Reinforcement Learning for NLP

Advanced Machine Learning for NLP

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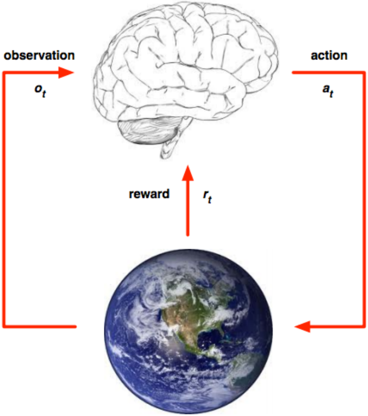
REINFORCEMENT OVERVIEW, POLICY GRADIENT

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

- I used to say that RL wasn't used in NLP ...
- Now it's all over the place
- Part of much of ML hype
- But what is reinforcement learning?

- I used to say that RL wasn't used in NLP . . .
- 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



- At each step t the agent:
  - Executes action a_t
  - Receives observation o_t
  - Receives scalar reward r_t
- The environment:
  - Receives action a_t
  - Emits observation o_{t+1}
  - Emits scalar reward r_{t+1}

Example

	QA	MT
State	Words Seen	Foreign Words Seen
Reward	Answer Accuracy	Translation Quality
Actions	Answer / Wait	Translate / Wait

State

- Experience is a sequence of observations, actions, rewards

$$o_1, r_1, a_1, \ldots, a_{t1}, o_t, r_t \tag{1}$$

- The state is a summary of experience

$$s_t = f(o_1, r_1, a_1, \ldots, a_{t1}, o_t, r_t) \tag{2}$$

- In a fully observed environment

$$s_t = f(o_t) \tag{3}$$

What makes an RL agent?

- Policy: agent's behaviour function
- Value function: how good is each state and/or action
- Model: agent's representation of the environment

Policy

- A policy is the agent's behavior
  - It is a map from state to action:
  - Deterministic policy: $a = \pi(s)$
  - Stochastic policy: $\pi(a \mid s) = p(a \mid s)$

Value Function

- A value function is a prediction of future reward: “How much reward will I get from action a in state s?”
- Q-value function gives expected total reward
  - from state s and action a
  - under policy π
  - with discount factor γ (future rewards mean less than immediate)

$$Q^{\pi}(s,a) = \mathbb{E}\left[r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \ldots \mid s,a\right] \tag{4}$$

A Value Function is Great!

- An optimal value function is the maximum achievable value

$$Q^*(s,a) = \max_{\pi} Q^{\pi}(s,a) = Q^{\pi^*}(s,a) \tag{5}$$

- If you know the value function, you can derive policy

$$\pi^* = \arg\max_{a} Q(s,a) \tag{6}$$

Approaches to RL

Value-based RL

- Estimate the optimal value function $Q(s,a)$
- This is the maximum value achievable under any policy

Policy-based RL

- Search directly for the optimal policy π^*
- This is the policy achieving maximum future reward

Model-based RL

- Build a model of the environment
- Plan (e.g. by lookahead) using model

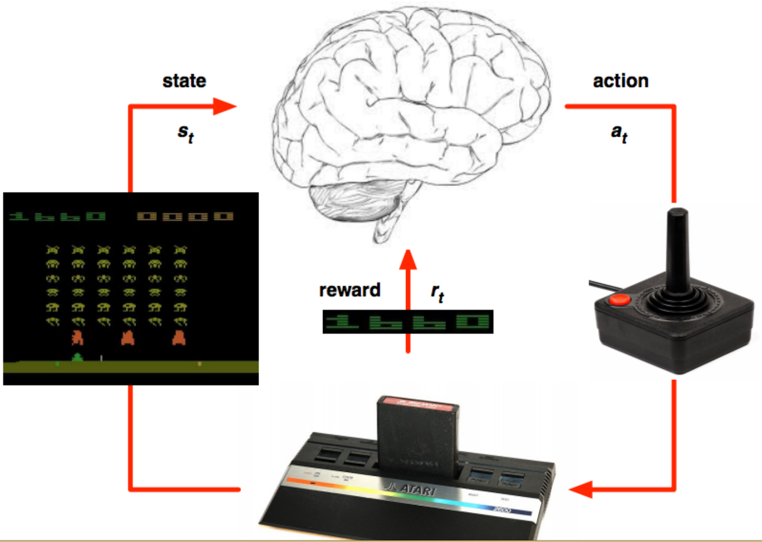
Deep Q Learning

- Optimal Q-values should obey equation

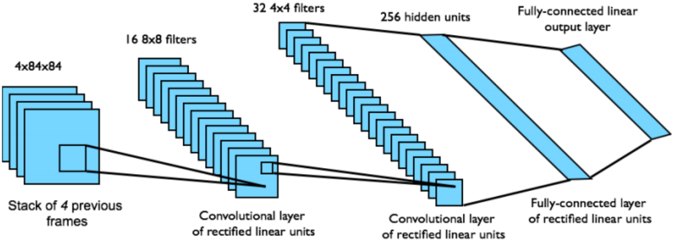
$$Q^*(s,a) = \mathbb{E}_{s'}\left[r + \gamma Q(s',a') \,|\, s,a\right] \tag{7}$$

- Treat as regression problem
- Minimize: $\left(r + \gamma \max_a Q(s',a',\vec{w}) - Q(s,a,\vec{w})\right)^2$
- Converges to Q using table lookup representation
- But diverges using neural networks due to:
  - Correlations between samples
  - Non-stationary targets

Deep RL in Atari

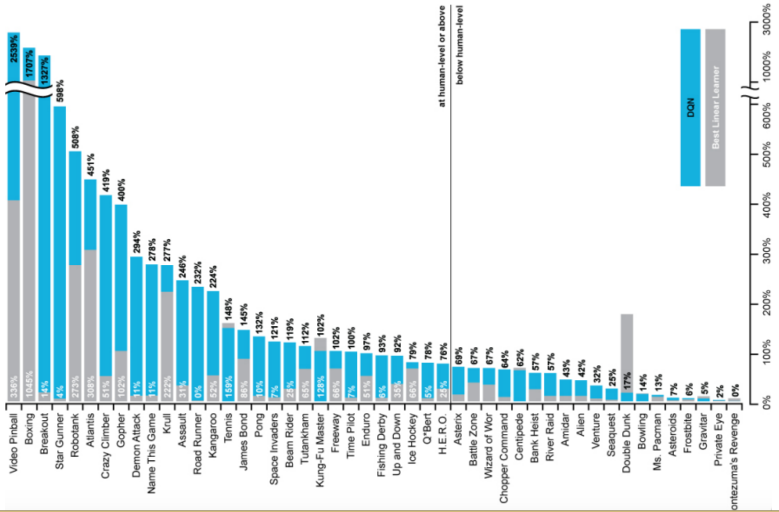


DQN in Atari



- End-to-end learning of values $Q(s, a)$ from pixels s
- Input state s is stack of raw pixels from last four frames
- Output is $Q(s, a)$ for 18 joystick/button positions
- Reward is change in score for that step

Atari Results



Policy-Based RL

- Advantages:
  - Better convergence properties
  - Effective in high-dimensional or continuous action spaces
  - Can learn stochastic policies
- Disadvantages:
  - Typically converge to a local rather than global optimum
  - Evaluating a policy is typically inefficient and high variance

Optimal Policies Sometimes Stochastic

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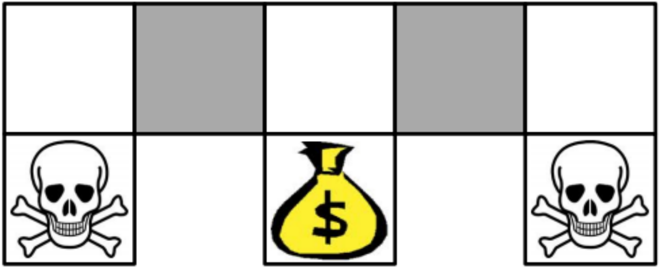
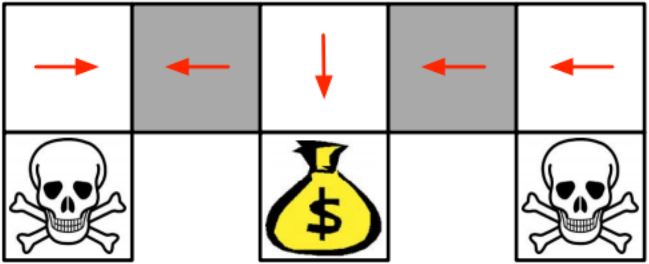


(Cannot distinguish gray states)

Optimal Policies Sometimes Stochastic

Deterministic



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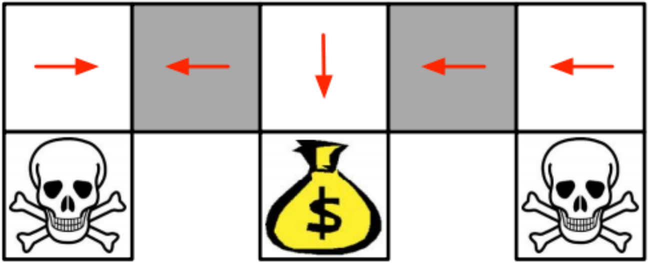
Optimal Policies Sometimes Stochastic

Deterministic

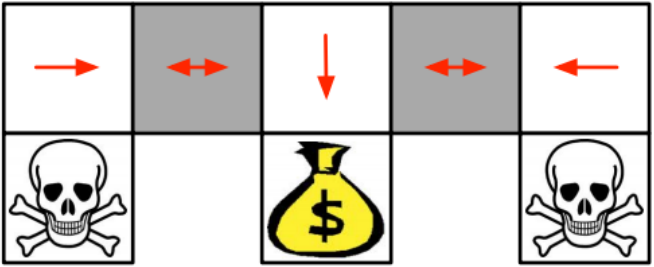


(Cannot distinguish gray states)

Value-based RL learns near deterministic policy!

Optimal Policies Sometimes Stochastic

Stochastic



(Cannot distinguish gray states, so flip a coin!)

Likelihood Ratio Policy Gradient

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

$$U(\theta) = \mathbb{E}_{\pi_\theta, U}\left[\sum_t^H R(s_t, u_t); \pi_\theta\right] = \sum_{tau} P(\tau; \theta) R(\tau). \tag{8}$$

Our goal is to find θ:

$$\max_\theta U(\theta) = \max_\theta \sum_t p(\tau; \theta) R(\tau) \tag{9}$$

Likelihood Ratio Policy Gradient

$$\sum_t p(\tau;\theta)R(\tau) \tag{10}$$

Taking the gradient wrt θ:

$$\tag{11}$$

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Taking the gradient wrt θ:

$$\nabla_\theta U(\theta) = \sum_\tau R(\tau)\frac{P(\tau;\theta)}{P(\tau;\theta)}\nabla_\theta P(\tau;\theta) \tag{11}$$

$$\tag{12}$$

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

Likelihood Ratio Policy Gradient

$$\sum_t p(\tau;\theta)R(\tau) \tag{10}$$

Taking the gradient wrt θ:

$$\nabla_\theta U(\theta) = \sum_\tau R(\tau)\frac{P(\tau;\theta)}{P(\tau;\theta)}\nabla_\theta P(\tau;\theta) \tag{11}$$

$$= \sum_\tau P(\tau;\theta)\frac{\nabla_\theta P(\tau;\theta)}{P(\tau;\theta)}R(\tau) \tag{12}$$

$$\tag{13}$$

Move derivative over probability

Likelihood Ratio Policy Gradient

$$\sum_t p(\tau;\theta)R(\tau) \tag{10}$$

Taking the gradient wrt θ:

$$\begin{aligned}
\nabla_\theta U(\theta) &= \sum_\tau R(\tau)\frac{P(\tau;\theta)}{P(\tau;\theta)}\nabla_\theta P(\tau;\theta) && (11)\\
&= \sum_\tau P(\tau;\theta)\frac{\nabla_\theta P(\tau;\theta)}{P(\tau;\theta)}R(\tau) && (12)\\
&= \sum_\tau P(\tau;\theta)\nabla_\theta\left[\log P(\tau;\theta)\right]R(\tau) && (13)
\end{aligned}$$

Assume softmax form

Likelihood Ratio Policy Gradient

$$\sum_t p(\tau;\theta)R(\tau) \tag{10}$$

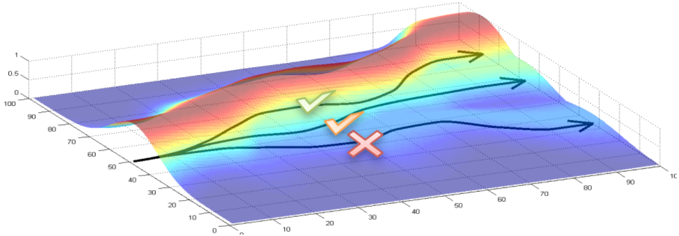
Taking the gradient wrt θ:

$$= \sum_\tau P(\tau;\theta)\nabla_\theta \left[\log P(\tau;\theta)\right] R(\tau) \tag{11}$$

Approximate with empirical estimate for m sample paths from π

$$\nabla_\theta U(\theta) \approx \frac{1}{m}\sum_1^m \nabla_\theta \log P(r^i;\theta)R(\tau^i) \tag{12}$$

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)

$$\nabla_\theta U(\theta) \approx \frac{1}{m} \sum_1^m \nabla_\theta \log P(r^i;\theta)(R(\tau^i) - b(\tau)) \tag{13}$$

- Combine with value estimation (critic)
  - Critic: Updates action-value function parameters
  - Actor: Updates policy parameters in direction suggested by critic