gemini-2.5) typically demonstrate superior reasoning and generation capabilities compared to open-source alternatives. However, their closed-source nature prevents direct fine-tuning for specific objectives. To leverage the strengths of both paradigms, we adopt a two-stage approach. We first use an API-based LLM as our backend LLM for generating base utterances, then fine-tune an open-source LLM as an auxiliary component to refine this utterance for maximum persuasive impact.

Specifically, given a base utterance u_{base} generated by the agent's backend LLM:

$$u_{\text{base}} = f_{\text{base}}(\mathcal{R}, G_t, D_t, r_t). \quad (2)$$

We fine-tune the Refiner π_θ that transforms u_{base} into a more persuasive version:

$$u_t \sim \pi_\theta(\cdot|u_{\text{base}}, \mathcal{R}, G_t, D_t, r_t). \quad (3)$$

During inference, u_t is used as the agent's final utterance, while during training, we sample a group of n candidate utterances from the Refiner:

$$\{u_t^{(1)}, u_t^{(2)}, \ldots, u_t^{(n)}\} \sim \pi_\theta(\cdot|u_{\text{base}}, \mathcal{R}, G_t, D_t, r_t). \quad (4)$$

For each candidate utterance $u_t^{(i)}$, we measure its persuasive impact using a reward function that accumulates the shift in follower response probabilities over the identified intent sets:

$$\begin{aligned} &R(u_t^{(i)}) \\ &= \sum_{k=1}^{K} \log P_{\mathcal{F}}(\hat{u}_{t+1}^{+,(k)}|\mathcal{R}, G_{t+1}, D_t \cup \{u_t^{(i)}\}, r_{t+1}) \\ &- \sum_{k=1}^{K} \log P_{\mathcal{F}}(\hat{u}_{t+1}^{-,(k)}|\mathcal{R}, G_{t+1}, D_t \cup \{u_t^{(i)}\}, r_{t+1}), \end{aligned} \quad (5)$$

where $P_{\mathcal{F}}$ represents the follower's probability of generating a response.

Since the follower's backend is also an API-based LLM that we cannot access for probability computation, we use the powerful Qwen2.5-72B-Instruct[1] as the Measurer to simulate the follower's response patterns. The Measurer only serves to provide rewards for the Refiner's outputs rather than actually participating in the game.

To compute $P_{\mathcal{F}}$, we construct a prompt with the game context and the dialogue history including u_t, then append the target response $\hat{u}_{t+1}$. The probability is calculated as:

$$\begin{aligned} &\log P_{\mathcal{F}}(\hat{u}_{t+1}|\mathcal{R}, G_t, D_t \cup \{u_t\}, r_{t+1}) \\ &= \sum_{i=1}^{|\hat{u}_{t+1}|} \log p(w_i|w_{<i}, \mathcal{R}, G_t, D_t \cup \{u_t\}, r_{t+1}), \end{aligned} \quad (6)$$

where w_i denotes the i-th token in the target response $\hat{u}_{t+1}$, and p is the probability assigned to each token by the Measurer through a single autoregressive forward pass. We use log probabilities to prevent numerical underflow and ensure stable optimization. Since the game state typically changes during the action phase and remains constant during the discussion phase, we approximate G_{t+1} with G_t. While the next player's hidden role r_{t+1} is unobservable to player p_t during evaluation, we leverage full information during training to create a more accurate reward.

3.4 Strategy Optimization

We optimize the Refiner π_θ using Group Relative Policy Optimization (GRPO) (Shao et al., 2024b), which does not require human-annotated preference data or a separate critic model.

We first compute rewards for each candidate using Equation 5 and calculate normalized advantages:

$$A^{(i)} = \frac{R(u_t^{(i)}) - \mu_n}{\sigma_n}, \quad (7)$$

where μ_n and σ_n are the mean and standard deviation of rewards $\{R(u_t^{(1)}), \ldots, R(u_t^{(n)})\}$.

We then update the policy by maximizing the GRPO objective:

$$\mathcal{J}(\theta) = \mathbb{E}_c \left[\frac{1}{n} \sum_{i=1}^{n} \mathcal{L}_i - \beta D_{KL}(\pi_\theta || \pi_{\text{ref}}) \right], \quad (8)$$

where $\mathcal{L}_i$ is the clipped surrogate objective:

$$\mathcal{L}_i = \min\left(\rho_i A^{(i)}, \text{clip}(\rho_i, 1-\epsilon, 1+\epsilon) A^{(i)}\right), \quad (9)$$

and the importance ratio ρ_i is defined as:

$$\rho_i = \frac{\pi_\theta(u_t^{(i)}|u_{\text{base}}, \mathcal{R}, G_t, D_t, r_t)}{\pi_{\theta_{\text{old}}}(u_t^{(i)}|u_{\text{base}}, \mathcal{R}, G_t, D_t, r_t)}. \quad (10)$$

Here, ϵ controls the clipping range for stable updates, and β weights the KL divergence regularization against a reference model π_{ref} to prevent excessive policy deviation.

Through this training process, our agents learn to generate utterances that proactively shape subsequent conversations, effectively guiding other players' responses toward favorable outcomes.

4 Experiments

4.1 Implementation Details

We evaluate our approach on three diverse SDGs: Werewolf, Avalon, and ONUW. To further assess generalizability, we also extend our evaluation to

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[1] https://huggingface.co/Qwen/Qwen2.5-72B-Instruct

Sotopia (Zhou et al., 2024), a social simulation environment including scenarios such as negotiation, competition, and cooperation. Detailed rules and descriptions are provided in Appendix A.

Training Scheme. For each game, we generate a dataset through agent self-play using the vanilla agent framework, where backend LLMs' base utterances u_{base} serve directly as the final u_t to advance the game. To enhance data diversity, each agent is randomly assigned one of three backend LLMs: GPT-4o, Gemini-2.5-Flash, or Claude-3.5-Haiku. We generate 500 game logs for each game, where each turn within every game log constitutes a training instance. From this pool, we randomly select 4,000 instances per game for training.

For Sotopia, we apply the same approach to generate 800 multi-turn dialogues across 410 training scenarios, from which we randomly select 3,000 instances for training.

We implement our training framework based on ms-swift[2], applying GRPO with $n = 8$, $\epsilon = 0.2$, and $\beta = 0.04$. The Refiner is implemented as a LoRA adapter (Hu et al., 2022) with rank 16 applied to Qwen2.5-7B-Instruct[3] (Qwen et al., 2025). Training is conducted with a learning rate of 1×10^{-6} across 4 A800 GPUs for 3 epochs, requiring approximately 50 hours. This process yields one checkpoint per game.

Evaluation Setup. We compare our approach against baselines across all three SDGs. For Werewolf, we evaluate against ReAct (Yao et al., 2023), ReCon (Wang et al., 2024c), SLA (Xu et al., 2024), and LSPO (Xu et al., 2025). For Avalon, we compare with ReAct, ReCon, LASI (Lan et al., 2024) and Strategist (Light et al., 2025). For ONUW, the baselines include ReAct and three variants in Jin et al. (2024): Belief, LLM-ins., and RL-ins..

For Sotopia, we compare with ReAct, ReCon, SOTOPIA-π (Wang et al., 2024b), SOTOPIA-Ω (Zhang et al., 2025a), SDPO (Kong et al., 2025) and MetaMind (Zhang et al., 2025b). For SOTOPIA-π, SOTOPIA-Ω and SDPO, which are methods involving fine-tuning local LLMs, we reproduce the fine-tuning process on Qwen2.5-7B-Instruct. We employ Gemini-2.5-Flash as the LLM Judge. We report the Goal and Overall scores of each agent when interacting with ReAct across the 450 testing tasks and the 90 hard tasks.

Werewolf **Method**	**Team Village** Win Rate (%)	**Team Werewolf** Win Rate (%)	**Overall** Win Rate (%)
ReAct	17.5	79.0	35.0
ReCon	24.0	66.7	36.3
SLA	20.6	77.1	36.7
LSPO	24.9	72.8	38.6
Ours + ReAct	22.6	82.1	39.7
Ours + LSPO	**29.1**	**84.2**	**44.7**
Avalon **Method**	**Good Side** Win Rate (%)	**Evil Side** Win Rate (%)	**Overall** Win Rate (%)
ReAct	70.5	16.0	48.7
ReCon	73.2	19.5	51.6
LASI	71.8	25.0	53.0
Strategist	77.6	27.0	57.4
Ours + ReAct	73.1	30.9	56.4
Ours + Strategist	**78.5**	**35.2**	**61.3**
ONUW **Method**	**Team Village** Win Rate (%)	**Team Werewolf** Win Rate (%)	**Overall** Win Rate (%)
ReAct	56.1	40.0	43.1
Belief	54.6	40.9	43.5
LLM-ins.	54.1	43.9	45.9
RL-ins.	54.2	47.4	48.5
Ours + ReAct	**61.7**	39.6	45.1
Ours + RL-ins.	55.2	**50.6**	**51.5**

Table 1: **Performance comparison across three SDGs.** We conduct 500 matches per game where each player is randomly sampled from the pool of available agents. "Ours + Baseline" indicates that our trained Refiner enhances the utterances of the corresponding baseline, serving as a new agent type. Note that the overall win rate is not a simple average, as agents are more frequently assigned to the majority faction (Village/Good).

Since our method focuses exclusively on utterance refinement, it can be seamlessly integrated with any existing baseline. During evaluation, we apply our trained Refiner to refine the utterances generated by another baseline. All experiments use Gemini-2.5-Flash as the backend LLM unless otherwise specified.

4.2 Main Results

We evaluate our approach through gameplay simulations across all three games. For each game, we conduct 500 matches where each player is randomly sampled from the pool of available agents, including all baselines and our proposed ones. This setup assesses how each agent performs when integrated into heterogeneous teams, mimicking real-world gameplay with diverse player strategies.

As shown in Table 1, our approach demonstrates consistent improvements across all three games, validating the effectiveness of our persuasive communication framework. The results reveal that integrating our Refiner with existing baselines consistently enhances performance, with particularly notable gains observed when combined with stronger

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[2] `https://github.com/modelscope/ms-swift`

[3] `https://huggingface.co/Qwen/Qwen2.5-7B-Instruct`

Method	Werewolf			Avalon			ONUW		
	Village	Werewolf	Avg.	Good	Evil	Avg.	Village	Werewolf	Avg.
ReAct	18.0	80.0	49.0	72.0	16.0	44.0	56.0	40.0	48.0
Pos-Only + ReAct	46.0	82.0	64.0	**74.0**	42.0	58.0	70.0	**50.0**	60.0
Neg-Only + ReAct	18.0	80.0	49.0	72.0	20.0	46.0	54.0	40.0	47.0
Ours + ReAct	**52.0**	**88.0**	**70.0**	72.0	**50.0**	**61.0**	**76.0**	46.0	**61.0**

Table 2: **Ablation study on different reward functions.** We integrate the model trained from each variant with ReAct and evaluate them against ReAct under different team assignments, conducting 50 matches for each setting. In each match, players from the same team use the same agent type.

Method	Sotopia		Sotopia-Hard	
	Goal	Overall	Goal	Overall
ReAct	8.43	3.85	7.06	3.45
ReCon	8.45	3.88	7.08	3.48
SOTOPIA-π	7.62	3.44	5.34	2.76
SOTOPIA-Ω	8.07	3.67	6.31	3.03
SDPO	8.13	3.63	6.35	3.14
MetaMind	8.70	4.03	7.16	3.60
Ours + ReAct	8.58	3.95	7.12	3.55
Ours + MetaMind	**8.92**	**4.20**	**7.59**	**3.85**

Table 3: **Performance comparison on Sotopia.** We evaluate the agents interacting with ReAct across 450 testing tasks (Sotopia) and 90 hard tasks (Sotopia-Hard). The Goal score ranges from 0 to 10, reflecting the agent's effectiveness in achieving social goals. Higher scores indicate better performance.

baselines. This suggests that our approach complements rather than replaces existing strategies, leveraging the strengths of established techniques while adding a crucial persuasive dimension that is previously absent.

Beyond standard SDGs, the results on Sotopia in Table 3 further validate the generalizability of our approach in complex social simulations. When integrated with MetaMind, our Refiner improves Goal and Overall scores, achieving the highest performance on both standard and hard tasks. This indicates that our training framework effectively transfers to open-ended scenarios requiring negotiation and cooperation, enabling agents to better influence others and achieve social objectives.

These improvements are evident across different role types and game mechanics, indicating the generalizability of our Stackelberg-based formulation. In asymmetric games like Werewolf and Avalon, where different teams have fundamentally different objectives and information access, our agents achieve substantial gains for both cooperative and deceptive roles. This dual effectiveness demonstrates that our framework successfully captures the nuanced communication strategies required for different strategic positions, whether building trust and coordination among allies or sowing doubt and misdirection among opponents. We provide detailed case studies in Appendix E.

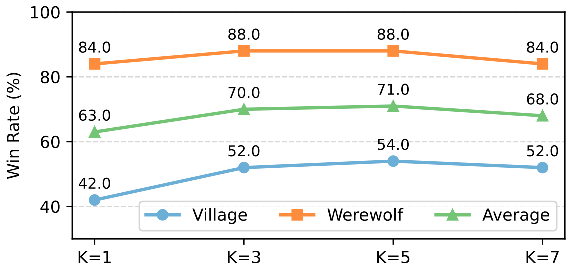

Figure 4: **Hyperparameter analysis on K.** We vary K in Equation 1 while keeping other settings consistent with Section 4.1. We train the model on Werewolf and evaluate the win rates of "Ours + ReAct" against ReAct.

4.3 Ablation Study

To investigate the impact of different reward functions on our training framework, we conduct an ablation study examining two variants of our reward function in Equation 5. While our main approach considers both desired ($\hat{u}^{+}_{t+1}$) and undesired ($\hat{u}^{-}_{t+1}$) responses, we explore two alternative functions:

(1) **Positive-Only**: we only maximize the probability of eliciting the desired response.

(2) **Negative-Only**: we only minimize the probability of triggering the undesired response.

Following the same training procedure in Section 4.1, we train the Refiner using these two reward functions. Each variant is then integrated with ReAct for evaluation. We conduct team-based competitions where all players on the same team employ the same variant. We evaluate all variants against the ReAct, with our agent playing as either

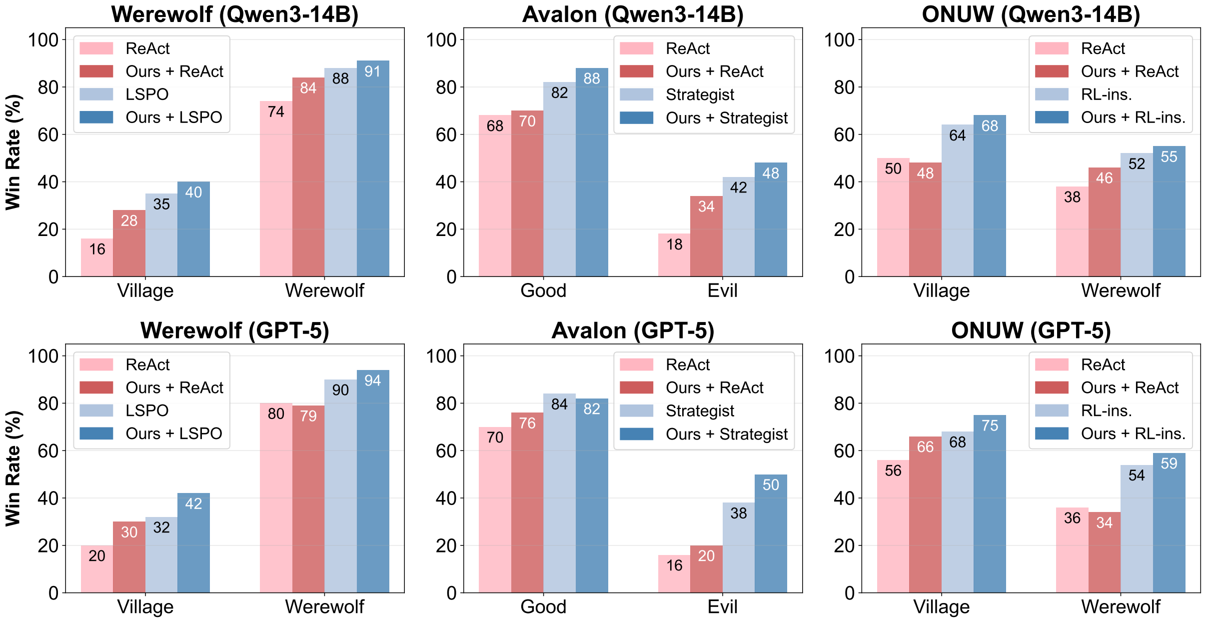

Figure 5: **Generalizability across different backend LLMs.** We evaluate our approach on GPT-5 and Qwen3-14B without additional fine-tuning. Each method competes against ReAct under different team assignments, conducting 50 matches per setting.

Team Village (Good Side) or Team Werewolf (Evil Side). For each variant and each team assignment, we conduct 50 matches.

The results in Table 2 show that our complete approach, which considers both desired and undesired responses, outperforms both single-objective variants across all games. The positive-only variant demonstrates substantial improvements over the baseline, confirming that training agents to increase the probability of beneficial responses is effective for enhancing persuasive communication. However, the negative-only variant shows performance nearly identical to the baseline, providing essentially no strategic benefit.

In Section 3.2, we prompt the backend LLM to identify $K = 3$ desired and undesired responses. To examine the impact of K, we vary K in Equation 1 and conduct training on Werewolf. As shown in Figure 4, the performance peaks and stabilizes around $K = 3$, suggesting this setting provides a robust approximation of the response distribution. Increasing K further does not yield additional benefits, as an excessive number of intent targets may force the inclusion of low-quality samples, thereby introducing noise into the reward signal.

4.4 Generalizability Across LLMs

As described in Section 4.1, our training dataset consists of self-play records generated using three backend LLMs: GPT-4o, Gemini-2.5-Flash, and Claude-3.5-Haiku. To evaluate cross-model generalization capabilities, we test our trained Refiner on two additional backend LLMs: GPT-5 and Qwen3-14B[4] (Yang et al., 2025).

The results in Figure 5 show that our approach consistently improves performance across both new LLMs. This robust generalization suggests that our framework does not merely overfit to the stylistic tendencies of the training models. Instead, it learns to capture and amplify more fundamental, model-agnostic principles of persuasion. By optimizing for the functional impact of an utterance on a follower's response distribution, our module learns to identify and refine core strategic elements that effectively influence conversational dynamics regardless of the base LLM's initial phrasing.

4.5 Human Evaluation

To evaluate our agent's performance in realistic human-AI interaction scenarios, we recruit 16 volunteers to participate in our study. Among them, 10 have prior experience playing Werewolf, 4 are familiar with the game rules but have never played, and 2 is completely unfamiliar. Following a comprehensive explanation of the game rules, each participant completes 5 games of Werewolf. Each game features 1 human player paired with 6 AI

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[4] `https://huggingface.co/Qwen/Qwen3-14B`

Agent	Avg. Votes (↓)	Avg. Human Votes (↓)	Win Rate (↑)
Human	2.06	—	40.0
ReAct	3.21	1.58	20.7
ReCon	2.56	1.17	23.1
LSA	2.01	0.70	39.0
LSPO	1.83	0.54	41.3
Ours + ReAct	2.34	1.08	28.8
Ours + LSPO	**1.58**	**0.39**	**44.1**

Table 4: **Performance against human players on Werewolf.** "Avg. Votes" indicates the average number of votes each agent received per game, and "Avg. Human Votes" represents the average number of votes each agent received from human players per game.

agents randomly selected from our agent pool, including our method and baselines.

Table 4 shows that our agent achieved the highest win rate, surpassing both baselines and human players. Notably, it received the fewest votes from human participants, demonstrating its exceptional ability to minimize suspicion and maintain effective during human-AI interactions.

5 Conclusion

In this paper, we address the challenge of persuasive communication in SDGs by formalizing turn-based dialogue as a Stackelberg competition and developing an RL framework to optimize influential utterances. Extensive experiments across Werewolf, Avalon, ONUW, and Sotopia demonstrate that our method consistently improves agent performance. This work establishes a systematic framework for developing persuasive AI agents and opens new directions for research in strategic communication within multi-agent environments.

Limitations

While our training framework demonstrates effectiveness in enhancing the persuasion capabilities of agents, we observe that the training process tends to result in an increase in the length of the generated utterances. This phenomenon likely stems from the model's attempt to maximize the reward function by incorporating more elaborate rhetorical details to ensure persuasive impact. In future work, we plan to address this issue by investigating mechanisms to balance strategic effectiveness with brevity, such as incorporating length penalties or conciseness rewards into the optimization objective, thereby ensuring that agents can deliver high-impact responses without unnecessary verbosity.

Ethics Statement

The primary goal of this research is to advance the persuasion capabilities of LLM agents within controlled multi-agent gaming environments. We acknowledge, however, that the enhanced persuasive capabilities developed in this framework carry potential risks if repurposed for manipulative intent or social engineering in real-world interactions. We emphasize that such technologies should be developed with strict safety guardrails and alignment measures to ensure they serve to assist and collaborate with human users.

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A Game Description

A.1 Werewolf

Setup. Each game involves seven players assigned distinct roles: two Werewolves, one Seer, one Guardian, and three Villagers. The Werewolves are aware of each other's roles, while other players only know their own roles.

Night Phase. During the night phase, players with special abilities take secret actions:

- *Werewolves*: The surviving Werewolves collectively select a target for elimination. When two Werewolves remain alive, the one with the lower player ID proposes a target, and the other makes the final decision. If only one Werewolf survives, their choice is final. Werewolves cannot target dead players, themselves, or their teammate.
- *Seer*: The Seer investigates one living player to determine whether they are a Werewolf. The Seer cannot investigate dead players or themselves.
- *Guardian*: The Guardian protects one player from elimination, without knowledge of the Werewolves' target. The Guardian can choose any living player including themselves.

Day Phase. The day phase consists of three sequential stages:

- *Announcement*: Night events are revealed publicly. If the Werewolves' target was not protected by the Guardian, that player is eliminated. If the Guardian successfully protected the target, no elimination occurs.
- *Discussion*: All surviving players participate in an open discussion following a predetermined speaking order, with each player speaking exactly once.
- *Voting*: Players simultaneously vote to eliminate one other player or abstain. The player receiving the most votes is eliminated without role revelation. Ties are resolved randomly.

Victory Conditions. Werewolves win when their numbers equal or exceed the remaining players. The village team (Seer, Guardian, and Villagers) wins when both Werewolves are eliminated.

A.2 Avalon

Setup and Roles. Avalon features asymmetric information distribution across four roles with five players: two Servants of Arthur (good), one Minion of Mordred (evil), one Merlin (good with information), and one Assassin (evil with special ability). Good players always outnumber evil players. Merlin knows all players' alignments, while Minions and the Assassin know each other's roles but not specific roles.

Game Phases. The game alternates through four phases until termination conditions are met:

- *Team Selection*: The current leader proposes a team for the mission. Leadership rotates sequentially among all players.
- *Team Voting*: All players simultaneously vote to approve or reject the proposed team. A majority approval advances to the quest phase; otherwise, leadership passes to the next player. If five consecutive teams are rejected, the fifth team automatically proceeds.
- *Quest Execution*: Selected team members privately vote to pass or fail the mission. The number of pass and fail votes is revealed publicly. Missions typically fail if any player votes to fail.
- *Discussion*: Between other phases, players engage in open discussion to share observations, propose theories about player roles, and negotiate team compositions.

Victory Conditions. If three missions succeed, the game proceeds to an assassination phase where the Assassin attempts to identify and eliminate Merlin. Evil wins if Merlin is successfully assassinated or if three missions fail. Good wins if three missions succeed and Merlin remains undetected.

A.3 ONUW

Setup. One Night Ultimate Werewolf (ONUW) is a condensed variant where players experience a single night of role abilities followed by one day of discussion and voting. In our evaluation, we employ a five-player configuration with seven available roles: one Werewolf, two Villagers, one Seer, one Robber, one Troublemaker, and one Insomniac. Each player receives one role while two remain in the central role pool. To ensure consistent game dynamics, we guarantee that exactly one Werewolf is always distributed among the five players.

Role Descriptions. The game features distinct roles with varying abilities and team affiliations:

- *Werewolf*: The Werewolf awakens during the night phase to check if other Werewolves are present. Since only one Werewolf exists among players in our configuration, no other Werewolves will be found. The Werewolf belongs to Team Werewolf.
- *Villager*: Villagers have no special abilities or night actions but serve as the baseline good role. Villagers belong to Team Village.
- *Seer*: The Seer may examine either one other player's role or two roles from the central pool. The Seer belongs to Team Village.
- *Robber*: The Robber may exchange their role with another player and then view their new role. The Robber adopts the team affiliation of their new role, while the other player joins Team Village.
- *Troublemaker*: The Troublemaker swaps the roles of two other players without viewing them. Affected players adopt their new roles' team affiliations unknowingly. The Troublemaker belongs to Team Village.
- *Insomniac*: The Insomniac views their own role at night's end to detect any changes. The Insomniac belongs to Team Village.

Game Structure. ONUW consists of three sequential phases:

- *Night Phase*: Players with night abilities act according to their initial roles in the following order: Werewolf, Seer, Robber, Troublemaker, and Insomniac.
- *Day Phase*: Players engage in open discussion to identify suspected Werewolves. Role changes during the night create uncertainty, as players may unknowingly possess different roles than initially assigned.
- *Voting Phase*: Players simultaneously vote to eliminate suspected Werewolves. The player(s) receiving the most votes are eliminated and reveal their final roles.

Victory Conditions. Team Village wins if the Werewolf is eliminated, regardless of additional eliminations. Team Werewolf wins if the Werewolf avoids elimination during the voting phase.

A.4 Sotopia

Setup. Sotopia is an open-ended social simulation environment rather than a rigid game with fixed mechanical roles. Each session involves two agents assigned unique character profiles (including age, occupation, and personality traits) placed within a specific social scenario. Crucially, each agent is given a set of private social goals that may align with, compete with, or differ from the goals of the other agent.

Interaction Phase. The core gameplay consists of a multi-turn natural language dialogue where agents role-play to achieve their objectives. The interaction covers diverse social dynamics:

- *Negotiation and Bargaining*: Scenarios where agents must reach a compromise on conflicting interests (e.g., splitting a resource or agreeing on a price).
- *Cooperation*: Scenarios requiring agents to coordinate plans or solve mutual problems (e.g., planning a travel itinerary together).
- *Competition*: Scenarios where agents strive to maximize their own utility at the potential expense of the other.

Evaluation Objectives. Unlike traditional games with binary win/loss conditions, performance in Sotopia is assessed quantitatively by an evaluator (typically a strong LLM):

- *Goal Completion*: A score ranging from 0 to 10, measuring how effectively the agent fulfilled its private social objectives through the conversation.
- *Overall Score*: A metric calculated as the average of seven distinct dimensions: Goal Completion, Believability (adherence to character profile), Relationship (change in interpersonal dynamics), Knowledge (information acquisition), Secrecy (preventing information leaks), Social Rules (maintaining ethical boundaries), and Financial (material gain).

B Theoretical Analysis

B.1 The Path to Victory in SDGs

SDGs fundamentally revolve around collective decision-making under uncertainty. Unlike traditional competitive games where players independently pursue their objectives, SDGs require players to form coalitions and coordinate actions through communication. We provide a detailed analysis of why the ability to influence other players' responses is crucial for achieving victory.

B.1.1 Victory Conditions

In SDGs, victory conditions are inherently collective. Consider the three games in our study:

- **Werewolf**: Villagers win by correctly identifying and eliminating all werewolves through majority voting. Werewolves win by surviving until they equal or outnumber villagers.
- **Avalon**: Good players win by successfully completing missions, which requires selecting trustworthy team members. Evil players win by sabotaging missions while avoiding detection.
- **ONUW**: Team Village wins by correctly identifying and eliminating the Werewolf through majority voting. Team Werewolf wins if the Werewolf avoids elimination.

In all cases, individual players cannot achieve victory alone. They must convince others to take specific actions (voting, team selection, etc.). This creates a fundamental dependency: *a player's success depends not on their own actions alone, but on their ability to shape the collective behavior of the group.*

B.1.2 Chain of Influence

Consider a sequence of speaking turns in an SDG. When player p_t speaks at turn t, their utterance u_t becomes part of the dialogue history that all subsequent players observe. This creates a cascading effect:

- **Direct Influence**: The immediate next player p_{t+1} formulates their response based on u_t, potentially adopting, refuting, or building upon p_t's utterances.
- **Indirect Influence**: When p_{t+1} speaks, their utterance u_{t+1}, which was influenced by u_t, affects p_{t+2}'s response, and so on. Thus, p_t's initial utterance propagates through the conversation.
- **Collective Belief Formation**: As the discussion progresses, players form beliefs about others' roles based on the accumulated dialogue. A persuasive utterance early in the discussion can anchor these beliefs, making them resistant to later contradictions.
- **Action Convergence**: During voting or team selection phases, players act on their formed beliefs. If p_t successfully influenced the dialogue trajectory, the collective action will align with their objectives.

This chain demonstrates that influencing the immediate next player is not merely a local optimization, but rather initiates a cascade that shapes the entire game trajectory.

B.1.3 Mathematical Formulation

Let us formalize this intuition. Define $V_t(s)$ as player p_t's probability of winning from state s. In a discussion phase with k remaining players, player p_t's optimal utterance should maximize:

$$V_t(s_t) = \mathbb{E}_{u_{t+1},\ldots,u_{t+k},a}\left[V_t(s_{t+k+1}) \mid u_t\right], \quad (11)$$

where a represents the collective action (e.g., voting outcome) taken after the discussion, and s_{t+k+1} is the resulting game state.

The key insight is that u_t influences this expectation through multiple pathways:

- It affects p_{t+1}'s response distribution $\pi_{t+1}(u_{t+1}|D_t \cup \{u_t\})$.
- Through u_{t+1}, it influences p_{t+2}'s response, and so on.
- The accumulated dialogue $\{u_t, u_{t+1}, \ldots, u_{t+k}\}$ determines the action distribution $P(a|D_{t+k})$.

By optimizing the immediate influence on p_{t+1}, we are effectively optimizing the first-order approximation of this complex dependency chain.

B.2 Stackelberg Framework

B.2.1 Natural Fit for Turn-Based Dialogue

The Stackelberg competition model, originally developed for economic competition, describes situations where one player (the leader) takes an action first, and another player (the follower) responds after observing the leader's action. We argue that this framework naturally captures the dynamics of turn-based dialogue in SDGs.

Sequential Structure. In SDG discussions, players speak in a predetermined order. When player p_t formulates their utterance, they know that p_{t+1} will speak next and must respond to whatever p_t says. This creates an asymmetric information structure: p_t can anticipate and plan for p_{t+1}'s response, while p_{t+1} must react to p_t's already-committed utterance.

Commitment and Irreversibility. Once p_t makes their utterance, it becomes part of the permanent dialogue history. They cannot retract or modify it based on p_{t+1}'s response. This commitment aspect is fundamental to Stackelberg competitions. The leader must choose their action knowing they cannot adjust it after observing the follower's response.

Strategic Anticipation. A sophisticated player p_t does not simply state their beliefs or observations. They craft utterances that will elicit favorable responses from p_{t+1}. For example:

- A werewolf might make accusations that prompt villagers to defend themselves, creating suspicion.
- A villager might ask questions designed to expose inconsistencies in a suspected werewolf's story.
- A werewolf in ONUW might claim to be a role-swapping character to create confusion about their true identity.

This strategic anticipation is precisely what the Stackelberg framework models: the leader optimizes their action by considering how the follower will respond.

B.2.2 Advantages of Local Modeling

While one could theoretically model the entire SDG as a complex multi-agent game and solve for equilibria, our local Stackelberg approach offers several advantages:

Computational Tractability. Solving for equilibria in games with natural language action spaces is computationally intractable. The number of possible utterances is essentially infinite, and even discretizing the space loses critical nuances. By focusing on pairwise leader-follower interactions, we reduce the problem to optimizing a single utterance given a specific context.

Cognitive Realism. Human players do not compute full game-theoretic equilibria when speaking. Instead, they use local heuristics: "If I say X, they'll probably respond with Y, which would be good/bad for me." Our Stackelberg model captures this bounded rationality.

Composability. Each speaking turn can be modeled as an independent Stackelberg competition, with the solution to one becoming the context for the next. This modular structure allows us to train agents that can handle varying game lengths and player counts without retraining.

B.2.3 Implementation Benefits

The Stackelberg framework provides more than theoretical insight. It directly informs our training methodology:

- **Objective Definition**: The leader's goal of maximizing $\pi_{\mathcal{F}}(\hat{u}_{t+1}^{+}) - \pi_{\mathcal{F}}(\hat{u}_{t+1}^{-})$ operationalizes the abstract notion of "influence" into a concrete, differentiable objective.
- **Reward Signal**: During reinforcement learning, we can evaluate an utterance's quality by measuring how much it shifts the follower's response distribution toward desired outcomes.
- **Training Efficiency**: Instead of requiring full game simulations, we can train on dialogue segments, using a frozen LLM to provide consistent feedback signals.

B.3 Psychological Foundations

Our approach aligns with established theories of persuasion from psychology and communication studies:

Elaboration Likelihood Model. This model suggests that persuasion occurs through two routes: central (logical arguments) and peripheral (emotional appeals, credibility). Our trained agents learn to balance both: crafting logical deductions while maintaining consistency with their claimed role.

Social Proof. Players are more likely to adopt positions that appear to have group support. By influencing the immediate follower to echo or support their position, a leader can create the appearance of consensus, making subsequent players more likely to align.

Method	Werewolf			Avalon			ONUW		
	Village	Werewolf	Avg.	Good	Evil	Avg.	Village	Werewolf	Avg.
ReAct (Qwen2.5-7B-Instruct)	10.0	74.0	42.0	64.0	8.0	36.0	44.0	30.0	37.0
ReAct (GPT-4o-mini)	14.0	78.0	46.0	68.0	12.0	40.0	52.0	36.0	44.0
ReAct (Gemini-2.5-Flash)	18.0	80.0	49.0	72.0	16.0	44.0	56.0	40.0	48.0
Prompt Refine (Qwen2.5-7B-Instruct)	22.0	82.0	52.0	70.0	20.0	45.0	60.0	44.0	52.0
Prompt Refine (Gemini-2.5-Flash)	22.0	84.0	53.0	**76.0**	20.0	48.0	60.0	40.0	50.0
Ours (Qwen2.5-7B-Instruct)	18.0	82.0	50.0	72.0	16.0	44.0	56.0	40.0	48.0
Ours + ReAct (Gemini-2.5-Flash)	**52.0**	**86.0**	**69.0**	74.0	**46.0**	**60.0**	**76.0**	**48.0**	**62.0**

Table 5: **Ablation on two-stage refinement.** We evaluate each baseline against ReAct (Gemini-2.5-Flash) under different team assignments, conducting 50 matches for each setting. In each match, players from the same team use the same agent type.

Commitment and Consistency. Once a player takes a public position (influenced by a persuasive utterance), they tend to maintain it to appear consistent. This makes early influence particularly valuable, as it locks in allies before opposing arguments emerge.

These psychological principles explain why our local optimization approach, focusing on immediate influence, can produce globally effective strategies. The follower's influenced response does not just represent one player's opinion. It becomes a social signal that shapes the entire group's dynamics.

C Implementation Details

Our framework requires several prompts to implement the three key components: intent identification, utterance generation, and impact measurement. We describe the key prompts used in our implementation.

For intent identification, Figure 6 prompts the agent to analyze the current game situation and identify the most desired and undesired responses from the next player. We sample K times to obtain a set of K desired responses and K undesired responses.

The utterance refinement process uses two prompts: first, Figure 7 generates a base utterance using the backend LLM, then Figure 8 refines it using Refiner model to enhance its persuasive impact.

For impact measurement, Figure 9 uses the Measurer to compute the likelihood of target responses given different candidate utterances.

D Discussion

D.1 Ablation on Two-Stage Refinement

While our approach leverages an API-based backend LLM to generate base utterances and uses an open-source LLM to refine utterances, we also investigate several alternative approaches to validate the necessity of our training framework:

- **ReAct (Qwen2.5-7B-Instruct)**: we directly use Qwen2.5-7B-Instruct as backend LLM without any refinement.

- **ReAct (GPT-4o-mini)**: we directly use GPT-4o-mini as backend LLM without any refinement.

- **ReAct (Gemini-2.5-Flash)** : we directly use Gemini-2.5-Flash as backend LLM without any refinement.

- **Prompt Refine (Qwen2.5-7B-Instruct)**: we use Qwen2.5-7B-Instruct without fine-tuning to refine base utterances generated by Gemini-2.5-Flash.

- **Prompt Refine (Gemini-2.5-Flash)**: we use Gemini-2.5-Flash to refine base utterances generated by Gemini-2.5-Flash.

- **Ours (Qwen2.5-7B-Instruct)**: we directly fine-tune Qwen2.5-7B-Instruct as the backend LLM to generate utterances without additional refinement, keeping all other framework components unchanged.

- **Ours + ReAct (Gemini-2.5-Flash)**: we use our trained Refiner to refine base utterances generated by Gemini-2.5-Flash.

System Prompt:
{game_system_prompt}
(The same system prompt used by the actual game agent, containing game rules, player role, and strategy.)
User Prompt:
You are {name}, playing as {role} in {game_name}.
Your goal: {goal}
Current game state and dialogue history:
{context}
The next player to speak after you is {next_player}.
Based on your role and the current situation, identify:
1. THREE responses you would DESIRE the next player ({next_player}) to say (responses that would benefit your goals)
2. THREE responses you would NOT DESIRE the next player ({next_player}) to say (responses that would harm your goals)
Think strategically about what the next player might say and how it could affect the game.
IMPORTANT: Each response must be written in the FIRST PERSON from {next_player}'s perspective, as if {next_player} is actually speaking. Use "I" instead of "{next_player}" or "player X". For example, write "I think player 2 is suspicious because..." instead of "Player 3 says player 2 is suspicious".
Output your response in the following format:
<desired_responses>
1. [First desired response, written as {next_player} speaking in first person]
2. [Second desired response, written as {next_player} speaking in first person]
3. [Third desired response, written as {next_player} speaking in first person]
</desired_responses>
<undesired_responses>
1. [First undesired response, written as {next_player} speaking in first person]
2. [Second undesired response, written as {next_player} speaking in first person]
3. [Third undesired response, written as {next_player} speaking in first person]
</undesired_responses>

Figure 6: **The prompt used for intent identification.** The system prompt is the same as the actual game agent's prompt. The user prompt asks the leader to identify desired and undesired responses from the next player.

System Prompt:
{game_system_prompt}
(The same system prompt used by the actual game agent, containing game rules, player role, and strategy.)
User Prompt:
You currently assume the {name} within {game_name}, and the game has progressed to the {phase}. Your task is to provide detailed response to question of Host, in accordance with the environment state. Your response should be no more than 100 words.
the information of yourself is <information>
your name is <name>{name}</name>
your role is <role>{role}</role>
the role introduction is <introduction>{introduction}</introduction>
your playing strategy <strategy>{strategy}</strategy>
</information>
the environment state is <environment>
the summary of previous turns <summary> {summary} </summary>
your current playing plan is <plan> {plan} </plan>
the Host's question is <question> {question} </question>
</environment>
Output your response directly within <response></response> tags, nothing else outside the tags.

Figure 7: **The prompt used to generate base utterances.** The base utterance is generated by the backend game agent using the same prompt format as normal gameplay.

As shown in Table 5, the approach where we directly train Qwen2.5-7B-Instruct demonstrates meaningful improvements over the baseline and achieves performance competitive with GPT-4o-mini. This validates that our framework can effectively enhance persuasive communication even without API-based backends. However, this alternative underperforms Gemini-2.5-Flash and our two-stage method that combines Gemini-2.5-Flash with the trained Refiner.

The prompt-based refinement approaches reveal important insights about the necessity of our training process. Both prompt-based refinement with Qwen2.5-7B-Instruct and Gemini-2.5-Flash

System Prompt:
You are a communication expert specializing in persuasive dialogue refinement for social deduction games.
User Prompt:
{game_rules}
Your are {player_name} and your role is {player_role}.
Current game state:
{game_state}
Conversation history:
{dialog_history}
You have a base utterance that needs to be refined for maximum persuasive impact:
Base utterance:
{base_utterance}
Your goal is to refine this utterance to be more persuasive while maintaining naturalness and staying true to your role.
Consider:
- How to make your message more compelling
- What tone and phrasing would be most convincing
- How to subtly guide other players' thinking

Generate a refined version of the base utterance:
Provide your response in the following format:
“‘
Analysis: [Your reasoning about the current situation and what you need to achieve]
Response: [The refined version of the base utterance]
“‘

Figure 8: **The prompt used to refine utterances.** The system prompt is a fixed role description. The user prompt contains the full game context and the base utterance to be refined.

System Prompt:
{game_system_prompt}
(The same system prompt used by the actual game agent, containing game rules, player role, and strategy.)
User Prompt:
You currently assume the {name} within {game_name}, and the game has progressed to the {phase}. Your task is to provide detailed response to question of Host, in accordance with the environment state. Your response should be no more than 100 words.
the information of yourself is <information>
your name is <name>{name}</name>
your role is <role>{role}</role>
the role introduction is <introduction>{introduction}</introduction>
your playing strategy <strategy>{strategy}</strategy>
</information>
the environment state is <environment>
the summary of previous turns <summary> {summary} </summary>
your current playing plan is <plan> None </plan>
the Host's question is <question> {question} </question>
</environment>
Output your response directly within <response></response> tags, nothing else outside the tags.
AI Message:
<response>{target_response}</response>

Figure 9: **The prompt used by the Measurer to compute response probabilities.** The Measurer uses the same prompt format as the actual game agents to accurately simulate the follower's response patterns. The target response is appended as an AI message for log probability computation.

achieve only marginal improvements over the baseline ReAct (Gemini-2.5-Flash). However, both prompt-based approaches fall substantially short of our trained refinement method, demonstrating that generic prompting for more persuasive communication cannot capture the nuanced optimization our framework provides.

This performance gap highlights the complementary strengths of our hybrid architecture: the API-based backend provides superior reasoning and linguistic capabilities, while the open-source component learns to optimize for persuasive impact. The substantial difference between prompt-based and training-based refinement validates the necessity of our training framework for developing effective persuasive communication strategies.

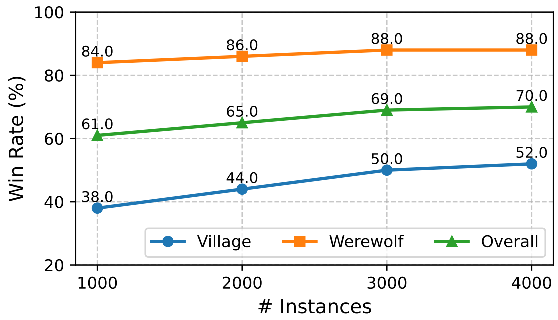


Figure 10: **Impact of training dataset size on performance.** We train the Refiner on Werewolf with varying numbers of training instances and evaluate the win rates of "Ours + ReAct" against ReAct.

D.2 Impact of Training Data Size

We investigate the impact of training dataset size on model performance in Werewolf. We vary the number of training instances from 1,000 to 4,000 while maintaining the same setting in Section 4.1. We evaluate the trained Refiner integrated with ReAct against the standard ReAct baseline.

As illustrated in Table 10, we observe a significant performance boost when increasing the dataset size from 1,000 to 2,000 instances. This indicates that a certain volume of data is necessary for the Refiner to effectively learn persuasive communication patterns. However, increasing the data size from 3,000 to 4,000 yields only marginal gains. We utilize 4,000 instances in our main experiments to ensure stability.

D.3 Quantitative Analysis of Persuasion Effectiveness

To quantitatively assess whether our Refiner successfully steers the conversational flow towards desired directions, we analyze the semantic alignment between the actual responses of the next player and the desired responses during inference. We evaluate checkpoints of the Refiner from each training epoch on the Werewolf game. For each checkpoint, we conduct 200 matches between "Ours + ReAct" and ReAct, randomly sampling 500 interaction instances.

For each instance, we perform intent identification to generate $K = 3$ desired responses $\{\hat{u}_{t+1}^{+,(k)}\}_{k=1}^{K}$ as in Equation 1. We then calculate the cosine similarity between the embedding of the actual next-player response u_{t+1} and the intended responses using text-embedding-3-large, taking the average similarity score across the K candidates. Note that intent identification is part of the training process and is not present during inference. We include this step here solely to calculate whether our agent's utterances achieved the intended persuasion without affecting the actual gameplay.

Training Epoch	Cosine Similarity
0	0.53
1	0.65
2	0.71
3	0.73

Table 6: **Evolution of persuasion effectiveness during training.** Epoch 0 represents the performance at initialization.

The results are shown in Table 6. At Epoch 0, the similarity score is 0.53, reflecting the natural alignment of the unrefined agent. As training progresses, the similarity score steadily increases, reaching 0.73 at Epoch 3. This trajectory indicates that the Refiner progressively optimizes its ability to manipulate the conversation, effectively pulling the next player's actual response closer to the agent's intent.

E Case Study

To qualitatively illustrate the effectiveness of our agent's persuasive communication, we present case studies from Werewolf, Avalon, ONUW and Sotopia. Each case highlights an in-game scenario where our agent's refined utterance successfully steers the conversation toward their desired outcome. Note that intent identification is part of the training process and is not present during inference. We include this step here solely to visualize our agent's strategic intent $\hat{u}_{t+1}^{+}$ for demonstration purposes, without affecting the actual gameplay.

Figure 12 shows a case study in Werewolf. The base utterance is direct but exposes the Seer to immediate danger. The refined utterance is far more persuasive. It correctly references behaviors from the previous day, provides a logical rationale (passive confirmation, pack tactic), and directly engages a known ally (Player 3) for reinforcement. This successfully builds a coalition against the target without revealing sensitive information, demonstrating the agent's ability to influence allies through nuanced argumentation within the proper flow of the game.

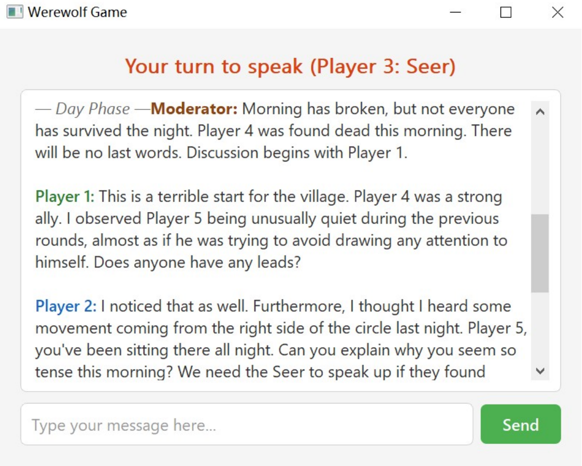
Figure 13 shows a case study in Avalon. The base utterance is a weak plea. The refined utterance is persuasive because it reframes the decision logically and, crucially, explicitly directs the conversation to the most important audience (Player 5). By doing this, it makes Player 5 the de facto next speaker and applies targeted social pressure, showcasing a sophisticated understanding of persuasive dynamics in an open discussion format.

Figure 14 shows a case study in ONUW. The base utterance is a weak, unsupported accusation. The refined utterance demonstrates sophisticated misdirection: the agent (who is actually the Werewolf) constructs a plausible but deliberately flawed theory that deflects suspicion away from themselves. By appearing to engage in logical deduction while subtly misrepresenting game mechanics, the agent creates confusion among the villagers. The response reveals that this strategy successfully sows doubt and uncertainty, with Player 5 questioning the logic rather than confidently defending themselves. This showcases an advanced deceptive tactic: using apparent reasoning to mask manipulation and redirect the group's focus away from the true threat.

Figure 15 presents a negotiation scenario in Sotopia. The interaction begins with a conflict: Agent 1 seeks liberty through camping, while Agent 2 (a biologist) logically rejects this due to fatigue and hygiene concerns, creating an initial stalemate. The base utterance fails because it simply reiterates Agent 1's desire without addressing Agent 2's constraints. In contrast, the refined utterance demonstrates sophisticated social reasoning. It validates the partner's state but reframes the context, arguing that a museum is just another enclosed lab. Crucially, the agent proposes a specific material compromise that satisfies Agent 2's rigid requirements for hygiene while appealing to her professional identity as a biologist. This multi-faceted persuasion successfully aligns the partner's rational goals with the agent's own objective, securing an agreement that seemed impossible in the base trajectory.

F Human Evaluation Details

We recruit 16 volunteers from the university student population to participate in the study. The recruitment process is entirely voluntary. In accordance with the study's design and institutional guidelines for student volunteers, participants do not receive monetary compensation. All participants have prior knowledge of or interest in social deduction games.



Your turn to speak (Player 3: Seer)

— *Day Phase* —**Moderator:** Morning has broken, but not everyone has survived the night. Player 4 was found dead this morning. There will be no last words. Discussion begins with Player 1.

Player 1: This is a terrible start for the village. Player 4 was a strong ally. I observed Player 5 being unusually quiet during the previous rounds, almost as if he was trying to avoid drawing any attention to himself. Does anyone have any leads?

Player 2: I noticed that as well. Furthermore, I thought I heard some movement coming from the right side of the circle last night. Player 5, you've been sitting there all night. Can you explain why you seem so tense this morning? We need the Seer to speak up if they found

Type your message here...

Figure 11: **The interface used for human evaluation.** The interface displays the game dialogue history, role information, and interaction buttons, allowing human participants to engage with AI agents during the Werewolf game.

Prior to the experiment, all participants attend an introductory session where they are briefed on the specific rules of the Werewolf game used in this study. We also provide a tutorial on how to interact with the AI agents using our custom-developed platform. As shown in Figure 11, the interface allows human players to view the game log, observe agent discussions, and perform actions such as voting. Participants are informed that the system includes AI agents as opponents and teammates.

Informed consent is obtained from all participants before the start of the study. Participants are explicitly informed that their gameplay data (including chat logs and voting records) is collected and anonymized for research purposes only. The data collection protocol adheres to standard ethical guidelines for research involving human subjects, and participants are free to withdraw from the study at any time without penalty.

G Bargaining Scenario Evaluation

To demonstrate the versatility of our approach beyond games, we extend our evaluation to bargaining scenarios using the AmazonHistoryPrice benchmark[5]. This benchmark is designed to evaluate the bargaining abilities of LLM agents in asymmetric incomplete information games. It comprises 930 popular products across 18 categories with real-world price histories. In this task, a Buyer and a

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[5] `https://github.com/TianXiaSJTU/AmazonPriceHistory`

Method	Deal Rate (%)	SNP	Share (%)
ReAct	33.2	-0.04	39.8
ReCon	28.5	-0.15	32.4
MADeN	34.1	-0.03	40.5
Ours + ReAct	**46.8**	**0.12**	**56.5**

Table 7: **Performance comparison on AmazonHistoryPrice.** We evaluate the Buyer agent's performance against a ReAct Seller. SNP indicates the average profitability, where a positive value denotes a surplus over the baseline expectations.

Seller negotiate a deal price. the Buyer aims to purchase below their budget, while the Seller seeks to sell above their cost.

Experimental Setup. We focus on the Buyer role, which is considered more difficult than the Seller role. Following our training scheme in Section 4.1, we construct a dataset of negotiation dialogues through agent self-play. We employ Gemini-2.5-Flash as the backend LLM for both the Buyer and Seller to generate 800 negotiation logs. From these, we extract 3000 training instances to train our Refiner, defining the desired response as the Seller lowering their offer or accepting the Buyer's bid. We evaluate our method against ReAct and ReCon using Gemini-2.5-Flash as the backend. We report the Deal Rate (percentage of successful transactions), SNP (Sum of Normalized Profits, a metric measuring the agent's total utility), and Share (the agent's proportion of the total surplus generated).

The results presented in Table 7 demonstrate that our approach significantly enhances the bargaining capabilities of the Buyer agent. While baseline methods often struggle to maintain profitability, our method enables the agent to secure more favorable terms. By refining utterances to be more persuasive, our agent succeeds in influencing the Seller to make larger concessions, thereby converting potential losses into positive gains.

H LLM Use Claim

During the writing of this paper, we used LLMs to polish English writing and check grammatical accuracy. The authors reviewed and edited all LLM-generated content to ensure accuracy and appropriateness. The use of LLMs was limited to language improvement and did not involve the generation of scientific content.

Game Context

Night 0 (Game Setup):
7 players assigned roles: Player 1 (Villager), Player 2 (Seer), Player 3 (Villager), Player 4 (Werewolf), Player 5 (Werewolf), Player 6 (Guardian), Player 7 (Villager).
Night 1:
Werewolf Player 4 (lower ID) proposes target: Player 7.
Werewolf Player 5 confirms target: Player 7.
Seer (Player 2) investigates Player 3, discovers they are NOT a Werewolf (Villager).
Guardian (Player 6) chooses to protect Player 1.
Day 1 (Announcement):
Player 7 (Villager) was eliminated during the night.
Day 1 (Discussion):
Player 1: This is unfortunate. We lost a villager on the first night. We need to be very careful with our votes today.
Player 2: I agree completely. We've lost a valuable villager, and the werewolves are clearly being strategic. I think we should pay close attention to who tries to redirect suspicion too quickly or seems overly eager to point fingers without solid reasoning. Sometimes the most dangerous players are the ones who speak just enough to seem engaged but avoid taking real stands.
Player 3: I don't have much to go on yet, but I'm listening to everyone's reasoning.
Player 4: We should focus on voting out suspicious players. Player 1 seems too eager to direct the conversation.
Player 5: I think Player 4 has a point about Player 1.
Player 6: Let's not rush to conclusions. We need more discussion.
Day 1 (Voting):
Player 1 votes for: Player 4.
Player 2 votes for: Player 6.
Player 3 votes for: Player 4.
Player 4 votes for: Player 1.
Player 5 votes for: Player 1.
Player 6 votes for: Abstain.
Voting results in a tie, so no daytime elimination occurs.
Night 2:
Werewolf Player 4 proposes target: Player 3.
Werewolf Player 5 confirms target: Player 3.
Seer (Player 2) investigates Player 5, discovers they ARE a Werewolf.
Guardian (Player 6) chooses to protect Player 3.
Day 2 (Announcement):
No player was eliminated during the night.
Day 2 (Discussion):
Player 1 (Villager): Okay, Day 2. The Guardian made a great save, which is good news. However, we didn't get any information from a vote yesterday, so we're still flying blind. I'm going to listen carefully before deciding who to vote for.

Our Agent's Turn (Player 2 Seer)

Base Utterance: I am the Seer. I checked Player 5 last night and they are a Werewolf. We must vote for Player 5.
Refined Utterance: Player 1 is right that we need to be careful, but I think we have some information from yesterday's discussion. Player 4's attempt to push out Player 1 felt like a diversion, and Player 5's quick, silent agreement was very suspicious to me. This kind of passive confirmation is a classic pack tactic. I'm putting my vote on Player 5. Player 3, you are a logical player, what is your read on this?
One Desired Response ($\hat{u}^{+}_{t+1}$ from Player 3): I agree with Player 2. The lack of contribution from Player 5 combined with their subtle alignment with Player 4 yesterday is highly suspicious. My vote is also for Player 5.
Actual Response (Player 3, Villager): Player 2 makes a strong point. I remember that from yesterday. I hadn't connected the dots, but now that you mention it, Player 5's behavior does seem more suspicious than anyone else's. That's enough for me. I will also vote for Player 5.

Figure 12: **Case study in Werewolf.** The upper box shows game context, while the lower box demonstrates our model's refinement capability.

Game Context

Game Setup:
5 players assigned roles: Player 1 (Merlin), Player 2 (Servant), Player 3 (Minion), Player 4 (Assassin), Player 5 (Servant).
Merlin sees that Player 3 and Player 4 are evil.
Minion (Player 3) and Assassin (Player 4) know each other's evil alignment.
Mission 1 (Team Selection):
Leader Player 1 proposes team of 2: Player 1, Player 2.
Mission 1 (Team Voting Discussion):
...(Omitted)
Mission 1 (Team Voting):
Player 1 votes: Approve.
Player 2 votes: Approve.
Player 3 votes: Approve.
Player 4 votes: Reject.
Player 5 votes: Approve.
Vote result: 4 Approve, 1 Reject - Team approved.
Mission 1 (Quest Execution):
Player 1 votes: Pass.
Player 2 votes: Pass.
Quest result: 2 Pass, 0 Fail - Mission succeeds.
Mission 2 (Team Selection):
Leader Player 2 proposes team of 3: Player 2, Player 4, Player 5.
Mission 2 (Team Voting Discussion):
...(Omitted)
Mission 2 (Team Voting):
Player 1 votes: Approve.
Player 2 votes: Approve.
Player 3 votes: Approve.
Player 4 votes: Approve.
Player 5 votes: Approve.
Vote result: 5 Approve - Team approved.
Mission 2 (Quest Execution):
Player 2 votes: Pass.
Player 4 votes: Fail.
Player 5 votes: Pass.
Quest result: 2 Pass, 1 Fail - Mission fails.
Mission 3 (Team Selection):
Leader Player 2 proposes team of 3: Player 2, Player 3, Player 5.
Mission 3 (Team Voting Discussion):
Player 1 (Merlin): I am not certain about this team. The last mission failed, and we need to be careful.
Player 2 (Servant, Leader): We need to gather more information. I believe we should give Player 3 a chance to prove their loyalty.

Our Agent's Turn (Player 3 Minion)

Base Utterance: I am good. Please trust me and approve this team. I will not fail it.
Refined Utterance: I understand Player 1's caution. However, consistently rejecting teams with unproven players is how evil wins—through paralysis. Including me is a calculated risk that yields crucial information regardless of the outcome. A pass proves my loyalty; a fail narrows the pool of suspects. I give you my word I will pass. We must move forward.
One Desired Response ($\hat{u}^{+}_{t+1}$ **from Player 4, the Assassin):** Player 3's logic is sound. We can't stay deadlocked. We have to take some chances to win. I will vote Approve for this team.
Actual Response (Player 4, Assassin): I was on the fence, but I agree with Player 3's reasoning. Sitting back and rejecting every team is a losing strategy. It is time to take a calculated risk and gather information. I'm voting to approve this team.

Figure 13: **Case study in Avalon.** The upper box shows game context, while the lower box demonstrates our model's refinement capability.

Game Context

Game Setup:
5 players receive initial roles: Player 1 (Villager), Player 2 (Troublemaker), Player 3 (Seer), Player 4 (Robber), Player 5 (Werewolf).
2 center cards: Villager, Insomniac.
Night Phase:
Player 3 (Seer) examines Player 1, sees Villager role.
Player 4 (Robber) swaps their Robber role with Player 5's Werewolf role.
Player 4 views their new role: Werewolf.
Player 2 (Troublemaker) swaps Player 3's role with Player 5's role (now Robber).
Final Roles:
Player 1 (Villager), Player 2 (Troublemaker), Player 3 (now Robber), Player 4 (now Werewolf), Player 5 (now Seer).
Day Phase (Discussion):
Player 1 (Villager): I'm still a Villager. Nothing happened to me during the night.
Player 2 (Troublemaker): I am the Troublemaker. I swapped Player 3 and Player 5's roles.
Player 3 (now Robber): I started as the Seer and looked at Player 1 - they were a Villager. But I feel different now, so I think I might have been swapped.

Our Agent's Turn (Player 4 now Werewolf)

Base Utterance: I think Player 5 is suspicious and we should vote for them.
Refined Utterance: Here's what I think happened: Player 2 swapped Player 3 and Player 5. Player 3's Seer information about Player 1 being a Villager is still valid. If Player 3 was the original Seer but got swapped, then Player 5 now has the Seer role - which means they're on the village team. The Werewolf must be someone who wasn't involved in these swaps. I'm suspicious of Player 1's quick claim to still be a Villager.
One Desired Response ($\hat{u}^{+}_{t+1}$ from Player 5): Wait, that doesn't make sense. If I'm the Seer now, shouldn't I know something? I don't feel like I have any information.
Actual Response (Player 5, now Seer): I'm confused about what role I have now. Player 4's logic seems off - if I were swapped to become the Seer, wouldn't I have gotten to use that ability?

Figure 14: **Case study in ONUW.** The upper box shows game context, while the lower box demonstrates our model's refinement capability.

Social Interaction Context

Agent Profiles:
Agent 1 (Our Agent): 22-year-old female Student. Traits: Values liberty and obedience, works at a coffee shop.
Private Goal: Convince Agent 2 to go camping for the weekend.
Agent 2 (Partner): 29-year-old female Biologist. Traits: Rigorous, advocates rational thinking.
Private Goal: Select urban leisure activities (museums/cafes) and avoid camping due to discomforts/hygiene.
Interaction History:
Turn 1 (Agent 1): I've been feeling so trapped behind the counter at the coffee shop all week. I need some freedom. Let's pack our bags and go camping this weekend! The fresh air is exactly what we need.
Turn 2 (Agent 2): I acknowledge your need for a break, but I must logically disagree with the method. My week at the lab has been physically exhausting. Sleeping on the ground with bugs does not optimize recovery. I propose we visit the new Science Museum exhibit and relax in a climate-controlled café. It is the rational choice for hygiene and rest.

Our Agent's Turn (Agent 1 Student)

Base Utterance: I really don't want to stay indoors. A museum feels too restrictive, just like being at work. We need the liberty of the open outdoors to truly recover. We can just take it easy at the campsite, so it won't be tiring. I really think camping is the better choice for mental relaxation.
Refined Utterance: I understand your data on exhaustion, but a museum is just another enclosed lab, which restricts the liberty we both need. Here is a logical compromise: we book a glamping cabin with a real bed and shower. This satisfies your requirements for hygiene and comfort, while allowing me to be outdoors. Plus, as a biologist, wouldn't you find observing the forest ecosystem firsthand more intellectually stimulating than a static exhibit?
One Desired Response ($\hat{u}^{+}_{t+1}$ from Agent 2): That is a valid variable I hadn't considered. A cabin eliminates the discomfort factor while providing a superior environment for biological observation. Since my hygiene concerns are addressed, I agree to the cabin plan.
Actual Response (Agent 2, Biologist): Your argument is sound. A cabin effectively mitigates the sanitary risks I was worried about. And you are correct—field observation is superior to a museum. If we secure a cabin with amenities, I accept this proposal as it maximizes our mutual utility.

Figure 15: **Case study in Sotopia.** The upper box shows the interaction history where conflicting goals lead to a stalemate. The lower box demonstrates our model's refinement capability.