Meta Reinforcement Learning with Autonomous Inference of Subtask Dependencies

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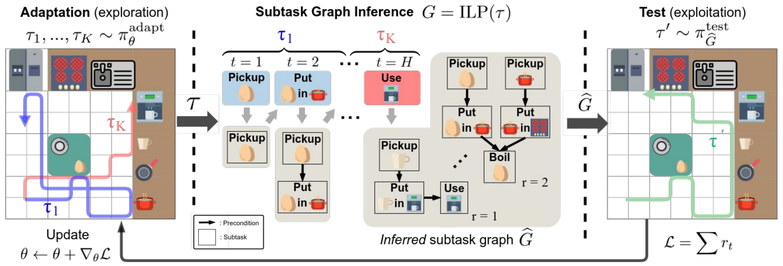
Summary

Goal: Solve a meta RL problem by *explicitly inferring the underlying task structure* in order to quickly adapt to the task
Idea: Infer the subtask reward and dependencies in adaptation phase, and solve the task in test phase
Result: Better generalization and performance on complex tasks

Subtask Graph Inference Problem

- A task is characterized by the **subtask graph** which defines the subtasks, their *rewards* and *preconditions*.
- The subtask graph is **unknown** to the agent
- Few-shot RL: after *K* episodes of adaptation, the agent needs to maximize the return in test phase.

MSGI: Meta-Learner with Subtask Graph Inferencer



Adaptation: Adaptation policy ($\pi_\theta^{\text{adapt}}$) learns to efficiently collect experience to accurately infer the task
Inference: ILP algorithm infers the subtask reward and precondition in the form of subtask graph $\widehat{G} = (\widehat{G}_{\mathbf{r}}, \widehat{G}_{\mathbf{c}})$
Execution: execution policy ($\pi_{\widehat{G}}^{\text{test}}$) executes the inferred subtask graph

Algorithm / Training

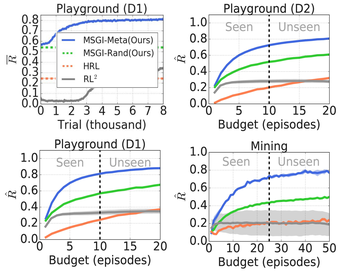
- Adaptation policy
  - **UCB**-like intrinsic bonus: $r_t^{\text{UCB}} = w_{\text{UCB}} \cdot \mathbb{I}(\mathbf{x}_t \text{ is novel})$
  - Trained via actor-critic method with GAE [1]
- Subtask graph inference

$$\widehat{G}^{\text{MLE}} = (\widehat{G}_{\mathbf{c}}^{\text{MLE}}, \widehat{G}_{\mathbf{r}}^{\text{MLE}}) = \arg\max_{G_{\mathbf{c}}, G_{\mathbf{r}}} p(\tau | G_{\mathbf{c}}, G_{\mathbf{r}})$$

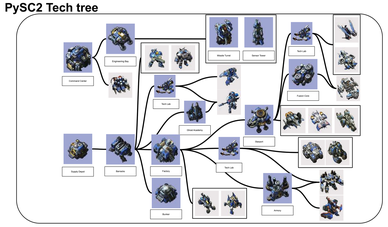
  - **Precondition** ($G_{\mathbf{c}}$): CART-based logic induction algorithm to infer the precondition function ($\mathbf{e} = \widetilde{f}_{G_{\mathbf{c}}}(\mathbf{x})$)
  - **Subtask reward** ($G_{\mathbf{r}}$): $G_{\mathbf{r}}^i \sim \mathcal{N}(\widehat{\mu}^i, \widehat{\sigma}^i)$, $\widehat{G}_{\mathbf{r}}^{\text{MLE},i} = \widehat{\mu}_{\text{MLE}}^i = \mathbb{E}\left[r_t \mid \mathbf{o}_t = \mathcal{O}^i\right]$

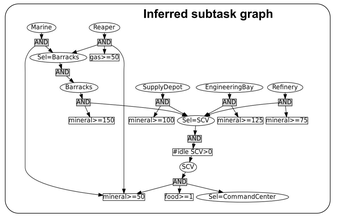
Experiments

- Setting
  - Domain: Playground [2], Mining [2], SC2LE [3]
  - Agents: Random, HRL [4], RL^2 [5], MSGI-random (ours), MSGI-meta (ours)
- Result on Playground and Mining domain
  - Adaptation: our learned adaptation policy enables faster adaptation (MSGI-meta V.S. MSGI-random)
  - Generalization: MSGI (ours) consistently outperforms baselines on unseen tasks with **longer** (**unseen**) adaptation horizon
- Result on StarCraft II (SC2LE)
  - Subtask graph inference: given 20 episodes budget with 2.5K environment steps, our method correctly infers **93%** of the preconditions



PySC2 Tech tree





References

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