Alignment

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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

Ronald J. Williams
College of Computer Science
Northeastern University
Boston, MA 02115

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:

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

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Connecting to Generation

- τ are internal states of decoder and the tokens they produce.
- Reward is how good the output is (more on that later).
- θ are the encoder/decoder parameters

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$$\tag{4}$$

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

$$\tag{5}$$

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

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$$\tag{6}$$

Move derivative over probability

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$$= \sum_{\tau} P(\tau;\theta) \nabla_\theta \left[\log P(\tau;\theta)\right] R(\tau) \tag{6}$$

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

Likelihood Ratio Policy Gradient

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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

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

For generation

- (Gradient of) probability of outputting sequence
- How good that sequence is
- Averaged over samples

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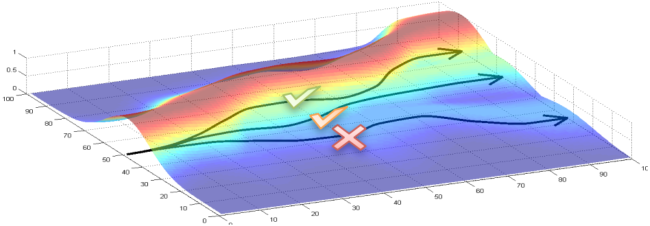
Policy Gradient Intuition



- Increase probability of paths with positive R
- Decrease probability of paths with negative 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)
  - Actor: What actions to take
  - Critic: How good those actions are
  - Advantage Actor Critic with temporal difference (remember TD Gammon?) term

$$A_{\pi_\theta} = r(s_t, a_t) + V_{\pi_\theta}(s_{t+1}) - V_{\pi_\theta}(s_t) \tag{7}$$

- 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