Distilling LLM Reasoning into an Interpretable Policy Tree for Human-AI Collaboration

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Abstract

Constructing efficient and reliable policies to assist humans is indispensable for human-AI collaboration. Existing methods mainly follow two lines of work. The major parts of prior work rely on multi-agent reinforcement learning (MARL) to learn black-box policies. This limits the interpretability and raises safety concerns. Recent methods query large language models (LLMs) at each decision step, causing slow responses and high inference costs. We propose Collaboration Policy Tree (Co-π-tree), a closed-loop method that learns an executable policy tree consisting of a partner-behavior prediction tree and an agent-action selection tree. Co-π-tree constructs a policy through distilling LLM reasoning into policy tree code. Co-π-tree then evaluates the policy through partner interaction and obtains feedback, and uses natural language to summarize interaction feedback to improve problematic branches. Experiments in Overcooked-AI show that Co-π-tree improves average reward by 6.4% over the strongest LLM baseline, while reducing the number of LLM queries by 77.7% and test-time latency by 97.1%. Project page: https://beiwenzhang.github.io/Co-pi-tree/.

1 Introduction

Constructing efficient and reliable policies that enable AI agents to better assist human partners is essential for human-AI collaboration, especially in domains such as healthcare, autonomous driving, and assistive robotics (Topol, 2019; Paden et al., 2016). A core challenge in human-AI collaboration is zero-shot coordination (ZSC), where agents must cooperate effectively with previously unseen partners (Carroll et al., 2019; Hu et al., 2020). Most existing ZSC methods rely on multi-agent reinforcement learning (MARL), typically training an agent to cooperate with simulated partners that cover different behaviors and strategies (Strouse et al., 2021; Zhao et al., 2023; Li et al., 2023). Their effectiveness therefore depends on partner diversity, while their black-box policies limit interpretability and may lead to unpredictable or unsafe actions in human coordination (Endsley, 2023; Sahin et al., 2025; Anne et al., 2025).

Since human collaboration relies heavily on language for establishing common ground, sharing intentions, and coordinating joint actions (Clark and Brennan, 1991), natural language provides an effective medium for human-AI collaboration. With strong language understanding, reasoning, and planning abilities (Du et al., 2026; Shinn et al., 2023; Liu et al., 2024b), large language models (LLMs) offer a promising tool for supporting such language-mediated collaboration. Recent studies have begun to operationalize this idea by converting observations and partner behaviors into textual contexts, querying LLMs to generate coordination plans, and translating the responses into executable actions (Zhang et al., 2024; Liu et al., 2024a; Sun et al., 2025).

However, current LLM-based ZSC collaboration methods still face an efficiency bottleneck in real-time coordination. They typically require an LLM query before each action, causing delayed responses and high inference costs (Zhang et al., 2024; Liu et al., 2024a; Zhang et al., 2025). In contrast, MARL-based methods support low-latency execution but learn black-box policies with limited interpretability. We therefore ask: *Can we obtain executable policies for human-AI collaboration that preserve the language-based coordination reasoning of LLMs while requiring only limited LLM queries and low test-time latency?*

Since tree structures offer fast and interpretable execution by selecting actions through explicit condition branches (Rudin, 2019; Xiong et al., 2024), we propose Collaboration Policy Tree (Co-π-tree), which distills LLM-based coordination reasoning

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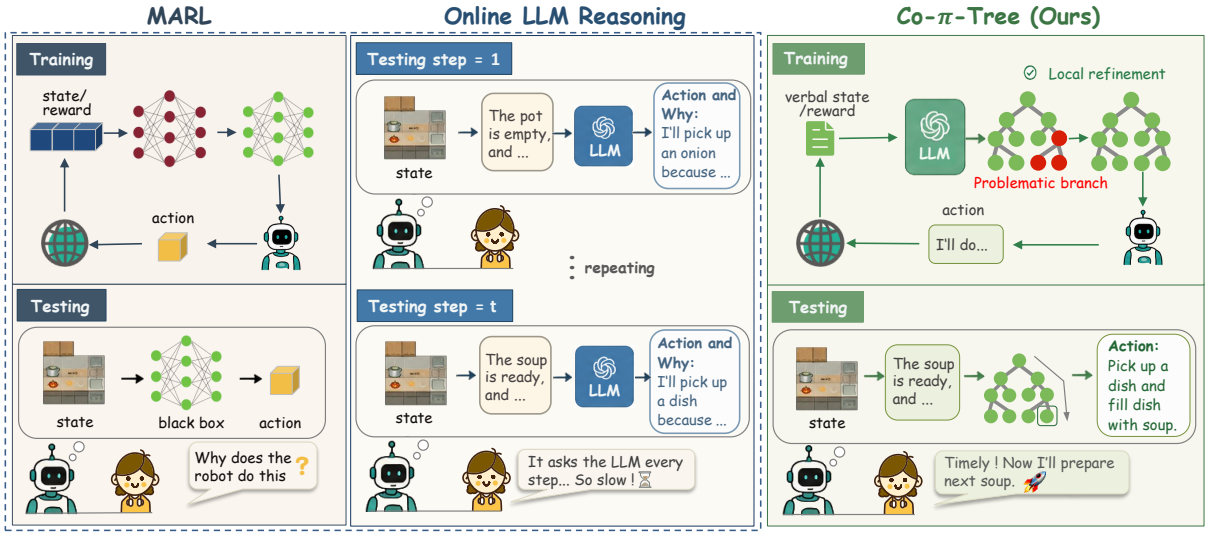

Figure 1: Left: MARL methods update all policy parameters during training and directly use the learned black-box policy to collaborate with humans. Middle: online LLM agents require no training but query the LLM before every decision. Right: Co-π-tree uses the LLM to locate and revise problematic branches, and directly executes the refined policy tree with humans.

into an executable policy tree. Co-π-tree contains two components: a partner-behavior prediction tree that predicts how the partner may act, and an agent-action selection tree that adapts to the predicted partner behavior to choose cooperative actions. Co-π-tree training consists of three stages: (1) the policy construction stage distills LLM reasoning into executable policy tree code; (2) the environment grounding stage evaluates the policy through partner interaction and obtains feedback; and (3) the policy refinement stage uses natural language to summarize interaction feedback and improve problematic branches. The resulting policy tree can then be directly executed without querying the LLM at each decision step.

Our work makes three contributions. (1) We introduce a policy-tree structure for human-AI collaboration, enabling efficient and interpretable execution. (2) We design a closed-loop algorithm that distills LLM reasoning into a policy tree and refines problematic branches through natural-language feedback. (3) We validate Co-π-tree in Overcooked-AI (Carroll et al., 2019) with AI and human partners, showing that it improves average reward by 6.4% over the strongest LLM baseline, while reducing the number of LLM queries by 77.7% and test-time latency by 97.1%.

2 Related Work

ZSC in Human-AI Collaboration. To assist different humans effectively, collaborative policies need to generalize to previously unseen partners at test time (Carroll et al., 2019), which is the ZSC problem in human-AI collaboration (Hu et al., 2020; Gessler et al., 2025). Existing MARL-based ZSC methods typically first train a diverse set of simulated partner policies, and then train an agent to cooperate with these partners to improve generalization to unseen human partners (Strouse et al., 2021; Zhao et al., 2023; Li et al., 2023; Jha et al., 2025). However, their performance depends heavily on the diversity and coverage of the simulated partners, while the learned black-box policies limit interpretability and human oversight (Endsley, 2023; Sahin et al., 2025; Anne et al., 2025).

LLM Reasoning for Coordination. LLMs have shown strong capabilities in multi-step reasoning and planning across a wide range of tasks (Wei et al., 2022; Zhou et al., 2024; Yao et al., 2023). Beyond direct online generation, some studies convert LLM outputs into reusable decision forms, such as executable programs or decision trees (Gallego, 2026; Xiong et al., 2024), while others use language feedback to improve model outputs (Hu et al., 2024). SMAC-R1 (Deng et al., 2024) and RL-LLM-DT (Lin et al., 2024) further apply LLMs to generate and refine executable decision trees through environment-based evaluation. These studies suggest that LLM reasoning can be used not only for one-time response generation, but also for constructing reusable and improvable decision structures. However, SMAC-R1 and RL-LLM-DT

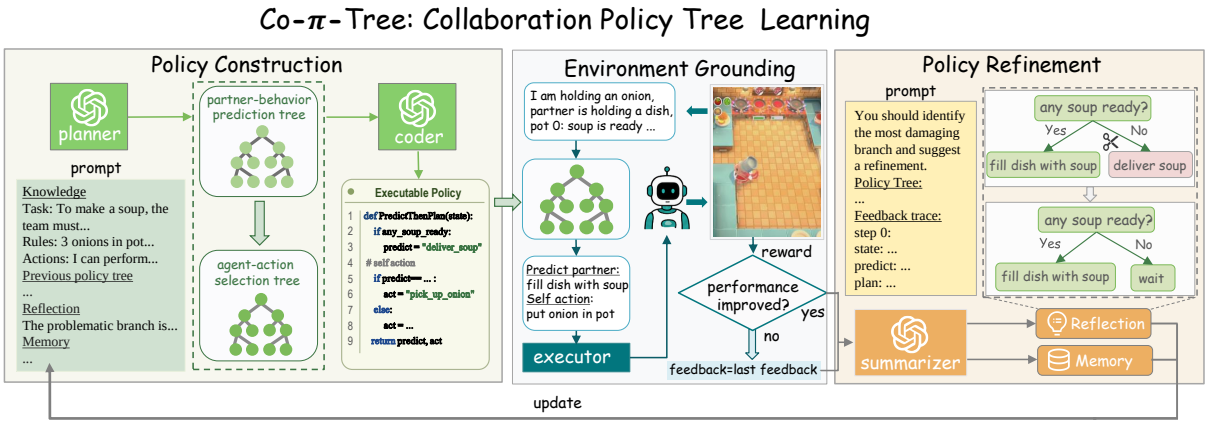

Figure 2: Overview of the Co-π-tree pipeline.

target fixed game settings and do not learn policies that predict and adapt to unseen partners during collaboration.

Recent studies have also explored LLM-based reasoning for collaborative decision making. ProAgent verbalizes observations and partner behaviors to infer intent and replan actions (Zhang et al., 2024), HLA uses natural-language communication for command interpretation and macro-action generation (Liu et al., 2024a), and CausalPlan augments LLM action selection with causal scores over candidate actions (Nguyen et al., 2026). These methods demonstrate the potential of language-based reasoning for coordination. However, they often rely on LLM-driven decisions during interaction, requiring repeated inference and introducing latency and inference cost (Zhang et al., 2025; Parashar et al., 2025; Xiao et al., 2025; Pan et al., 2025).

3 Methodology

To address the opacity of MARL policies and the high test-time cost of online LLM agents, we propose Co-π-tree, a policy learning algorithm that distills LLM reasoning into an executable policy tree. Figure 2 illustrates the overall pipeline, which learns an interpretable policy through three stages. In the policy construction stage, the planner and coder generate a candidate policy tree and translate it into executable code. In the environment grounding stage, the executor runs the candidate policy through partner interaction and obtains natural-language feedback. The resulting reward determines whether the candidate policy is accepted. In the policy refinement stage, the summarizer uses the feedback to identify problematic branches and produce a reflection for the next iteration.

3.1 Dec-POMDP

We formulate the human-AI collaboration problem as a Decentralized Partially Observable Markov Decision Process (Dec-POMDP),

$$\mathcal{G} = (\mathcal{I}, \mathcal{S}, \mathcal{A}, \Omega, P, Z, R, \gamma), \tag{1}$$

where $\mathcal{I}$ is the agent set, $\mathcal{S}$ is the state space, $\mathcal{A}$ is the joint action space, Ω is the joint observation space, P and Z are the transition and observation functions, respectively, R is the shared team reward, and γ is the discount factor.

The problem objective is to learn a policy π for the controlled agent that can be executed with previously unseen partners. We optimize π to maximize episodic team reward over horizon H:

$$J(\pi) = \mathrm{E}_{\tau\sim\pi}\left[\sum_{t=0}^{H-1} \gamma^t r_t\right]. \tag{2}$$

3.2 Policy Construction Stage

This stage converts LLM reasoning into a structured and executable policy. It first uses the planner to generate a candidate two-component policy tree T, and then uses the coder to translate T into executable code c.

Planner: Policy Tree Construction. Let $\mathcal{M}$ denote the LLM and $\|$ denote prompt concatenation. At the k-th iteration, the planner takes as input two specialized prompts p_{pred} and p_{act}, memory $\mathcal{B}_{<k}$, which stores concise summaries of previously accepted policies, the previous accepted policy tree $T^{\star}_{k-1}$, and the corresponding reflection ρ_{k-1}.

The planner first uses p_{pred} to generate T_k^{pred}, which predicts the partner's likely behavior. It then uses T_k^{pred} to generate T_k^{act}, which selects the controlled agent's action conditioned on the predicted

partner behavior. Together, these two trees form the candidate policy tree T_k:

$$\begin{aligned} T_k^{\text{pred}} &= \mathcal{M}\big(p_{\text{pred}} \| \mathcal{B}_{<k} \| T_{k-1}^{\star} \| \rho_{k-1}\big), \\ T_k^{\text{act}} &= \mathcal{M}\big(p_{\text{act}} \| \mathcal{B}_{<k} \| T_{k-1}^{\star} \| \rho_{k-1} \| T_k^{\text{pred}}\big), \\ T_k &= (T_k^{\text{pred}}, T_k^{\text{act}}). \end{aligned} \tag{3}$$

The generated trees operate on a structured policy input $x_t = \phi(s_t, h_t)$, where s_t is the current environment state and h_t records recent agent behavior. The mapping ϕ converts raw observations into a readable context that exposes task progress, partner intent, and coordination needs. During execution, the policy first predicts the partner's behavior and then selects the controlled agent's action:

$$\hat{z}_t = T_k^{\text{pred}}(x_t), \qquad a_t = T_k^{\text{act}}(x_t, \hat{z}_t). \tag{4}$$

Here, $\hat{z}_t$ denotes the predicted partner behavior used by the agent-action selection tree. We use a tree structure for π because it is easy for humans to inspect and revise. Each branch is an explicit `if/elif` condition-action rule, exposing why a partner behavior is predicted and why the controlled agent selects an action in a given scene. This locality supports branch-level diagnosis and revision, which is preferable to opaque neural policies when decisions need to be audited (Rudin, 2019).

Coder: Executable Code Generation. The coder takes the textual policy tree T_k as input and feeds it, together with the code-generation prompt p_{code}, into the LLM:

$$c_k = \mathcal{M}(p_{\text{code}} \| T_k). \tag{5}$$

The output is an executable Python function c_k that implements the same partner-behavior prediction and agent-action selection logic:

$$c_k(x_t) = (\hat{z}_t, a_t). \tag{6}$$

The coder preserves the policy tree logic with explicit `if/elif` branches, while grounding to executable environment actions and feasibility checks are handled by the executor.

Prompt and Output Design. p_{pred} and p_{act} specialize the planner into two connected generation tasks. p_{pred} asks the LLM to generate a tree for predicting the partner's likely behavior. It includes a knowledge library (task objective, task rules, and available actions), the required tree structure, and the input-output format. This enables the LLM to express partner prediction as explicit decision branches. p_{act} asks the LLM to generate a tree for selecting the controlled agent's action. Its prompt composition is similar to p_{pred}, but it additionally requires the action tree to condition on the predicted partner-behavior tree, so the selected action can be complementary to the predicted partner behavior. We also include a small set of demonstration scenes to ground action semantics and clarify how scene conditions and partner behavior should affect branch construction (Brown et al., 2020; Dong et al., 2024).

Both the planner and coder are constrained to follow prescribed output structures and code interfaces (OpenAI, 2024; Shen et al., 2025). These constraints turn LLM generations into machine-readable policy tree descriptions rather than free-form text, and allow the coder to translate the tree into executable functions. Detailed prompt schemas, demonstration format, and code interface constraints are provided in Appendix A.18.

3.3 Environment Grounding Stage

This stage connects the executable code with environment interaction by grounding tensor states into textual states, grounding tree output actions into executable environment actions, and returning feedback for policy refinement.

Tensor States to Textual States. Co-π-tree first grounds tensor states into textual states that the LLM can read and uses task semantic fields to describe the current scene. Tensor states in RL environments encode environment variables such as agent locations, orientations, object states, and layout configurations, while textual states make task progress, object status, and partner behavior explicit for LLM reasoning. For execution, these textual states are then converted into an input dictionary with a fixed format, which serves as the input to the policy tree code. The full grounding schema is provided in Appendix A.11.

Output Actions to Executable Actions. Tree output actions are mapped to executable environment actions by an executor. In Overcooked-AI, the executor maps an action, such as picking up an onion, to executable environment actions such as movement and interaction commands. The executor selects a feasible destination and the next executable environment action, and logs failures in the execution trace when the action is not executable. This separation allows the LLM to focus on action reasoning, while the executor handles navigation, reachability, and other environment constraints.

Executor and Feedback. The executor evaluates

a candidate policy by running the code in the environment for five independent rollouts. It returns feedback $\mathcal{F}_k = (S_k, \tau_k)$, where S_k is the mean return over the five rollouts and τ_k denotes their grounded execution traces. Each trace records the scene state, whether the selected action was executable, and whether the predicted partner behavior is correct. The realized partner behavior is derived from the action labels recorded by the environment after each interaction. The score S_k determines whether the candidate policy is accepted. If the candidate improves or matches the best accepted score $S^\star_{k-1}$, Co-π-tree accepts the candidate policy tree; otherwise, it reverts to the previous accepted policy tree. The accepted policy and its feedback are updated as

$$(T^\star_k, \mathcal{F}^\star_k) = \begin{cases} (T_k, \mathcal{F}_k), & \text{if } S_k \geq S^\star_{k-1}, \\ (T^\star_{k-1}, \mathcal{F}^\star_{k-1}), & \text{otherwise.} \end{cases} \tag{7}$$

3.4 Policy Refinement Stage

This stage converts feedback into language-level updates for the next policy construction stage. Given the accepted policy tree $T^\star_k$ and its feedback $\mathcal{F}^\star_k$, Co-π-tree produces a policy summary m_k for memory and a reflection ρ_k for refining problematic branches in the next planner call.

Summarizer: Reflection from Feedback. The input to the summarizer is the accepted policy tree $T^\star_k$ and its feedback $\mathcal{F}^\star_k = (S^\star_k, \tau^\star_k)$. The execution trace $\tau^\star_k$ contains compact language-based scene descriptions, which allow the summarizer to analyze feedback at the scene level; the trace format and example entries are given in Appendix A.11. Following the principle of verbal reinforcement learning (Shinn et al., 2023), the summarizer feeds this information, together with a summarization prompt p_{sum}, into the LLM to generate information for updating the partner-behavior prediction tree and the self-action selection tree:

$$g_k = (m_k, \rho_k) = \mathcal{M}(p_{\text{sum}} \| T^\star_k \| \mathcal{F}^\star_k), \tag{8}$$

where m_k is a compact policy tree summary and ρ_k is a reflection for policy refinement.

This design converts sparse execution feedback into structured language supervision. The reflection ρ_k identifies a damaging or inefficient branch, explains the failure pattern observed in the feedback, and proposes a localized reflection for the next planner call. This branch-level reflection addresses credit assignment, which refers to identifying which decision branch is responsible for an episode failure. This is challenging because sparse team reward does not directly reveal whether the failure comes from a specific local decision, such as an incorrect partner-behavior prediction or premature dish handling in Overcooked-AI (Zhang, 2026). Because each decision corresponds to an explicit branch, the summarizer can assign episode failures to local branches of the policy tree rather than returning only a global critique. This branch-level diagnosis then guides the planner to preserve unchanged branches and refine only the exposed branch, reducing uncontrolled changes to unrelated branches.

Memory. Past accepted policies can inform future planning (Madaan et al., 2023), so Co-π-tree maintains a memory pool $\mathcal{B}$ of accepted policy tree summaries m_k. This memory enables reuse of high-quality policies and helps the planner prioritize effective behaviors. To avoid placing all historical policies and feedback into the LLM context, which can increase inference cost and dilute key information in long-context prompting (Jiang et al., 2024), Co-π-tree stores concise summaries and instructs the planner to prefer higher-scoring policies.

Algorithm 1 summarizes the Co-π-tree policy-learning loop. Additional parameter details are provided in Appendix A.9.

Algorithm 1: Co-π-tree Policy Learning

Input: LLM $\mathcal{M}$, number of iterations K
Initialize: $\mathcal{B} \leftarrow \emptyset$, $T^\star \leftarrow \emptyset$, $c^\star \leftarrow \emptyset$, $\mathcal{F}^\star \leftarrow \emptyset$, $S^\star \leftarrow -\infty$, $\rho \leftarrow \emptyset$, $u \leftarrow 0$
for $k = 1, \ldots, K$ **do**
  $\vartheta_k \leftarrow \min(\vartheta_{\max}, \vartheta_{\text{base}}(1 + \log(1 + u)))$
  $T^{\text{pred}}_k \leftarrow \text{plannerInf}(\mathcal{B}, T^\star, \rho, \vartheta_k)$
  $T^{\text{act}}_k \leftarrow \text{plannerAct}(\mathcal{B}, T^\star, \rho, T^{\text{pred}}_k, \vartheta_k)$
  $T_k \leftarrow (T^{\text{pred}}_k, T^{\text{act}}_k)$
  $c_k \leftarrow \text{coder}(T_k, \vartheta_k)$
  $\mathcal{F}_k \leftarrow \text{executor}(c_k, N_{\text{rollout}} = 5)$
  $S_k \leftarrow \frac{1}{5}\sum_{r=1}^{5} \text{return}(\mathcal{F}^{(r)}_k)$
  $S_{\text{old}} \leftarrow S^\star$
  if $S_k \geq S^\star$ **then**
    $(m_k, \rho_k) \leftarrow \text{summarizer}(T_k, \mathcal{F}_k)$
    $T^\star \leftarrow T_k$
    $c^\star \leftarrow c_k$
    $\mathcal{F}^\star \leftarrow \mathcal{F}_k$
    $S^\star \leftarrow S_k$
    $\mathcal{B} \leftarrow \mathcal{B} \cup \{m_k\}$
    $\rho \leftarrow \rho_k$
    if $S_k > S_{\text{old}}$ **then** $u \leftarrow 0$ **else** $u \leftarrow u + 1$
  else
    $(_, \rho^\star) \leftarrow \text{summarizer}(T^\star, \mathcal{F}^\star)$
    $\rho \leftarrow \rho^\star$
    $u \leftarrow u + 1$
  end if
end for
return executable policy $c^\star$ and interpretable policy tree $T^\star$

4 Experiments

We evaluate Co-π-tree in the Overcooked-AI benchmark (Carroll et al., 2019), a standard testbed for ZSC and human-AI collaboration. Our experiments are designed to answer three questions: **Q1.** How effectively does Co-π-tree collaborate with both unseen AI partners and real human partners compared with existing ZSC methods? **Q2.** How do the main components of Co-π-tree, including partner prediction and iterative refinement, affect collaborative performance? **Q3.** How scalable is the learned policy tree when transferred across layouts, and how interpretable is it when inspected through its explicit decision branches?

4.1 Experimental Setup

Environments. We use five layouts from Overcooked-AI: *cramped room*, *coordination ring*, *counter circuit*, *asymmetric advantages*, and *forced coordination*, abbreviated as *Cramped Rm.*, *Coord. Ring*, *CT. Circuit*, *Asymm. Adv.*, and *Forced Coord.*, respectively. A detailed description of each layout is provided in the appendix. Each episode lasts 400 environment steps, and performance is measured by the team reward, which is determined by the number of delivered soups.

Baselines. We compare with two groups of ZSC methods. The first group includes MARL policies and imitation policies commonly used in ZSC: Self-Play (SP), Population-Based Training (PBT), Fictitious Co-Play (FCP) (Strouse et al., 2021), Maximum Entropy Population-Based Training (MEP) (Zhao et al., 2023), Cooperative Open-ended Learning (COLE) (Li et al., 2023), and a human proxy trained by behavior cloning (BC) (Carroll et al., 2019). The second group includes two LLM-based methods: ProAgent (Zhang et al., 2024) and CausalPlan (Nguyen et al., 2026). Additional details on baseline selection are provided in Appendix A.2.

Co-π-tree Variants. To understand the roles of partner-behavior prediction and partner-conditioned action selection, we design two ablation variants. Co-π-tree is the full two-component method introduced in Section 3.2. Co-π-tree-PI asks the LLM to generate both trees, but the agent-action selection tree does not explicitly use the predicted partner behavior. In this variant, the partner-behavior prediction tree serves only as an intermediate reasoning step for generating the agent-action selection tree, similar to chain-of-thought prompting. Co-π-tree-w/o P removes partner-behavior prediction and directly asks the LLM to generate an agent-action selection tree independent of partner behavior. Additional details are provided in Appendix A.9.

Evaluation Protocol. We follow the standard ZSC evaluation protocol. For each evaluated method, the agent controlled by this method is paired with each partner agent from {SP, PBT, FCP, MEP, COLE, BC}, and we report the average team reward across all pairings. We evaluate both role assignments, where the evaluated method controls Agent 0 and Agent 1, respectively. We also report NQ as the total number of LLM queries and latency as the average test-time decision time. Further details on the evaluation protocol are provided in Appendix A.3.

4.2 Collaborating with Other AI Partners

To answer Q1 in the standard ZSC setting with unseen AI partners, Table 1 reports the main results against the MARL, BC, and LLM-based baselines. Co-π-tree achieves strong performance across all layouts, outperforming all baselines in 8 of the 10 layout-role settings. Averaged over all layout-role settings, Co-π-tree improves average reward by 6.4% over the strongest LLM baseline. The gains are especially clear in CT. Circuit and Asymm. Adv., where successful collaboration requires stable role specialization. The main exception is Forced Coord., where Co-π-tree is competitive as Player 0 but weaker as Player 1. We provide a brief discussion in Appendix A.8.

Beyond reward, Figure 4 compares Co-π-tree with ProAgent and CausalPlan in terms of NQ and test-time latency. We repeat each evaluation five times and report averages. ProAgent and CausalPlan rely on online test-time LLM reasoning, so each evaluation requires repeated model queries and incurs response delay during interaction. For all methods, NQ is counted for one complete algorithm run. Once the final policy tree is produced, additional evaluations do not require extra LLM queries. As a result, Co-π-tree reduces NQ by 77.7% and test-time latency by 97.1% relative to the mean of the two online LLM baselines.

4.3 Collaborating with Human Partners

To answer Q1 in the standard ZSC setting with real human partners, following prior human-agent evaluations in Overcooked-AI, we further evaluate whether the learned policy tree transfers to such partners. Humans interacted with the evalu-

	AI Baseline					LLM Baseline			Ours
	SP	PBT	FCP	MEP	COLE	BC	ProAgent	CausalPlan	Co-π-tree
Cramped Rm.	155.0± 43	161.3± 45	175.8± 30	161.3± 42	153.8± 29	131.3± 37	171.0± 26	174.5± 20	**182.3**± 18
	157.5± 32	158.8± 53	170.3± 33	168.8± 35	153.8± 37	130.0± 37	168.3± 18	170.2± 16	**180.1**± 16
Coord. Ring	103.8± 49	118.8± 39	136.3± 28	152.0± 21	150.3± 32	96.3± 37	151.0± 34	155.7± 24	**165.9**± 28
	127.5± 49	127.5± 37	137.5± 24	140.0± 39	144.0± 31	96.3± 41	143.3± 28	152.0± 26	**162.1**± 24
CT. Circuit	30.0± 33	43.8± 49	42.5± 45	53.8± 35	85.0± 30	47.5± 35	108.3± 24	108.8± 21	**117.8**± 15
	36.3± 26	35.0± 39	37.5± 45	65.0± 41	86.3± 34	40.0± 35	106.0± 19	104.9± 21	**116.0**± 17
Asymm. Adv.	151.3± 60	147.5± 73	141.3± 68	116.3± 74	187.5± 46	150.0± 56	256.7± 31	250.4± 25	**274.6**± 31
	190.0± 32	136.3± 76	170.0± 46	177.5± 59	150.0± 70	82.5± 75	228.3± 15	228.6± 20	**239.1**± 18
Forced Coord.	12.5± 17	21.3± 22	56.3± 42	23.8± 25	40.0± 32	40.0± 23	56.7± 22	**64.3**± 25	62.7± 31
	28.8± 25	**61.3**± 42	18.8± 26	35.0± 32	41.3± 24	21.3± 22	33.3± 34	34.5± 28	35.6± 22

Table 1: ZSC with AI partners. Each entry reports mean team reward ± std. For each layout, the two rows correspond to assigning the evaluated policy to Player 0 and Player 1, respectively. Bold and underline denote the best and second-best result in each layout-role row.

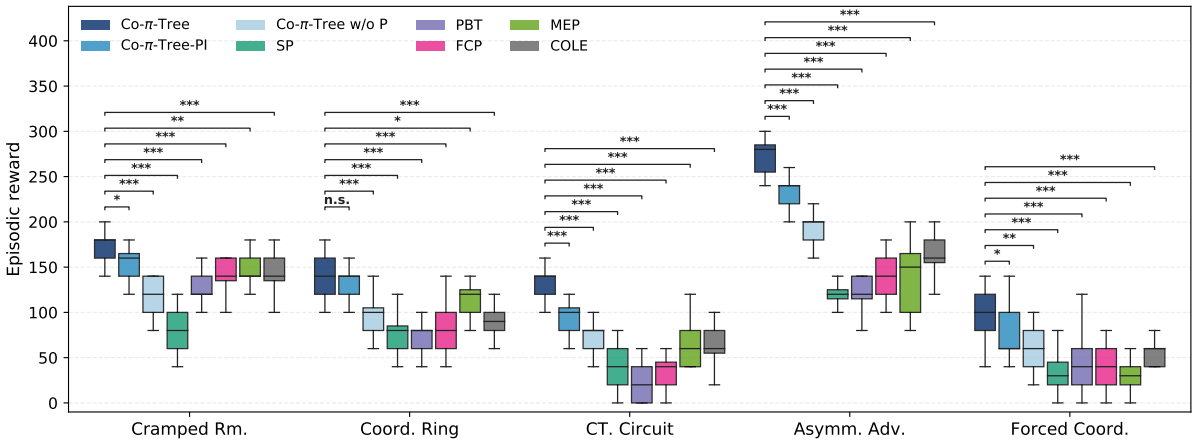

Figure 3: Box plots of human-agent collaboration rewards by layout. Each box shows per-volunteer average rewards for one method, averaging the two player-role assignments. Significance markers compare each method with Co-π-tree within the same layout using Holm-corrected two-sided Mann–Whitney U tests; n.s. denotes not significant, and *, **, *** denote $p < 0.05$, $p < 0.01$, and $p < 0.001$.

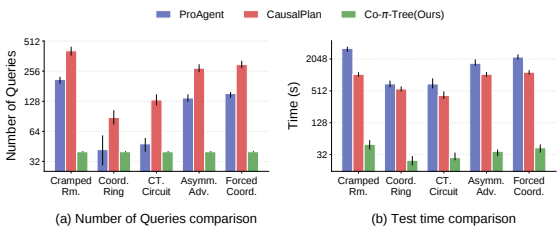

Figure 4: Comparison among ProAgent, CausalPlan, and Co-π-tree in terms of NQ and test-time latency.

ated agents through the human-AI web application of Overcooked-AI[1], and we report average rewards. Detailed participant information, protocol details, and the rationale for method selection are provided in Appendix A.4, following Wang et al. (2024).

[1] https://github.com/HumanCompatibleAI/overcooked_ai/tree/master/src/overcooked_demo

Figure 3 shows the results for the full Co-π-tree and the two variants. The full method obtains the highest mean reward on all five layouts, followed by Co-π-tree-PI and then Co-π-tree-w/o P. Here, p denotes the p-value of the Holm-corrected two-sided Mann–Whitney U test. Smaller p values and more stars indicate stronger evidence that Co-π-tree differs from the compared method, while n.s. indicates no significant difference. Together with the higher mean rewards, these markers support that the full method is stronger in most human-AI collaboration comparisons.

These results suggest that partner-behavior prediction improves human-AI coordination, and that explicitly conditioning action selection on the predicted partner behavior further strengthens this effect. For example, when a soup is ready, predicting

	Co-π-tree	Co-π-tree-PI	Co-π-tree-w/o P
Cramped Rm.	**182.3**± 18	176.7± 24	168.0± 25
	180.1± 16	176.0± 19	165.7± 22
Coord. Ring	165.9± 28	**168.0**± 26	158.0± 29
	162.1± 24	**169.3**± 23	152.0± 25
CT. Circuit	**117.8**± 15	110.7± 16	106.0± 18
	116.0± 17	114.0± 18	105.2± 21
Asymm. Adv.	274.6± 31	**282.7**± 35	266.7± 34
	239.1± 18	**242.0**± 15	234.7± 22
Forced Coord.	62.7± 31	**66.0**± 24	62.0± 28
	35.6± 22	**44.1**± 26	32.8± 23

Table 2: Ablation on partner prediction. Each entry reports mean team reward ± std.

Layout	Accuracy
Asymm. Adv.	84.33%
Coord. Ring	79.56%
CT. Circuit	78.18%
Cramped Rm.	79.61%
Forced Coord.	79.17%
Average	**80.17%**

Table 3: Partner-behavior prediction accuracy by layout.

that the human partner will deliver it allows the agent to prepare onions for the next pot instead of duplicating the delivery task.

4.4 Ablation Studies

This subsection answers Q2 by isolating the effects of partner-behavior prediction and iterative policy refinement.

Effect of Partner Prediction. We evaluate the partner prediction from two perspectives. Table 2 compares the full method with two variants, while Table 3 directly measures how often the predicted partner behavior matches the actual partner behavior.

The prediction tree achieves an average accuracy of 80.17% across the five layouts, showing that it captures useful partner-behavior patterns while still leaving room for prediction errors. In Table 2, Co-π-tree-w/o P removes partner-behavior prediction entirely and is consistently worse than Co-π-tree-PI, suggesting that partner reasoning provides a useful signal for coordination. At the same time, Co-π-tree-PI often performs best when collaborating with other AI partners, showing that directly tying action selection to the predicted partner behavior is less stable than using partner prediction as an intermediate reasoning signal in these settings.

Effect of Iterative Refinement. Table 4 evaluates

	Co-π-tree	Co-π-tree w/o R
Cramped Rm.	**182.3**± 18	163.1± 16
	180.1± 16	161.5± 22
Coord. Ring	**165.9**± 28	153.8± 29
	162.1± 24	148.3± 27
CT. Circuit	**117.8**± 15	104.0± 18
	116.0± 17	100.7± 16
Asymm. Adv.	**274.6**± 31	260.3± 25
	239.1± 18	226.6± 22
Forced Coord.	62.7± 31	**66.8**± 29
	35.6± 22	**35.8**± 23

Table 4: Ablation on iterative refinement. Each entry reports mean team reward ± std.

the effect of policy refinement. We construct an ablation variant, Co-π-tree w/o R, which removes policy refinement and uses only the initial prompt construction. The full method improves most layouts, indicating that episode verbal feedback helps the planner repair weak branches and improve the final policy tree. Detailed reward growth curves covering all five layouts and different partners are provided in Appendix A.13.

4.5 Additional Experiments

Beyond the main comparisons and ablations above, we provide additional analyses that further address the questions in this section. For Q2, Appendix A.13 and Appendix A.14 report reward growth curves and refinement statistics, and the backbone sensitivity study below tests how robust the policy-construction stage is to the choice of LLM. For Q3, Appendix A.16 evaluates cross-layout transfer, and Appendix A.17 provides interpretability evidence through structural statistics, a user study, and a local refinement visualization.

Backbone Sensitivity. As a supplementary analysis for Q2, we evaluate the sensitivity of the policy-construction pipeline to the LLM backbone by comparing GPT-4o with Llama-3.1-8B-Instruct and GPT-3.5-turbo-1106. Figure 5 reports scores averaged over both player roles. Co-π-tree degrades with Llama-8B and trails both online LLM baselines on four layouts, while with GPT-3.5 it outperforms both baselines on all five layouts. These results show that the method benefits from stronger backbone capabilities and remains sensitive to the choice of LLM. The complete settings and results are provided in Appendix A.15.

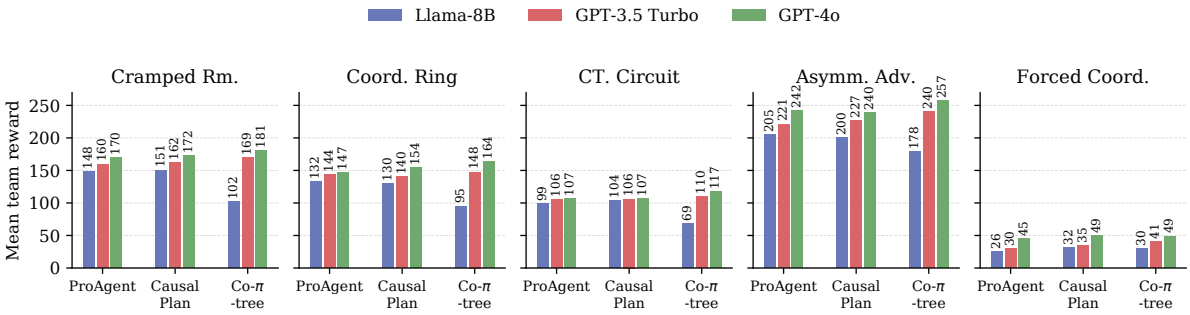

Figure 5: Backbone sensitivity on five Overcooked-AI layouts. Scores are averaged over both player roles.

5 Conclusion

In this paper, we presented Co-π-tree, a closed-loop policy learning algorithm that distills LLM reasoning into interpretable policy tree structures for human-AI collaboration. By learning a two-component policy tree that predicts partner behavior and selects the agent's action, and by using grounded rollout feedback to revise problematic branches, Co-π-tree moves LLM reasoning from test-time control to policy learning while retaining partner-conditioned coordination. Experiments in Overcooked-AI involving both unseen AI partners and human partners show that the learned policies achieve strong ZSC performance, while requiring substantially fewer LLM queries and lower test-time latency than online LLM-based collaboration methods. Our results further suggest that reasoning about a partner is broadly useful. Overall, Co-π-tree provides a practical path toward efficient, auditable, and generalizable collaborative agents.

Limitations

This work has three limitations. (1) Although we evaluate Co-π-tree with both AI partners and human partners in Overcooked-AI, its effectiveness in physically embodied collaboration settings remains to be further validated. (2) Co-π-tree currently relies on a manually defined action space and an executor that grounds tree output actions into executable environment actions. Future work may explore more automatic and adaptive action grounding methods, reducing the need for specific executor design. (3) The performance degradation with Llama-3.1-8B-Instruct shows that Co-π-tree remains sensitive to backbone capability.

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A Additional Details

A.1 Layout Descriptions

We evaluate Co-π-tree on five standard Overcooked-AI layouts, which cover different coordination bottlenecks. Cramped Room is a compact kitchen with one pot and one serving location. Because both players operate in a small shared area, good performance requires avoiding blocking while keeping the single pot continuously in use. Asymmetric Advantages places the two players in kitchens with different access costs: one side is closer to onions and the other is closer to serving-related resources. This layout rewards stable role specialization and timely handoff between ingredient preparation and soup delivery. Coordination Ring is a ring-shaped layout in which players must move around narrow corridors and avoid obstructing each other. Efficient play usually requires both pots to be used and for the players to maintain compatible movement directions. Forced Coordination separates the resources needed for cooking across the two sides of the map. One side has access to ingredients and dishes, while the other side handles pot interaction and serving, so successful completion depends on passing objects through counters and performing complementary subtasks. This makes Forced Coordination especially sensitive to player roles and handoff conventions. Counter Circuit is a larger ring-like layout with onions, dishes, pots, and serving locations distributed across different regions. Its narrow passages make movement conflicts frequent, and high reward often requires placing intermediate objects on counters so that the other player can continue the cooking pipeline. Figure 6 visualizes the five layouts used in our experiments.

A.2 Baseline Selection Details

For the main AI-partner experiment, we include standard MARL and BC baselines commonly used in Overcooked-AI ZSC evaluation, together with two LLM-based baselines, ProAgent and CausalPlan. CausalPlan was publicly available as an ICLR 2026 submission on OpenReview at the time of our experiments. We evaluate the code snapshot downloaded from its OpenReview submission page in May 2026. Our results therefore correspond to this specific public implementation snapshot and should not be interpreted as an evaluation of a later or final archival version.

We also considered other recent LLM-based collaborators, including the LLM-powered hierarchical language agent of Liu et al. (2024a). That method targets real-time human-AI coordination with natural-language commands: its agent interprets human messages, maintains dialogue context, and maps commands to macro actions. Its testbed is also a modified gym-cooking environment with additional mechanics such as multiple ingredients, chopping, order timeouts, fire, and a chat interface. Directly comparing it under our Overcooked-AI ZSC protocol would therefore conflate policy quality with access to an extra communication channel and different environment dynamics, so we do not include it as a baseline. More generally, methods are excluded when they lack public implementations or use incompatible task settings.

A.3 AI-Partner Evaluation Protocol

For AI-partner evaluation, we consider both player role assignments in each layout: the evaluated agent as Player 0 with the partner as Player 1, and the swapped role setting. The unseen partner pool is {SP, PBT, FCP, MEP, COLE, BC}. For each baseline in this six-partner pool, we evaluate it with the other five held out partners and report the average pairwise team reward. ProAgent and CausalPlan are evaluated against the same six-partner pool and averaged in the same way.

For Co-π-tree and its ablation variants, the held out test partners are never used during policy construction, execution feedback, or refinement. Within each layout, we select one partner as the source partner for policy construction and refinement, and then evaluate the learned policy with the remaining partners held out from that process. Results are averaged over all source partner choices, so each number reflects zero-shot coordination with unseen partners from the same reference pool. For each algorithm pair and role assignment, we run five evaluation episodes and collect episode returns. Across all tables, rewards are reported as mean$\pm$std. Bold indicates the best result in each row and underlining indicates the second highest result.

A.4 Human Study Protocol

Following prior Overcooked human-agent evaluation protocols, we recruited 20 volunteers from a local university, including 9 female and 11 male participants, with ages ranging from 18 to 30. Nearly all participants were unfamiliar with Overcooked before the study. We therefore provided compre-

Figure 6: Overcooked-AI layouts used in our evaluation.

hensive task instructions and allowed each participant to complete at least five practice rounds before evaluation. Before the study, participants were told that the purpose was to evaluate human-AI collaboration in a cooperative cooking game, that their gameplay records would be used only for research analysis, and that only anonymized and aggregate results would be reported. The instructions explained the game goal, basic controls, evaluation procedure, expected duration, compensation, and that there were no known risks beyond ordinary interaction with a computer game. Participation was voluntary, and participants provided consent before starting the practice rounds. The order of evaluated agents was randomized within each layout to reduce order effects. Participants then interacted with the evaluated agents through the human-AI interface of Carroll et al. (2019), accessed through a web browser. We evaluated every participant on all five layouts. For each layout and each evaluated method, each participant completed two evaluation episodes, one under each player-role assignment, and we recorded the average reward over the two episodes. In the main paper, the box plots aggregate these per-volunteer average rewards, so the two role assignments are merged rather than reported separately. Participants were recruited through local university channels and received a fixed payment for their time, independent of game score. The payment amount was set according to local campus participation norms and the short duration of the study.

We do not include BC in the human-partner study because BC is used as a proxy model of human behavior rather than as a real-time collaborative policy for direct human interaction. We also exclude ProAgent and CausalPlan because their action-by-action online LLM querying introduces prohibitive response latency in the real-time web interface used for human evaluation.

A.5 Artifact Licenses

We use public research artifacts under their stated licenses or terms of use. The Overcooked-AI environment and Stable-Baselines components used in our implementation are released under MIT licenses, and we retain their license notices in the supplementary material. Public baseline implementations are used for experimental comparison according to their accompanying licenses or public release terms. LLM calls are made through the corresponding model provider interface under its terms of use. The code and generated policy-tree artifacts distributed with this paper include the applicable license and attribution information.

A.6 Data Privacy and Content

Our experiments use Overcooked-AI simulator states, actions, rewards, and execution traces. These records contain game-state information such as held objects, pot states, selected actions, and execution outcomes, but do not contain free-form participant messages or naturally occurring text. For the human study, we assign anonymous participant identifiers and report only aggregate rewards and coarse demographic statistics. We do not include names, contact information, or other personally identifying information in the paper or supplementary artifacts. Because the task domain is a constrained cooking game and the stored traces use fixed symbolic fields rather than open-ended user text, the data do not contain offensive content. Before release, we exclude any metadata that could identify individual participants.

A.7 Partner-Prediction Accuracy

For each prediction event recorded in an AI-partner rollout, we compare the discrete behavior label emitted by the partner-behavior prediction tree with the partner behavior realized in the subsequent trace. Accuracy is the number of matching labels divided by the number of prediction events. The accuracies for Asymm. Adv., Coord. Ring, CT. Circuit, Cramped Rm., and Forced Coord. are 84.33%, 79.56%, 78.18%, 79.61%, and 79.17%, respectively, with a mean of 80.17%. Since the current policy outputs deterministic labels rather than probability distributions, calibration is not defined for this evaluation.

Diagnostic	Value
Post-Ready Serving Share	25.5%
Dish-Opportunity Stall Rate	30.8%

Table 5: Serving-related diagnostics for Co-π-tree as Player 1 in Forced Coordination.

A.8 Forced Coordination Analysis

The results on Forced Coord. are more sensitive to player roles than those on the other layouts. This is expected from the design of the layout: the two players have access to different resources, and each soup requires successful object passing through counters. As a result, a policy tree learned with one source partner can fit that partner's handoff habit, such as when to leave an onion or dish on a counter. When a held out partner follows a different habit, the same branch may still choose legal actions but produce lower reward. We therefore further analyze Player 1 episodes using two serving-related diagnostics. Post-Ready Serving Share measures the fraction of post-ready steps spent on serving-related actions, while Dish-Opportunity Stall Rate measures the fraction of states in which soup is ready and a dish is available but no serving progress is made.

For SP in the same Player 1 setting, the ready-stall rate and dish-opportunity stall rate are both 100%, with a mean ready-stall duration of 253 steps. These diagnostics indicate that the Player 1 performance drop is primarily a failure to follow serving conventions rather than a failure to prepare ingredients. In particular, several AI partners pick up objects only from specific positions. Even when soup is ready, they may ignore reachable dishes and fail to begin delivery. Success therefore depends on matching the partner's serving convention.

The refinement statistics in Appendix A.14 suggest that this failure is not simply caused by the ten-iteration budget: the best accepted score occurs after 3.56 iterations on average, and no run requires all ten iterations. Nevertheless, local branch refinement may be structurally ill-suited for some convention shifts. We therefore treat the Forced Coord. result as a limitation of matching partner conventions and local refinement, rather than as a failure of the executor or the policy-tree format.

A.9 Policy-Learning Details

Algorithm 1 in the main methodology summarizes the Co-π-tree policy-learning loop. This section provides the implementation and parameter details omitted from the algorithm block.

LLM settings and temperature schedule. Unless otherwise stated, Co-π-tree runs for 10 refinement iterations. All LLM modules use the same GPT-4o backbone. The planner and coder use the stuck-aware temperature schedule shown below. Let u_k denote the stuck counter, which increases when a newly generated policy fails to improve over the best accepted policy. The sampling temperature for planner and coder calls is

$$\vartheta_k = \min(\vartheta_{\max}, \vartheta_{\text{base}}\,(1 + \log(1 + u_k)))\,, \quad (9)$$

where $\vartheta_{\text{base}} = 0.4$ and $\vartheta_{\max} = 1.2$. This schedule keeps early iterations relatively stable while gradually encouraging broader exploration when refinement becomes stuck. The summarizer uses the same backbone to convert the accepted rollout trace into a compact policy summary and a localized policy tree reflection. We set the maximum generation length to 2048 tokens for the policy tree generation, code-generation, and summarization calls.

A.10 Computational Details and Package Settings

Co-π-tree does not train neural networks or update their parameters. Its policy-learning process uses GPT-4o through an API to generate and refine an executable policy tree, and the final policy is ordinary Python code executed without LLM calls at test time. The exact number of GPT-4o parameters and the provider-side inference infrastructure are not publicly disclosed. We therefore report the controllable computation in terms of LLM query count (NQ) and test-time latency in Section 4 and Figure 4. Local computation consists of Overcooked-AI simulator rollouts, deterministic executor calls, and policy-tree execution. No local GPU training is used for Co-π-tree, so our method uses 0 hours of GPU training locally.

We use the public Overcooked-AI implementation for environment dynamics, layouts, rewards, and the human-AI interface accessed through a web browser. Episodes last 400 environment steps, and we evaluate the five layouts, partner pool, and role assignment protocol described in Section 4 and Appendix A.3. Baseline policies are evaluated with their public implementations, checkpoints, and default environment interfaces when available. For Co-π-tree, all variants use the same symbolic state

schema, action vocabulary, deterministic executor, LLM backbone, temperature schedule, number of refinement iterations, and maximum generation length described in Appendix A.9 and Appendix A.12. We did not perform a separate hyperparameter search.

A.11 Environment Grounding

This section details the environment grounding interface used to connect the generated policy tree with Overcooked-AI execution. The raw simulator state contains player positions and orientations, held objects, object locations, pot contents, cooking timers, and layout-specific counter information. Before calling the generated policy, the executor extracts the task-relevant symbolic state and stores it in a fixed dictionary:

Symbolic State Dictionary

```
state_dict = {
    'hold': [None, None],  # [player0_hold, player1_hold], each in
    {'empty','onion','dish','soup'}
    'pot': [],             # list of dicts: {'count': int, 'state':
    'idle'|'cooking'|'ready', 'timers': int|None}
    'any_soup_ready': None,
    'any_pot_not_full': None,
    'teammate_last_completed_skill': None,
    'teammate_last_inferred_skill': None,
    'self_last_skill': None,
    # optional for Forced Coordination:
    'num_empty_counters': None,
    'num_onion_counters': None,
    'num_dish_counters': None,
}
```

The generated Python policy receives this dictionary and returns two symbolic decisions: the predicted teammate behavior and the selected action for the controlled agent. Both are represented with the same action vocabulary. The selected action is then passed to a deterministic executor. For object-manipulation actions such as `pickup_onion`, `put_onion_in_pot`, `pickup_dish`, `fill_dish_with_soup`, `deliver_soup`, and `place_obj_on_counter`, the executor selects feasible interaction targets, computes the next executable environment action, and records whether the action could be executed in the current state.

The same grounding layer also constructs the rollout trace τ_k used by the summarizer. Each trace entry keeps the symbolic dictionary together with a compact language description of the scene, the policy-selected action, the execution outcome, and, in AI-partner rollouts, the partner's realized action. For example, a trace entry may describe that the controlled agent holds an onion, the teammate holds a dish, one pot is cooking with three onions, another pot still needs onions, and the selected action was executable. This representation gives the summarizer scene-level evidence for local branch revision while avoiding the cost of storing full tensor trajectories in the LLM context.

A.12 Grounding Interfaces and Executor

Baselines are evaluated with their own environment grounding interfaces, as provided by their implementations or required by their action spaces. For Co-π-tree, the executor is a deterministic grounding layer: given a tree output action selected by the policy tree, it chooses a reachable target and outputs the next executable environment action. It does not choose the tree output action, query the LLM, use reward feedback, or adapt to partner identity. Our executor extensions mainly support the policy-tree state schema, stable target selection, feasibility checks, and execution-trace logging. All Co-π-tree variants use the same executor, so ablation results isolate partner prediction and iterative refinement rather than executor design.

A.13 Iterative Reward Growth

Figure 7 visualizes reward growth during iterative refinement across all five layouts. Each panel corresponds to one combination of a layout and source partner and reports the accepted reward trajectory over 10 refinement iterations. The curves show that accepted policy performance often improves over the early iterations and then stabilizes, which is consistent with the accept/revert mechanism in Algorithm 1. The trend is most visible in layouts where local branch repairs can immediately improve role division or object handoff. In more partner-sensitive layouts, such as Forced Coord., the trajectory can be flatter because final reward also depends heavily on whether the partner completes the complementary subtasks required by the layout.

A.14 Refinement Dynamics

We summarize refinement behavior over 360 runs, where a run corresponds to one policy-construction and refinement process under a layout and source-partner setting. The mean acceptance rate is 68.24%. The best accepted score occurs at iteration 3.56 on average, and the mean longest consecutive rejection streak is 2.12 iterations. None of the runs requires all ten iterations to reach its best accepted policy. These statistics indicate that the ten-iteration budget is usually sufficient in the

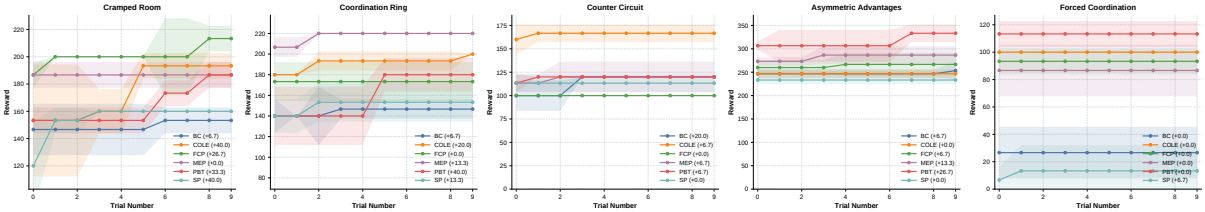


Figure 7: Reward growth over iterative refinement across five Overcooked-AI layouts. Each panel shows one representative training run with a different source partner. We plot the accepted reward trajectory across 10 refinement iterations. Shaded bands indicate one standard deviation over evaluation episodes.

Layout	ProAgent	CausalPlan	Co-π-tree
Cramped Rm.	148.3	150.6	101.5
Coord. Ring	132.5	130.2	95.3
CT. Circuit	98.6	104.3	68.9
Asymm. Adv.	204.6	200.3	178.5
Forced Coord.	25.8	32.1	30.4

Table 6: Backbone sensitivity with Llama-3.1-8B-Instruct. Scores are averaged over both player roles.

Layout	ProAgent	CausalPlan	Co-π-tree
Cramped Rm.	159.8	162.2	169.4
Coord. Ring	143.7	140.3	147.6
CT. Circuit	105.8	106.1	110.3
Asymm. Adv.	221.3	226.9	240.4
Forced Coord.	29.6	35.0	40.7

Table 7: Backbone sensitivity with GPT-3.5-turbo-1106. Scores are averaged over both player roles.

evaluated settings, while not ruling out cases where longer refinement could be useful.

A.15 Backbone Sensitivity Details

We replace the GPT-4o backbone used by all policy-construction modules with Llama-3.1-8B-Instruct and GPT-3.5-turbo-1106. For each method and backbone, we use the same five layouts, partner protocol, random seeds, action interface, and role assignments as in the main AI-partner evaluation. Each entry below is the reward averaged over Player 0 and Player 1.

The results indicate a clear dependence on backbone capability. With Llama-3.1-8B-Instruct, Co-π-tree trails both online LLM baselines on four layouts and lies between them on Forced Coordination. With GPT-3.5-turbo-1106, Co-π-tree achieves the highest score on all five layouts. In deployment, this sensitivity affects the cost, availability, and reproducibility of the offline policy-construction stage. After construction, however, the final policy requires no additional LLM calls at test time.

A.16 Cross-Layout Transfer

We further evaluate whether a policy learned on one layout can be reused on a different layout without additional LLM calls. For Co-π-tree, a policy tree is first learned on a *source layout* with BC as the source partner and is then directly deployed on a different *target layout*. During transfer, the policy code is reused as is: we do not query the LLM, regenerate the tree, refine the policy, or tune any layout-specific parameters. The only cost during target-layout evaluation is ordinary policy-tree execution. We compare this transfer setting, which requires no additional LLM calls, with ProAgent, which performs online LLM reasoning on each target layout, and with SP as a representative MARL baseline that also has zero LLM cost at test-time.

Because different Overcooked-AI layouts have different reward scales, we report normalized transfer retention rather than raw reward. Let $R_{s\to t}$ denote the mean reward obtained by a method trained or instantiated on source layout s and evaluated on target layout t. For a source layout s and target layout t, the cell value is computed as

$$\text{Retention}(s,t) = \frac{R_{s\to t}}{R_{t\to t}} \times 100\%.$$

Thus, the diagonal is 100% by definition, and entries outside the diagonal measure how much of the target-layout in-domain performance is retained under direct cross-layout test-time.

For SP, only a subset of pairs of source and target layouts can be executed directly in our current Overcooked implementation. SP consumes layout-specific tensor observations whose spatial shapes depend on the map geometry, so a source policy cannot generally be applied to a target layout whose observation tensor is incompatible with the source input shape. We therefore evaluate the compatible subset, using zero-padding when needed to embed smaller target observations into the source policy's expected tensor shape. Cells that still cannot be

executed are marked with "/" in Figure 8 and are shown with the lowest heatmap color only for visualization. Cells annotated as 0% denote executable pairs whose measured retention is near zero.

Figure 8 shows three different transfer behaviors. SP transfers poorly even on the compatible subset, confirming that the neural policy is strongly coupled to the training layout. ProAgent achieves the best cross-layout retention because it reasons online and can adapt its plan to the target layout, but this requires high test-time LLM consumption on every run. In contrast, Co-π-tree retains strong transfer performance with no additional LLM calls at transfer time. Several cells outside the diagonal are close to or above 100%, indicating that the learned policy tree is not merely memorizing a single layout but captures transferable subtask structure such as ingredient preparation, dish handling, delivery, and selecting a role that complements the partner. Transfer remains weaker for Forced Coord., where success depends heavily on layout-specific object passing and on whether the partner completes the required complementary subtask.

A.17 Interpretability Analysis

Structural statistics and user study. We analyze 3,600 generated policy trees. On average, a tree contains 18.98 `if` statements, has maximum conditional depth 3.01, contains 65.9 lines of code, and uses 1.39 helper functions. These statistics characterize the structural complexity of the generated policies but do not by themselves establish human interpretability.

To compare representations with identical policy content, we conducted a study in which all 20 undergraduate participants evaluated both representations. Each participant completed five trials for each task using both a policy tree and an equivalent flat rule list. The three tasks measured correct behavior prediction, localization of problematic branches, and rule editing. The resulting counts were 88/100 versus 77/100 for behavior prediction, 81/100 versus 64/100 for branch localization, and 75/100 versus 56/100 for rule editing, for the policy tree and flat rule list, respectively. Participants received study and compensation information, provided consent, and were represented using anonymous identifiers. We report only aggregate results.

Local policy tree refinement. Because Co-π-tree stores its policy as explicit branches, both the initial policy and the refined policy can be inspected directly. Below we show an Overcooked-AI example from Cramped Room with BC as the source partner. The initial policy obtains an average score of 160.0. In this Overcooked-AI case, the summarizer identifies a local dish-handling branch that can cause premature dish pickup when pot preparation is still useful. After refinement, the best accepted policy obtains an average score of 186.7. In the displayed trees, red marks the original branches targeted by accepted local reflections, and green marks the corresponding repaired branches.

Task	Policy tree	Flat rule list
Behavior prediction	88/100	77/100
Branch localization	81/100	64/100
Rule editing	75/100	56/100

Table 8: Interpretability user-study results. Both representations contain the same policy content.

Initial Policy Tree. The full initial policy tree is shown below.

Initial Policy Tree

```
### FunctionDescription:
  Name: PredictTeammateThenPlan
  Inputs:
    - current_scene:
        - holdings: {self: empty/onion/dish/soup, teammate:
        empty/onion/dish/soup}
        - pots: for each <Pot>: onion_count: {0,1,2,3}, state:
        {idle,cooking,ready}, timers
        - derived flags: any_soup_ready, any_pot_not_full
    - teammate_last_completed_skill: one of the 6 actions or None
    - teammate_last_inferred_skill: one of the 6 actions or None
    - self_last_skill: one of the 6 actions or None
  Outputs:
    - inferred_teammate_current_skill: one of the 6 actions
    - self_action_now: one of the 6 actions

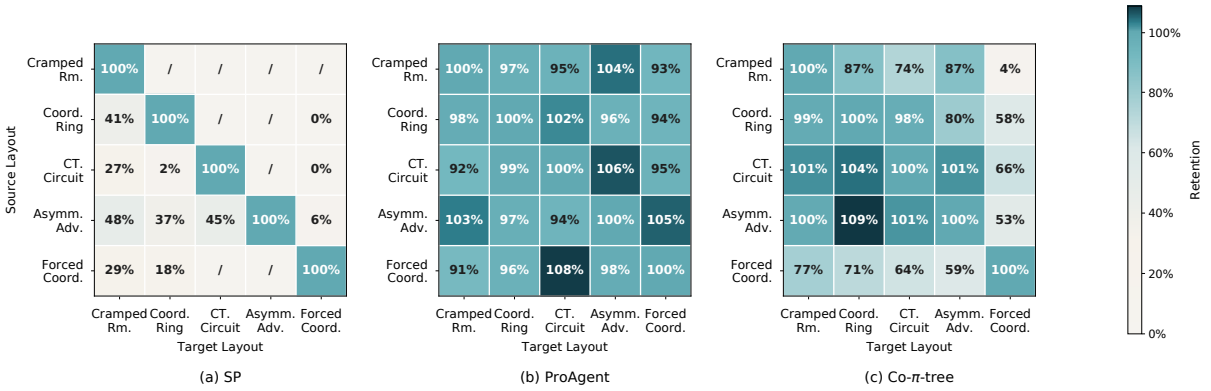
  **Partner-Inference Policy Tree**
  If `teammate_last_completed_skill` is `pickup_onion` and
  `teammate` is holding an onion:
      - inferred_teammate_current_skill = `put_onion_in_pot`
  If `teammate_last_completed_skill` is `put_onion_in_pot` and
  `teammate` is holding nothing:
      - inferred_teammate_current_skill = `pickup_onion`
  If `teammate_last_completed_skill` is `pickup_dish` and `teammate`
  is holding a dish:
      - inferred_teammate_current_skill = `fill_dish_with_soup`
  If `teammate_last_completed_skill` is `fill_dish_with_soup` and
  `teammate` is holding soup:
      - inferred_teammate_current_skill = `deliver_soup`
  If `teammate_last_completed_skill` is `deliver_soup` and
  `teammate` is holding nothing:
      - inferred_teammate_current_skill = `pickup_dish`
  If `teammate` is holding an onion and no recent action suggests
  otherwise:
      - inferred_teammate_current_skill = `put_onion_in_pot`
  If `teammate` is holding a dish and no recent action suggests
  otherwise:
      - inferred_teammate_current_skill = `fill_dish_with_soup`
  If `teammate` is holding soup and no recent action suggests
  otherwise:
      - inferred_teammate_current_skill = `deliver_soup`


  If `teammate` is holding nothing and no recent action suggests
  otherwise:
      - inferred_teammate_current_skill = `pickup_onion`



Self-Action Policy Tree

If `self_hold` is `soup`:
    - self_action_now = `deliver_soup`
```



(a) SP (b) ProAgent (c) Co-π-tree

Figure 8: Cross-layout transfer performance for SP, ProAgent, and Co-π-tree. Rows denote the source layout used to learn or instantiate the policy, and columns denote the target layout used for evaluation. Each cell reports normalized transfer retention, computed as the target-layout reward of a source-layout policy divided by the in-domain reward of the corresponding target-layout policy. Percentages make results comparable across layouts with different reward scales. For SP, "/" denotes pairs of source and target layouts that cannot be directly executed because of incompatible layout-specific tensor observations. Compatible pairs are evaluated with the zero-padding procedure described in the text.

```
If `self_hold` is `dish`:
    - If `current_scene['any_soup_ready']`:
        - self_action_now = `fill_dish_with_soup`
    - Else:
        - self_action_now = `place_obj_on_counter`



If `self_hold` is `onion`:
    - If there exists a `pot` that is not full:
        - self_action_now = `put_onion_in_pot`
    - Else:
        - self_action_now = `place_obj_on_counter`

If `self_hold` is `empty`:
    - If `current_scene['any_pot_not_full']`:
        - self_action_now = `pickup_onion`
    - Else:
        - If `current_scene['any_soup_ready']`:
            - self_action_now = `pickup_dish`
        - Else:
            - self_action_now = `pickup_onion`

If `current_scene['any_pot_not_full']` is `True` and `self_hold` is
`empty`:
    - self_action_now = `pickup_onion`


If `current_scene['any_soup_ready']` is `True` and `self_hold` is
`empty`:
    - self_action_now = `pickup_dish`



If `current_scene['any_pot_not_full']` is `False` and
`current_scene['any_soup_ready']` is `False`:
    - If `self_hold` is `empty`:
        - self_action_now = `pickup_onion`

If `self_hold` is `empty` and the teammate's inferred action is
`pickup_onion`:
    - self_action_now = `pickup_onion`

If `self_hold` is `empty` and the teammate's inferred action is
`put_onion_in_pot`:
    - self_action_now = `pickup_onion`

If `self_hold` is `empty` and the teammate's inferred action is
`pickup_dish`:
    - If `current_scene['any_soup_ready']`:
        - self_action_now = `pickup_onion`
    - Else:
        - self_action_now = `pickup_dish`

If `self_hold` is `empty` and the teammate's inferred action is
`fill_dish_with_soup`:
    - If `current_scene['any_pot_not_full']`:
        - self_action_now = `pickup_onion`
    - Else:
        - self_action_now = `pickup_dish`

If `self_hold` is `empty` and the teammate's inferred action is
`deliver_soup`:
    - If `current_scene['any_pot_not_full']`:
        - self_action_now = `pickup_onion`
    - Else:
        - self_action_now = `pickup_dish`

If `self_hold` is `empty` and the teammate's inferred action is
`place_obj_on_counter`:
    - self_action_now = `pickup_onion`
```

Policy Tree reflection. The refinement run generates multiple candidate reflections. We report only the three local reflections whose `After_Behavior` is directly absorbed by the later accepted policies and is visible in the final refined tree. We omit suggestions from unsuccessful resampling or from later unused proposals.

Accepted Local Reflections

```
Reflection 1
Target_Branch: Self Action Selection Tree - Condition 4 and 6
Modification_Scope: LOCAL_SINGLE_BRANCH
Before_Behavior: If `self_hold` is `empty` and
`current_scene['any_soup_ready']` is `True`, the player always
selects `pickup_dish` as the next action, even when
`current_scene['any_pot_not_full']` is also `True`.
After_Behavior:
  - If `self_hold` is `empty` and `current_scene['any_soup_ready']`
  is `True`, the player selects `pickup_dish` ONLY if
  `current_scene['any_pot_not_full']` is `False`. Otherwise,
  prioritize `pickup_onion` to prepare the next cooking cycle.
Unchanged_Assumptions:
  - The logic for handling soup delivery (`self_hold` is `soup`)
  remains unchanged.
  - The logic for handling onion placement (`self_hold` is `onion`)
  remains unchanged.
  - The teammate-behavior prediction process and its integration into
  self-action selection remain unchanged.
  - The overall prioritization of tasks based on game state flags
  (`any_soup_ready`, `any_pot_not_full`) remains intact.
Expected_Effect: By refining the condition to avoid premature dish
pickup, the player will focus on preparing onions when pots are not
full, reducing idle time and ensuring a smoother cooking cycle. This
change is expected to eliminate redundant dish handling and improve
overall efficiency, potentially increasing the game score.

Reflection 2
```

```
Target_Branch: Self Action Selection Tree, Rule 2 (If self_hold is
dish)
Modification_Scope: LOCAL_SINGLE_BRANCH
Before_Behavior: If self_hold is dish, the logic checks whether any
soup is ready. If soup is ready, the player fills the dish with soup.
If no soup is ready, the player either places the dish on the counter
or picks up an onion depending on the state of pots.
After_Behavior:
  - If self_hold is dish:
  - 1. Check if any soup is ready.
    - If soup is ready, self_action_now = fill_dish_with_soup.
  - 2. If no soup is ready, check if any pot is cooking or idle.
    - If any pot is cooking, self_action_now = place_obj_on_counter.
    - If all pots are idle, self_action_now = pickup_onion.
Unchanged_Assumptions:
  - The logic for handling actions when self_hold is empty remains
  unchanged.
  - The predicted teammate behavior logic remains unchanged.
  - The priority of filling dishes with soup when soup is ready
  remains unchanged.
  - The rules for handling onions and pots remain unchanged.
Expected_Effect: This modification prevents premature dish pickup and
holding while pots are still cooking, allowing the player to engage
in more productive tasks like onion collection or pot preparation. It
eliminates unnecessary holding time and improves overall efficiency.

Reflection 3
Target_Branch: Partner Inference Tree, Rule 9
Modification_Scope: LOCAL_SINGLE_BRANCH
Before_Behavior: If `teammate` is holding nothing and no recent
action suggests otherwise, inferred_teammate_current_skill =
`pickup_onion`.
After_Behavior:
  - If `teammate` is holding nothing and no recent action suggests
  otherwise:
    - If `current_scene['any_soup_ready']` is true and
    `current_scene['any_pot_not_full']` is false:
        inferred_teammate_current_skill = `pickup_dish`
    - Else:
        inferred_teammate_current_skill = `pickup_onion`
Unchanged_Assumptions:
  - The predicted teammate behavior is based on their last completed
  action, current holding state, and the current scene context.
  - The predicted teammate behavior is used to guide self-action
  prioritization.
  - The predicted teammate behavior cannot override explicit recent
  action observations (e.g., `teammate_last_completed_skill`).
  - The overall structure and order of other rules in the Partner
  Inference Tree remain unchanged.
Expected_Effect: This modification will reduce the misprediction of
the teammate's behavior during the soup cooking phase, ensuring that
the teammate is correctly predicted to prioritize picking up a dish
for soup delivery when all pots are full and soup is ready. This will
minimize redundant actions (e.g., picking up onions unnecessarily)
and improve the overall efficiency of the team, leading to higher
scores.
```

Example analysis. In this Overcooked-AI example, the initial tree has an over-eager dish-handling pattern around the soup-ready state. When the agent is empty-handed and `any_soup_ready` is true, it immediately chooses `pickup_dish`, even when `any_pot_not_full` is also true and onion preparation is still useful. The first reflection names this exact branch for an empty-handed agent and changes the rule so that dish pickup is selected only when no pot still needs ingredients. When some pot still needs ingredients, the agent continues with `pickup_onion`. The second reflection fixes the related case in which the agent is already holding a dish but no soup is ready: instead of using a single fallback action, the refined tree checks the pot state, puts the dish down while a pot is cooking, and returns to onion preparation when all pots are idle. The third reflection adjusts the partner-inference branch for an empty-handed teammate. The initial tree always predicts `pickup_onion`. In contrast, the refined tree predicts `pickup_dish` when soup is ready and no pot needs more onions. Together, these changes turn a coarse dish-first heuristic into coordination that responds to the current state when balancing dish delivery and the next onion cycle, increasing the average score from 160.0 to 186.7.

Refined Policy Tree. The full refined policy tree is shown below.

Refined Policy Tree

```
### FunctionDescription:
  Name: PredictTeammateThenPlan
  Inputs:
    - current_scene:
        - holdings: {self: empty/onion/dish/soup, teammate:
        empty/onion/dish/soup}
        - pots: for each <Pot>: onion_count: {0,1,2,3}, state:
        {idle,cooking,ready}, timers
        - derived flags: any_soup_ready, any_pot_not_full
    - teammate_last_completed_skill: one of the 6 actions or None
    - teammate_last_inferred_skill: one of the 6 actions or None
    - self_last_skill: one of the 6 actions or None
  Outputs:
    - inferred_teammate_current_skill: one of the 6 actions
    - self_action_now: one of the 6 actions

  **Partner-Inference Policy Tree**
  If `teammate_last_completed_skill` is `pickup_onion` and
  `teammate` is holding an onion:
      - inferred_teammate_current_skill = `put_onion_in_pot`
  If `teammate_last_completed_skill` is `put_onion_in_pot` and
  `teammate` is holding nothing:
      - inferred_teammate_current_skill = `pickup_onion`
  If `teammate_last_completed_skill` is `pickup_dish` and `teammate`
  is holding a dish:
      - inferred_teammate_current_skill = `fill_dish_with_soup`
  If `teammate_last_completed_skill` is `fill_dish_with_soup` and
  `teammate` is holding soup:
      - inferred_teammate_current_skill = `deliver_soup`
  If `teammate_last_completed_skill` is `deliver_soup` and
  `teammate` is holding nothing:
      - inferred_teammate_current_skill = `pickup_dish`
  If `teammate` is holding an onion and no recent action suggests
  otherwise:
      - inferred_teammate_current_skill = `put_onion_in_pot`
  If `teammate` is holding a dish and no recent action suggests
  otherwise:
      - inferred_teammate_current_skill = `fill_dish_with_soup`
  If `teammate` is holding soup and no recent action suggests
  otherwise:
      - inferred_teammate_current_skill = `deliver_soup`


  If `teammate` is holding nothing and no recent action suggests
  otherwise:
      - If `current_scene['any_soup_ready']` is true and
      `current_scene['any_pot_not_full']` is false:
          - inferred_teammate_current_skill = `pickup_dish`
      - Else:
          - inferred_teammate_current_skill = `pickup_onion`



### Self-Action Policy Tree

If `self_hold` is `soup`:
    - self_action_now = `deliver_soup`


If `self_hold` is `dish`:
    - If `current_scene['any_soup_ready']`:
        - self_action_now = `fill_dish_with_soup`
    - Else:
        - If there exists a `pot` that is cooking:
            - self_action_now = `place_obj_on_counter`
        - If all pots are idle:
            - self_action_now = `pickup_onion`



If `self_hold` is `onion`:
    - If there exists a `pot` that is not full:
        - self_action_now = `put_onion_in_pot`
    - Else:
        - self_action_now = `place_obj_on_counter`

If `self_hold` is `empty`:
    - If `current_scene['any_pot_not_full']`:
        - self_action_now = `pickup_onion`
    - Else:
        - If `current_scene['any_soup_ready']`:
```

```
            - If `teammate_last_inferred_skill` is `pickup_dish` or
            `fill_dish_with_soup`:
                - self_action_now = `pickup_onion`
            - Else:
                - self_action_now = `pickup_dish`
        - Else:
            - self_action_now = `pickup_onion`

If `self_hold` is `empty` and `current_scene['any_pot_not_full']` is
`True`:
    - self_action_now = `pickup_onion`


If `self_hold` is `empty` and `current_scene['any_soup_ready']` is
`True`:
    - If `current_scene['any_pot_not_full']` is `False`:
        - self_action_now = `pickup_dish`
    - Else:
        - self_action_now = `pickup_onion`



If `current_scene['any_pot_not_full']` is `False` and
`current_scene['any_soup_ready']` is `False`:
    - If `self_hold` is `empty`:
        - self_action_now = `pickup_onion`

If `self_hold` is `empty` and the teammate's inferred action is
`pickup_onion`:
    - self_action_now = `pickup_onion`

If `self_hold` is `empty` and the teammate's inferred action is
`put_onion_in_pot`:
    - self_action_now = `pickup_onion`

If `self_hold` is `empty` and the teammate's inferred action is
`pickup_dish`:
    - If `current_scene['any_soup_ready']`:
        - If `current_scene['any_pot_not_full']`:
            - self_action_now = `pickup_onion`
        - Else:
            - self_action_now = `pickup_dish`
    - Else:
        - self_action_now = `pickup_onion`

If `self_hold` is `empty` and the teammate's inferred action is
`fill_dish_with_soup`:
    - If `current_scene['any_pot_not_full']`:
        - self_action_now = `pickup_onion`
    - Else:
        - self_action_now = `pickup_dish`

If `self_hold` is `empty` and the teammate's inferred action is
`deliver_soup`:
    - If `current_scene['any_pot_not_full']`:
        - self_action_now = `pickup_onion`
    - Else:
        - self_action_now = `pickup_dish`

If `self_hold` is `empty` and the teammate's inferred action is
`place_obj_on_counter`:
    - self_action_now = `pickup_onion`
```

This example illustrates two forms of interpretability. First, the learned policy exposes the reason for an action through a small number of symbolic conditions. Second, refinement is local: the summarizer names the problematic branch, describes the before/after behavior, and leaves unrelated branches unchanged.

A.18 Prompt Templates

This section gives the prompt templates used by the three LLM modules in Co-π-tree. The planning prompt contains the task objective, task rules, the legal action library, the symbolic input schema, and a small set of demonstration scenes. Each demonstration specifies the structured scene description, the predicted partner behavior, the selected self action, and a short justification. The code prompt fixes the Python function signature, the input dictionary fields, and the required return tuple. Across source partners, we keep the prompt format and demonstration structure fixed, while task-specific information enters through the structured scene description and task description.

In our Overcooked-AI instantiation, layout-role prompts instantiate the placeholders for the controlled player, teammate player, executable action sets, and layout-specific symbolic fields. In most layouts, both players can execute all six Overcooked-AI actions. In Forced Coordination, the prompt additionally restricts the controlled player's action set for the separated side and includes counter features such as `num_empty_counters`, `num_onion_counters`, and `num_dish_counters`.

Following Section 3.2, the planner output is organized into two components: the `Partner Inference Tree` implements the partner-behavior prediction tree T^{pred}, and the `Self Action Selection Tree` corresponds to T^{act}. The template below shows the combined `FunctionDescription` used to store the final policy tree $T = (T^{\text{pred}}, T^{\text{act}})$. In a split planner implementation, the same schema is produced by generating the partner-behavior prediction component and then continuing with the self-action component.

Planner prompt. The planner receives task knowledge, legal actions, the symbolic input schema, demonstration scenes, and, after the first iteration, memory and reflection from the previous accepted policy. The concrete template below is the Overcooked-AI instantiation of this general prompt structure.

Planner Prompt Template

```
[Task and rule knowledge]
Instructions:
- The Overcooked_AI game requires two players to work together as a
team with the goal of achieving the highest possible score.
- To get points, the team must make soup according to the recipe, fill
the soup in a dish, and immediately deliver the soup. Once a delivery
is made, the team gets 20 points. The soup and dish then disappear.
- Recipe: three onions in the <Pot>.
- To make a soup, the team must pick up three onions one by one and
put them in a <Pot>. The <Pot> automatically starts cooking when it
contains three onions, and cooking takes 20 timesteps.
- Each player can hold at most one item. To put down the item a
player is holding and empty the hand, use place_obj_on_counter.
- <Pot> can ONLY hold three ingredients.
- After cooking starts, before the soup is finished:
  - If no soup is ready, do NOT pick up a dish.
  - If there is a <Pot> not full in the environment, prepare for
  another cooking cycle.

[Legal actions]
In this game, each player can ONLY perform the following allowed
actions. Do not use any other actions.
- pickup_onion
  - I need to have nothing in hand.
- put_onion_in_pot
  - I need to have an onion in hand.
- pickup_dish
  - Need to have a soup ready in <Pot>.
  - I need to have nothing in hand.
```

```
  - If there is no ready soup in the current scene, I should not
  pickup_dish.
- fill_dish_with_soup
  - I must do fill_dish_with_soup when soup is ready in <Pot>.
  - I need to have a dish in hand.
  - Then I must deliver_soup.
- deliver_soup
  - I must do deliver_soup after fill_dish_with_soup, when I hold
  soup.
  - I need to have soup in hand.
  - The dish and soup disappear after delivery.
- place_obj_on_counter
  - I need to have something in hand.
  - Do not use place_obj_on_counter when I hold soup.

Each player may only choose a subset of these actions:
- <SELF_PLAYER> can execute: <SELF_SKILL_SET>
- <TEAMMATE_PLAYER> can execute: <TEAMMATE_SKILL_SET>
<LAYOUT_SPECIFIC_RULES_AND_FIELDS>

[Role and output task]
Suppose you are an assistant proficient in the Overcooked_AI game.
Your goal is to control <SELF_PLAYER> and cooperate with
<TEAMMATE_PLAYER>, who is controlled by a certain strategy, to get a
high score.
- <SELF_PLAYER> and <TEAMMATE_PLAYER> cannot communicate.
- You cannot use move actions and do not use location information in
the observation.
- You must do deliver_soup when you hold soup.
- If there is no ready soup in the current scene, you should not
pickup_dish.
- You need to define ONE function called every timestep. It receives
the current scene and returns:
  1. The inferred current action of <TEAMMATE_PLAYER>, and
  2. Exactly one legal action for <SELF_PLAYER> now.

Required output format:
### FunctionDescription:
  Name: PredictTeammateThenPlan
  Inputs:
    - current_scene:
        - holdings: {self: empty/onion/dish/soup, teammate:
        empty/onion/dish/soup}
        - pots: for each <Pot>: onion_count: {0,1,2,3}, state:
        {idle,cooking,ready}, timers
        - derived flags: any_soup_ready, any_pot_not_full
        - optional layout fields: num_empty_counters,
        num_onion_counters, num_dish_counters
    - teammate_last_completed_skill: one of the legal actions or None
    - teammate_last_inferred_skill: one of the legal actions or None
    - self_last_skill: one of the legal actions or None
  Outputs:
    - inferred_teammate_current_skill: one legal teammate action
    - self_action_now: one legal self action

  **Partner Inference Tree**

  **Self Action Selection Tree**

[Demonstration format]
###
current_scene:
any_pot_not_full: false
any_soup_ready: true
holdings: {self: empty, teammate: dish}

inferred_teammate_current_skill: fill_dish_with_soup
self_action_now: pickup_dish

Explanation:
When a soup is ready, even if the teammate is already holding a dish
and likely heading to fill it, self should adopt an aggressive
strategy. Since the teammate's efficiency or final intent is
uncertain, self should also pickup_dish to ensure that at least one
person fills and delivers the soup quickly.
###
Scene <t>: <SELF_PLAYER> holds <item>. <TEAMMATE_PLAYER> holds
<item>. Kitchen states: <pot/counter status>.
Analysis: <brief scene-level reasoning>
Plan for <SELF_PLAYER>: "<one legal action>".
###

[Memory and local reflection, appended after the first iteration]
<DECISION_TREE_MEMORY>
You are given some previous decision tree memories.
ALWAYS prefer decision trees with higher Final_Score, and reuse these
to generate a new one.
Use the following memory for reference:
<POLICY_TREE_SUMMARY_MEMORY>

<THE_LAST_DECISION_TREE>
<LAST_ACCEPTED_POLICY_TREE>

<LAST_ISSUE_INFORMATION>
Analyze and modify the last decision tree using these improvement
requirements:
<TREE_REFLEXION_JSON_WITH_DECISION_TREE_SUMMARY_REMOVED>

<OUTPUT_REQUIREMENTS>
- The output must start directly with "### FunctionDescription:" and
end after the last line of the **Self Action Selection Tree**.
- Ensure that the generated decision tree covers the vast majority of
branches in the game.
- Decide whether coordination is required. If coordination is
required, condition self_action_now on
inferred_teammate_current_skill in the **Partner Inference Tree**. If
not, ignore inferred_teammate_current_skill.
- Provide one modified decision-tree function description strictly
following the Required output format and <LAST_ISSUE_INFORMATION>. If
no issue information is present, ignore it.
- Do NOT include explanations, introductions, or commentary outside
the tree.
- Make sure the conditions do not conflict with each other.
- If any_soup_ready is true, pay attention to it.
```

Coder prompt. The coder receives the textual policy tree T_k and converts it into an executable Python function. The concrete template below instantiates the code interface for Overcooked-AI action labels and state fields.

Coder Prompt Template

```
[System prompt]
Instructions:
You are an Overcooked_AI coder. Two players cooperate to maximize
score by cooking onion soup (3 onions per pot), filling a dish, and
delivering (+20). Pots auto-cook when full for 20 timesteps. Each
player holds at most one item. No movement/location logic is needed
here.

Each player may only choose a subset of these actions. Each action
label must be written exactly in snake_case.
- <SELF_PLAYER> can execute: <SELF_SKILL_SET>
- <TEAMMATE_PLAYER> can execute: <TEAMMATE_SKILL_SET>

Your goal is to control <SELF_PLAYER> and cooperate with
<TEAMMATE_PLAYER>.
- The players cannot communicate.
- Do not use move actions and do not use location information.
- You must do deliver_soup when you hold soup.
- If there is no ready soup in the current scene, you should not
pickup_dish.
- You will be given a function description, a textual decision tree,
in this format:
###
FunctionDescription:
  Name: PredictTeammateThenPlan
  Inputs:
    - current_scene:
        - holdings: {self: empty/onion/dish/soup, teammate:
        empty/onion/dish/soup}
        - pots: for each <Pot>: onion_count: {0,1,2,3}, state:
        {idle,cooking,ready}, timers
        - derived flags: any_soup_ready, any_pot_not_full
        - optional layout fields: num_empty_counters,
        num_onion_counters, num_dish_counters
    - teammate_last_completed_skill: one of the legal actions or None
    - teammate_last_inferred_skill: one of the legal actions or None
    - self_last_skill: one of the legal actions or None
  Outputs:
    - inferred_teammate_current_skill: one legal teammate action
    - self_action_now: one legal self action

  Partner Inference Tree:
    (textual if/else logic)

  Self Action Selection Tree:
    (textual if/else logic)
###

- Implement the decision tree as Python 3 using explicit if/elif
logic.
- Implement tiny helpers if useful, e.g., _legalize(action,
state_dict), to enforce hard legality rules and minimal fallbacks.
- Do not import external packages.
- Do not produce movement or location logic.
- Do not invent new action labels or change their spelling.

State input format:
###
state_dict = {
    'hold': [None, None],  # [player0_hold, player1_hold], each in
    {'empty','onion','dish','soup'}
    'pot': [],             # list of dicts: {'count': int, 'state':
    'idle'|'cooking'|'ready', 'timers': int|None}
    'any_soup_ready': None,
    'any_pot_not_full': None,
    'teammate_last_completed_skill': None,
    'teammate_last_inferred_skill': None,
```

```
    'self_last_skill': None,
    # optional for Forced Coordination:
    'num_empty_counters': None,
    'num_onion_counters': None,
    'num_dish_counters': None,
}
###

Required output format:
```python
def PredictTeammateThenPlan(state):
    ...
    return inferred_teammate_current_skill, self_action_now
```

[Runtime user prompt]
Make sure to check whether the list variables are empty or not.
The tactic is:
<POLICY_TREE_T_k>

Please implement the code in Python format. Return the code wrapped
with triple backticks (```python ... ```), and make sure the code is
complete and syntactically correct.

[Repair prompt when generated code fails]
The current Python code implementation is:
<CURRENT_CODE>
When executing this code, the following error occurred:
<EXECUTION_ERROR>
Please carefully analyze the error message and modify the code to fix
the issue.
```

Summarizer prompt. The summarizer receives the current policy tree and a language trace from the executor, then returns a compact memory entry and a single local reflection for the next planner call. The concrete template below instantiates the trajectory diagnostics for Overcooked-AI rollouts.

Summarizer Prompt Template

```
[System prompt]
[Meta-Analysis Constraints]
You are part of an iterative policy refinement system with
backtracking.

IMPORTANT:
- In each iteration, the decision tree is treated as FIXED except for
ONE small local branch.
- Your role is NOT to evaluate the entire tree, but to help identify
or justify a LOCAL adjustment.
- Even if the overall strategy seems reasonable, identify the most
promising small inefficiency that could be improved.
- Avoid answering "no change" unless the episode shows near-perfect
efficiency with no observable time waste.
- Prefer repeated throughput bottlenecks over isolated mistakes.
- Repeated illegal actions have the highest priority and should be
selected before legal-but-low-value actions.
- Treat legal-but-low-value actions as important evidence if they
repeatedly reduce soup throughput.
- Do NOT focus on teammate prediction errors unless they create
repeated downstream delay or redundant work.
- Never propose an After_Behavior that violates action preconditions,
such as selecting pickup_onion when self is holding a dish.

Assume:
- All existing rules, actions, and constraints are correct and must
remain unchanged.
- Every proposed After_Behavior must respect the listed action
preconditions.
- Reason about priorities, conditions, and coordination logic; do not
invent new rules.

[Task and action knowledge]
Use the same Overcooked task rules, legal actions, role-specific
action sets, and layout-specific symbolic fields as in the planner
prompt.

Suppose you are an Overcooked_AI critic. You need to analyze decision
quality. Do not propose or write code; do not rewrite the whole
decision tree.

[Runtime prompt]
You are analyzing the behavior of a collaborative agent controlled by
a FIXED decision tree, and then generating a Tree_Reflexion for a
planner.

You MUST reason over the full episode trajectory across multiple
scenes, instead of treating each scene independently.

IMPORTANT CONSTRAINTS:
- In the next iteration, ONLY ONE SMALL BRANCH of the decision tree
can be modified.
- All other branches, priorities, and logic MUST remain unchanged.
- Do NOT propose a full rewrite.
- Do NOT suggest multiple alternative fixes.

Your goal is to identify the SINGLE MOST DAMAGING and REPEATABLE
inefficiency that:
1) Causes clear throughput loss across multiple scenes, not just one
isolated mistake,
2) Appears as repeated wasted timesteps, redundant role overlap,
premature dish handling, delayed role switching, or
legal-but-low-value actions,
3) Can still be attributed to ONE specific branch, priority rule, or
missing condition in the decision tree.

PRIORITIZATION RULE:
- Prefer a bottleneck that repeatedly reduces soup throughput, even
if all actions are technically legal.
- Do NOT over-prioritize teammate prediction mistakes unless they
clearly create repeated downstream time loss.
- A valid-but-low-value action pattern is more important than a
one-off invalid action.
- Also consider timing-related inefficiencies:
  - Acting too early or too late,
  - Situations where waiting would be better than acting immediately,
  - Situations where the agent chooses a legal action but the wrong
  role for the current phase.

[Episode states]:
Scene <t>:
<LANGUAGE_STATE_DESCRIPTION>
[Misprediction] <OPTIONAL_PARTNER_PREDICTION_ERROR>
[DecisionTrace] <OPTIONAL_SELECTED_SKILL_AND_EXECUTABILITY_TRACE>
###
... repeated for all logged scenes ...

[The decision tree]:
<POLICY_TREE_T_k>

[Final score]:
<S_k>

Your task:
1. Scan all episode states and identify time-wasting behaviors.
2. Select exactly ONE primary inefficiency with the largest negative
impact on efficiency or score.
3. Identify the EXACT target branch or decision condition to modify.
4. Generate a Tree_Reflexion that guides a planner to perform a
SINGLE, LOCAL modification:
   - describe the CURRENT behavior of this branch (BEFORE),
   - describe the DESIRED behavior after modification (AFTER), using
   refined conditions, priority changes, or a single added guard
   condition,
   - explicitly list assumptions about what logic MUST remain
   unchanged.
5. The value in Decision_Tree_Summary.Final_Score MUST be exactly
<S_k>.

OUTPUT REQUIREMENTS:
- Output MUST be valid JSON.
- Do NOT include markdown, explanations, or extra text.
- Be concrete and implementable.
- Output must directly contain only these top-level keys:
  - "Decision_Tree_Summary"
  - "Tree_Reflexion"

Return JSON in the following format:
{
  "Decision_Tree_Summary": {
    "Summary": "Summarize the key strategies and critical decision
    points here.",
    "Final_Score": "<S_k>"
  },
  "Tree_Reflexion": {
    "Target_Branch": "",
    "Modification_Scope": "LOCAL_SINGLE_BRANCH",
    "Before_Behavior": "",
    "After_Behavior": [
      ""
    ],
    "Unchanged_Assumptions": [
      ""
    ],
    "Expected_Effect": ""
  }
}
```