

2025/02/20 회의 (RL 관련 공유)

Wise

AI Lab

2025-02-20

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Random variables

$$X : \Omega \rightarrow E$$

(Ω, Σ, P) : 확률 공간 (Sample space Ω , Event space Σ , Probability measure P)

(with some assumptions), we also have

Probability density function

$$\mathbb{E}_P[f(X)] := \int_{\Omega} f(X(\omega))dP(\omega) = \int_E f(x)p(x)dx =: \mathbb{E}_{x \sim p(x)}[f(x)]$$

Note

E might be complex..

Monte Carlo estimation

Goal: Calculate $\mathbb{E}_{x \sim p(x)}[f(x)]$

(Hint: [Law of Large Numbers](#))

Overview of RL

- Agent
- Environment
- \mathcal{S} : a finite set of states (상태 집합)
- \mathcal{A} : a finite set of actions (행동 집합)
- Policy $\pi : \mathcal{A} \times \mathcal{S} \rightarrow [0, 1]$
 - Optimal policy
 - $\pi^* = \arg \max_{\pi} \mathbb{E}_{s_0 \sim p_0(s)} [V_{\pi}(s_0)]$
 - $V_{\pi^*}(s) \geq V_{\pi}(s) \ (\forall s \in \mathcal{S}, \forall \pi)$
- Reward $R : \mathcal{A} \times \mathcal{S} \rightarrow \mathbb{R}$
- Value function $V : \mathcal{S} \rightarrow \mathbb{R}$
- Q-function $Q : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$

Terminologies

- Advantage function $A : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$
 - $A(s, a) := Q(s, a) - V(s)$
- Generalized advantage estimation (GAE)
 - Advantage function을 계산하려면 state와 action 값이 필요하다.
 - 그런데 이러한 state, action은 (policy와 initial state의 확률분포에 depend하는) random variable이다.
 - 따라서 Advantage function의 evaluation 결과 $A(s, a)$ 도 random variable
 - 이 random variable을 estimate하기 위해 R, V 를 통해 Monte Carlo estimate을 하는데 그 estimation의 variance를 줄이기 위해 나온 방법이 GAE

Overview of RL

GAE



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Overview of RL

GAE



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Objective function of RL

$$L(\theta) = \mathbb{E}_{s_0 \sim p_0(s)} [V_{\pi_\theta}(s_0)]$$

- policy를 neural network의 parameter θ 를 도입하여 위의 목적함수를 최대화하도록 훈련해서 optimal policy를 얻고자 하는 것이 RL의 목표

Overview of RL

- Value-based RL
 - Q function을 학습하여 $\pi(s) = \arg \max_{a \in \mathcal{A}} Q(s, a)$ 를 policy로 사용
 - 단점
 - function approximation (such as neural networks)
 - bootstrapped value function estimation (TD-like method)
 - off-policy learning
 - This combination : the deadly triad
 - RL 알고리즘 불안정함
- Policy-based RL
 - Policy search method
 - 대부분 policy gradient 방법론 사용
- Model-based RL (MBRL)

Overview of RL

Classification of RL


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Policy Gradient Theorem



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REINFORCE

- Monte Carlo version
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- 단점: estimation G_t 의 분산이 큼
 - 해결책: baseline을 사용

Policy Optimization

- PPO

Reinforcement Learning with LLMs

- InstructGPT



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RL with LLMs

- ChatGPT



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RL with LLMs



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RL with LLMs

- DeepSeek-R1-Zero
 - RL on the Base Model

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Reinforcement Learning with Verifiable Rewards

RLVR



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