Learning Hierarchical Policies from Unsegmented Demonstrations using Causal Information

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Abstract

The use of imitation learning to learn a single policy for a complex task that has multiple modes or hierarchical structure can be challenging. In fact, previous work has shown that when the modes are known, learning separate policies for each mode or sub-task can greatly improve the performance of imitation learning. In this work, we discover the interaction between sub-tasks from their resulting state-action trajectory sequences using a directed graphical model. We propose a new algorithm based on the generative adversarial imitation learning framework which automatically learns sub-task policies from unsegmented demonstrations. Our approach maximizes the directed information flow in the graphical model between sub-task latent variables and their generated trajectories. We also show how our approach connects with existing `Options' framework commonly used to learn hierarchical policies.

Imitation Learning

- ***Generative Adversarial Imitation Learning (GAIL)*** **[1]**
  Objective,
  $\min_{\pi} \max_{D} \mathbb{E}_{\pi}[\log D(s,a)] + \mathbb{E}_{\pi_E}[1 - \log D(s,a)] - \lambda H(\pi)$

- ***GAIL for mixture of experts*** **[2, 3]**
  c : Latent variable denoting expert

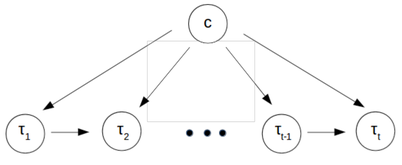


Figure 1: Graphical model in [2, 3]

Maximize lower bound to mutual information,

$L_1(\pi, Q) = \mathbb{E}_{c\sim p(c), a\sim\pi(\cdot|s,c)} \log Q(c|\tau) + H(c) \leq I(c;\tau)$

Overall objective,

$$\min_{\pi,q} \max_{D} \mathbb{E}_{\pi}[\log D(s,a)] + \mathbb{E}_{\pi_E}[1 - \log D(s,a)] - \lambda_1 L_1(\pi, q) - \lambda_2 H(\pi)$$

Options framework

- Option: $o \in \mathcal{O}$
- Sub-policy: $\pi(a|s,o)$
- Termination policy: $\pi(b|s,\bar{o})$
- Option activation policy: $\pi(o|s)$

* - Equal contribution

Method

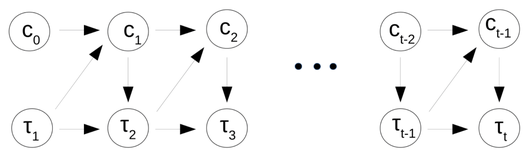


Figure 2: Graphical model used in this work

- *Using lower bound to mutual information,*

$$L(\pi, q) = \sum_t \mathbb{E}_{c^{1:t}\sim p(c^{1:t}), a^{t-1}\sim\pi(\cdot|s^{t-1}, c^{1:t-1})} \Big[\log q(c^t|c^{1:t-1}, \boldsymbol{\tau}) \Big] + H(\boldsymbol{c}) \leq I(\boldsymbol{\tau}; \boldsymbol{c})$$

Dependence of q on the entire trajectory $\boldsymbol{\tau}$ precludes its use at test time where only trajectory up to current time is known

- *Causal Information*

$$I(\boldsymbol{\tau} \to \boldsymbol{c}) = H(\boldsymbol{c}) - H(\boldsymbol{c}\|\boldsymbol{\tau}) = H(\boldsymbol{c}) - \sum_t H(c^t|c^{1:t-1}, \tau^{1:t})$$

- *Using lower bound to causal information,*

$$L_1(\pi, q) = \sum_t \mathbb{E}_{c^{1:t}\sim p(c^{1:t}), a^{t-1}\sim\pi(\cdot|s^{t-1}, c^{1:t-1})} \Big[\log q(c^t|c^{1:t-1}, \tau^{1:t}) \Big] + H(\boldsymbol{c}) \leq I(\boldsymbol{\tau} \to \boldsymbol{c})$$

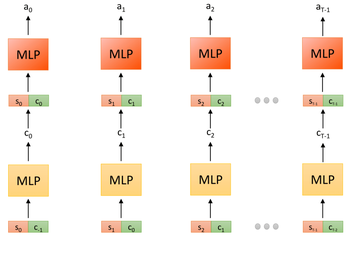
Using causal information removes dependence of q on future unobserved trajectory. Thus, q can now be used as a macro-policy to select the next sub-task latent variable.

Overall *Causal-Info GAIL* objective,

$$\min_{\pi,q} \max_{D} \mathbb{E}_{\pi}[\log D(s,a)] + \mathbb{E}_{\pi_E}[1 - \log D(s,a)] - \lambda_1 L_1(\pi, q) - \lambda_2 H(\pi)$$

where L_1 is the lower bound to *causal information.*

- *Variational Auto-encoder (VAE) pre-training*
  Learn approximate prior over latent variables using VAE



Experiments

- *Discrete environment*

  15x11 grid with 4 rooms connected via corridors. An object is placed at the center of a random room at the beginning of the episode. The agent spawns at a random location in the grid.

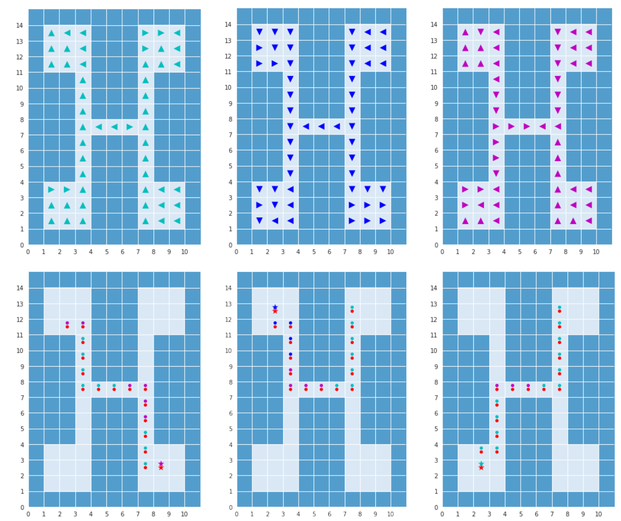


Figure 3: Visualization of sub-policy actions (top) and macro-policy actions (bottom)

- *Continuous environments*

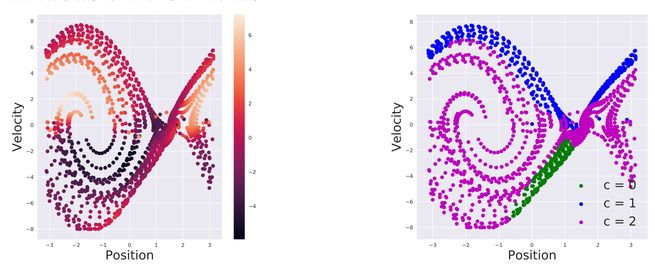


Figure 4: Visualization of sub-policy actions (left) and macro-policy actions (right) on Pendulum-v0

Environment	GAIL	VAE	Causal-Info GAIL
Pendulum	-121.4 ± 94.1	-142.9 ± 95.6	-125.4 ± 103.8
Inverted Pendulum	1000.0 ± 15.2	218.8 ± 8.0	1000.0 ± 15.0

Table 1: Returns over 300 episodes on continuous environments

References

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