Policy Gradient Methods for Deep Reinforcement Learning

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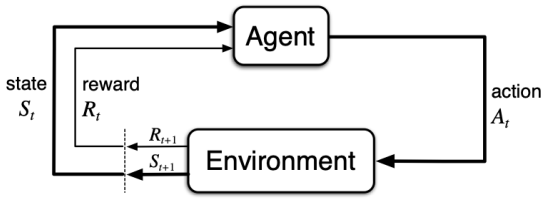
RL is big and rich, its history traces back to Pavlov's study on the psychology of animal learning (conditional response) back in 1902. The expository article History of Reinforcement Learning (http://incompleteideas.net/book/first/ebook/node12.html) is a good resource to learn how RL evolved in the last 100 years.
Policy Gradient Methods is a class of RL algorithms that directly learns a policy from interaction with the environment. In contrast, to this, one can also learn a state value estimate of the current state of the env and the candidate actions. This class of algorithms is called Q-learning.
Review about setups in RL The objective of RL is to find a policy π that gets the highest rewards from a *Markov Decision Process*



At time step t, the env is at state S_t, the agent takes action A_t, the env transition into S_{t+1} and the agent receives a reward of R_{t+1}.
The critical assumption of MPD is

- The transition probability $P(S_{t+1}, R_{t+1}|S_t, A_t)$ is independent from the history
- The agent's action does not alter the transition probability, i.e. $P(S_{t+1}, R_{t+1}|S_t, A_t)$ is the same whenver the agent sees S_t and takes action A_t

The transition probability $P(S_{t+1}, R_{t+1}|S_t, A_t)$ is call the *model* of the env. The objective of RL is to find a *optimal policy* (what action to take at S_t) that maximize the total reward
If $P(S_{t+1}, R_{t+1}|S_t, A_t) = 1$ for all S and A, then we say the env is deterministic, otherwise stochastic.
The total reward from time t is

$$G_t = R_{t+1} + R_{t+2} + \cdots + R_T$$

The MDP terminates at T.
To prioritize short term return over long term return, we use a discount factor $\gamma \in [0, 1]$ and define

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots + \gamma^k R_{t+k+1} + \cdots + \gamma^{T-t-1} R_T$$

A few ways to think about the discount factor

- prioritize short term reward
- A mathematical convenience for infinite episodic task; we want G_t to be a finite number even if the MDP never stops.

  $$\sum_{i=0}^{\infty} \gamma^i = \frac{1}{1-\gamma}$$

  so

  $$G_t \leq \frac{1}{1-\gamma} * R_{\max}$$

- a way to factor in the probability that agent dies. The agent survives with prob γ and die with prob $1 - \gamma$. i.e reward at time t is

  $$\gamma R_{t+1} + (1-\gamma) * 0$$

Let $\mathscr{S}$ be the state space, and $\mathscr{A}$ the action space. A *deterministic policy* is a mapping

$$\pi : \mathbb{S} \to \mathbb{A}$$

and a *stochastic* policy is a mapping

$$\pi : \mathbb{S} \to Dist(\mathbb{A})$$

where $Dist(\mathscr{A})$ denote the space of probability distributions over the action spaces.
Both determinstc env and determinsitc policy are special cases of their stochastic counterparts.(all probability concentrate at 1 point). So we only address the stochastic cases in the rest of the note.
Suppose the agent's current policy is π, then at state S_t π yields a probability distribution over the action space

$$\pi(\cdot|S_t)$$

from which the agent samples actions.
So with the model of the env, we can write down the expected total reward if we follow the policy π. Assume the initial state is s

$$v_\pi(s) := \mathbb{E}_\pi$$

A fundamental difference supervised learning and RL is that data is completely determined before any training, whereas in RL data is dynamically generated

through interaction with the environment. This means the distribution of the data for SL is static and the distribution of data for RL changes as the agent learns.
Talk about value iteration and policy iteration; Talk about how tabular methods can be used to achieve value/policy iteration; Talk about why tabular method is not sufficient and function approximator;
then talk about parametrized policy and policy gradient theorem
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