Machine Learning

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Policy Methods

Adapted from slides by David Silver, Pieter Abbeel, and John Schulman

Reinforcement Learning is Everywhere!

- RL used to be niche subfield ...
- Now it's all over the place
- Part of much of ML hype
- But what is reinforcement learning?

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- RL used to be niche subfield . . .
- Now it's all over the place
- Part of much of ML hype
- But what is reinforcement learning?
  - RL is a general-purpose framework for decision-making
  - RL is for an agent with the capacity to act
  - Each action influences the agent's future state
  - Success is measured by a scalar reward signal
  - Goal: select actions to maximise future reward

Simple Statistical Gradient-Following Algorithms for Connectionist Reinforcement Learning

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Appears in *Machine Learning, 8*, pp. 229-256, 1992.

Foundation of Policy Gradient

Likelihood Ratio Policy Gradient

Let τ be state-action $s_0, u_0, \ldots, s_H, u_H$. Utility of policy π parametrized by θ is

$$U(\theta) = \mathbb{E}_{\pi_\theta, U}\left[\sum_t^H R(s_t, u_t); \pi_\theta\right] = \sum_\tau P(\tau; \theta) R(\tau). \tag{1}$$

Our goal is to find θ:

$$\max_\theta U(\theta) = \max_\theta \sum_\tau p(\tau; \theta) R(\tau) \tag{2}$$

Likelihood Ratio Policy Gradient

$$\sum_{\tau} p(\tau; \theta) R(\tau) \tag{3}$$

Taking the gradient wrt θ:

$$\tag{4}$$

Likelihood Ratio Policy Gradient

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Taking the gradient wrt θ:

$$\nabla_\theta U(\theta) = \sum_{\tau} R(\tau)\frac{P(\tau;\theta)}{P(\tau;\theta)}\nabla_\theta P(\tau;\theta) \tag{4}$$

$$\tag{5}$$

Move differentiation inside sum (ignore $R(\tau)$ and then add in term that cancels out

Likelihood Ratio Policy Gradient

$$\sum_{\tau} p(\tau;\theta)R(\tau) \tag{3}$$

Taking the gradient wrt θ:

$$\begin{aligned}
\nabla_{\theta} U(\theta) &= \sum_{\tau} R(\tau)\frac{P(\tau;\theta)}{P(\tau;\theta)}\nabla_{\theta} P(\tau;\theta) && (4)\\
&= \sum_{\tau} P(\tau;\theta)\frac{\nabla_{\theta} P(\tau;\theta)}{P(\tau;\theta)}R(\tau) && (5)\\
& && (6)
\end{aligned}$$

Move derivative over probability

Likelihood Ratio Policy Gradient

$$\sum_{\tau} p(\tau;\theta)R(\tau) \tag{3}$$

Taking the gradient wrt θ:

$$\begin{aligned}
\nabla_\theta U(\theta) &= \sum_{\tau} R(\tau)\frac{P(\tau;\theta)}{P(\tau;\theta)}\nabla_\theta P(\tau;\theta) &(4)\\
&= \sum_{\tau} P(\tau;\theta)\frac{\nabla_\theta P(\tau;\theta)}{P(\tau;\theta)}R(\tau) &(5)\\
&= \sum_{\tau} P(\tau;\theta)\nabla_\theta\left[\log P(\tau;\theta)\right]R(\tau) &(6)
\end{aligned}$$

Assume softmax form ($\nabla_\theta \log z = \frac{1}{z}\nabla_\theta z$)

Likelihood Ratio Policy Gradient

$$\sum_{\tau} p(\tau;\theta) R(\tau) \tag{3}$$

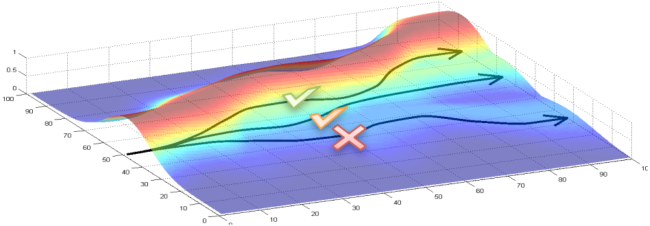
Taking the gradient wrt θ:

$$= \sum_{\tau} P(\tau;\theta) \nabla_{\theta} \left[\log P(\tau;\theta) \right] R(\tau) \tag{4}$$

Approximate with empirical estimate for m sample paths from π

$$\nabla_{\theta} U(\theta) \approx \frac{1}{m} \sum_{i}^{m} \nabla_{\theta} \log P(r^{i};\theta) R(\tau^{i}) \tag{5}$$

Policy Gradient Intuition



- Increase probability of paths with positive R
- Decrease probability of paths with negagive R

Extensions

- Consider baseline b (e.g., path averaging)

$$\nabla_\theta U(\theta) \approx \frac{1}{m} \sum_1^m \nabla_\theta \log P(r^i;\theta)(R(\tau^i) - b(\tau)) \tag{6}$$

- Combine with value estimation (critic)
  - Critic: Updates action-value function parameters
  - Actor: Updates policy parameters in direction suggested by critic
- Proximal policy optimization: policies should not change too much

Recap

- Reinforcement learning is active subfield of ML
- Deep learning option for learning policy / value functions
- Representation learning helps cope with large state spaces
- Still requires careful engineering and feature engineering