CSE 573: Artificial Intelligence
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Reinforcement Learning

slides from
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Outline

- Review: Q-Learning
- Policy Optimization
- Actor-Critic

(Tabular) Q-Learning

Algorithm:

Start with $Q_0(s, a)$ for all s, a.

Get initial state s

For k = 1, 2, … till convergence

Sample action a, get next state s’

If s’ is terminal:

$$\text{target} = R(s, a, s')$$

Sample new initial state s’

else:

$$\text{target} = R(s, a, s') + \gamma \max_{a'} Q_k(s', a')$$

$$Q_{k+1}(s, a) \leftarrow (1 - \alpha) Q_k(s, a) + \alpha \left[\text{target}\right]$$

$$s \leftarrow s'$$

Approximate Q-Learning

- Instead of a table, we have a parametrized Q function: $Q_\theta(s,a)$
  - Can be a linear function in features:

$$Q_\theta(s,a) = \theta_0 f_0(s,a) + \theta_1 f_1(s,a) + \cdots + \theta_n f_n(s,a)$$

  - Or a complicated neural net

- Learning rule:
  - Remember: $\mathrm{target}(s') = R(s,a,s') + \gamma \max_{a'} Q_{\theta_k}(s',a')$
  - Update:

$$\theta_{k+1} \leftarrow \theta_k - \alpha \nabla_\theta \left[\frac{1}{2} (Q_\theta(s,a) - \mathrm{target}(s'))^2 \right] \Big|_{\theta=\theta_k}$$

Connection to Tabular Q-Learning

- Suppose $\theta \in \mathbb{R}^{|S|\times|A|}, \quad Q_\theta(s,a) \equiv \theta_{sa}$

$$\nabla_{\theta_{sa}}\left[\frac{1}{2}(Q_\theta(s,a) - \text{target}(s'))^2\right]$$
$$= \nabla_{\theta_{sa}}\left[\frac{1}{2}(\theta_{sa} - \text{target}(s'))^2\right]$$
$$= \theta_{sa} - \text{target}(s')$$

- Plug into update: $\theta_{sa} \leftarrow \theta_{sa} - \alpha(\theta_{sa} - \text{target}(s'))$

$$= (1-\alpha)\theta_{sa} + \alpha[\text{target}(s')]$$

- Compare with Tabular Q-Learning update:

$$Q_{k+1}(s,a) \leftarrow (1-\alpha)Q_k(s,a) + \alpha\left[\text{target}(s')\right]$$

Policy Optimization?

- Often the policy can be simpler than Q or V
  - E.g., Robotic grasp
- V: doesn't prescribe actions
  - We need the dynamic model (+ compute 1 Bellman back-up)
- Q: need to be able to efficiently find the best action for every Q state
  - Challenge: What happens when actions are high-dimensional or continuous

Policy Optimization

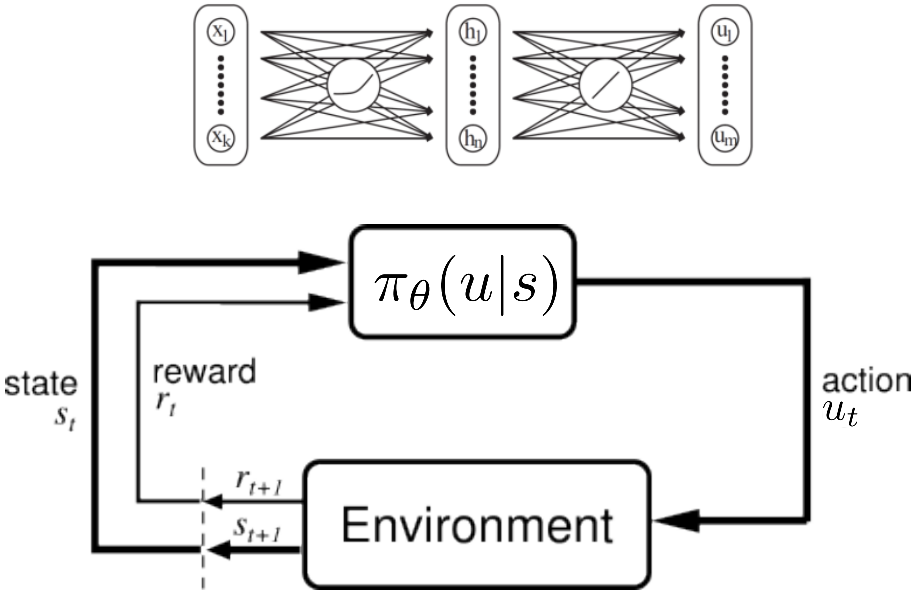
- Solution: learn policies that maximize rewards, not the values that predict them
  - On policy learning – learn directly from actions
  - Any model that can be trained, could be a policy: Allows continuous action spaces, learning a stochastic policy

- Policy search: start with an ok solution (e.g. Q-learning) then fine-tune by hill climbing on feature weights

Policy Search

- Simplest policy search:
  - Start with an initial linear value function or Q-function
  - Nudge each feature weight up and down and see if your policy is better than before
- Problems:
  - How do we tell the policy got better?
  - Need to run many sample episodes!
  - If there are a lot of features, this can be impractical
- Better methods exploit lookahead structure, sample wisely, change multiple parameters…

Policy Optimization Notation



- Consider control policy parameterized by parameter vector θ

$$\max_\theta \quad \mathrm{E}[\sum_{t=0}^{H} R(s_t)|\pi_\theta]$$

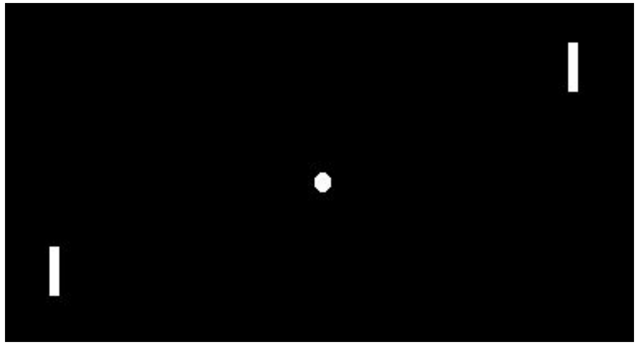
- Stochastic policy class (smooths out the problem):

$\pi_\theta(u|s)$: probability of action u in state s

Figure source: Sutton & Barto, 1998]

Example (Playing Pong)

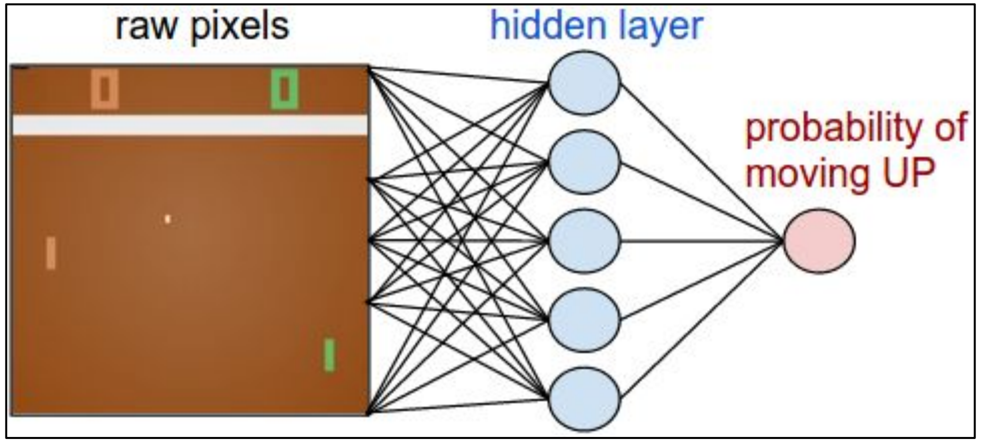
Suppose we had the training labels…
(we know what to do in any state)



(x1,UP)
(x2,DOWN)
(x3,UP)
...

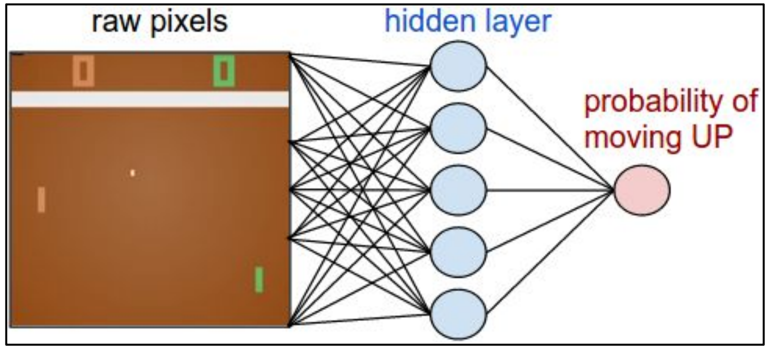
maximize:

$$\sum_i \log p(y_i \mid x_i)$$

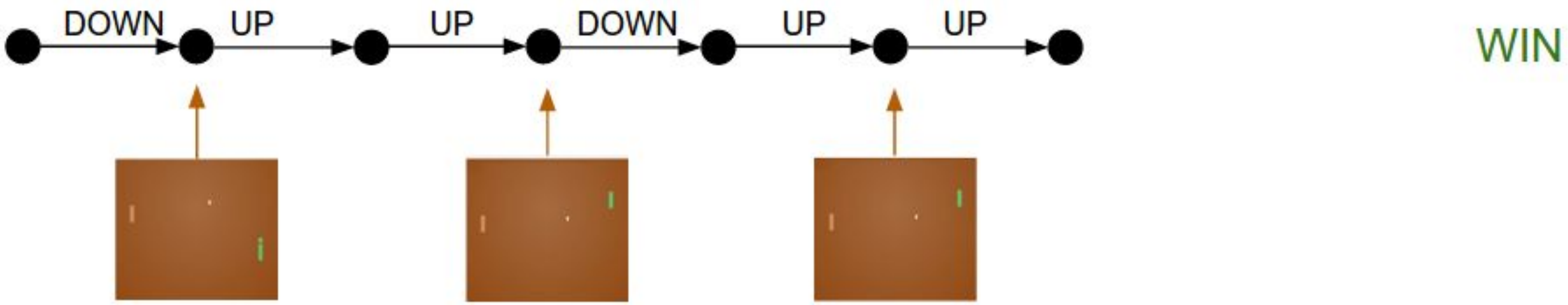


Reinforcement Learning

Let’s just act according to our current policy...



Rollout the policy and collect an episode

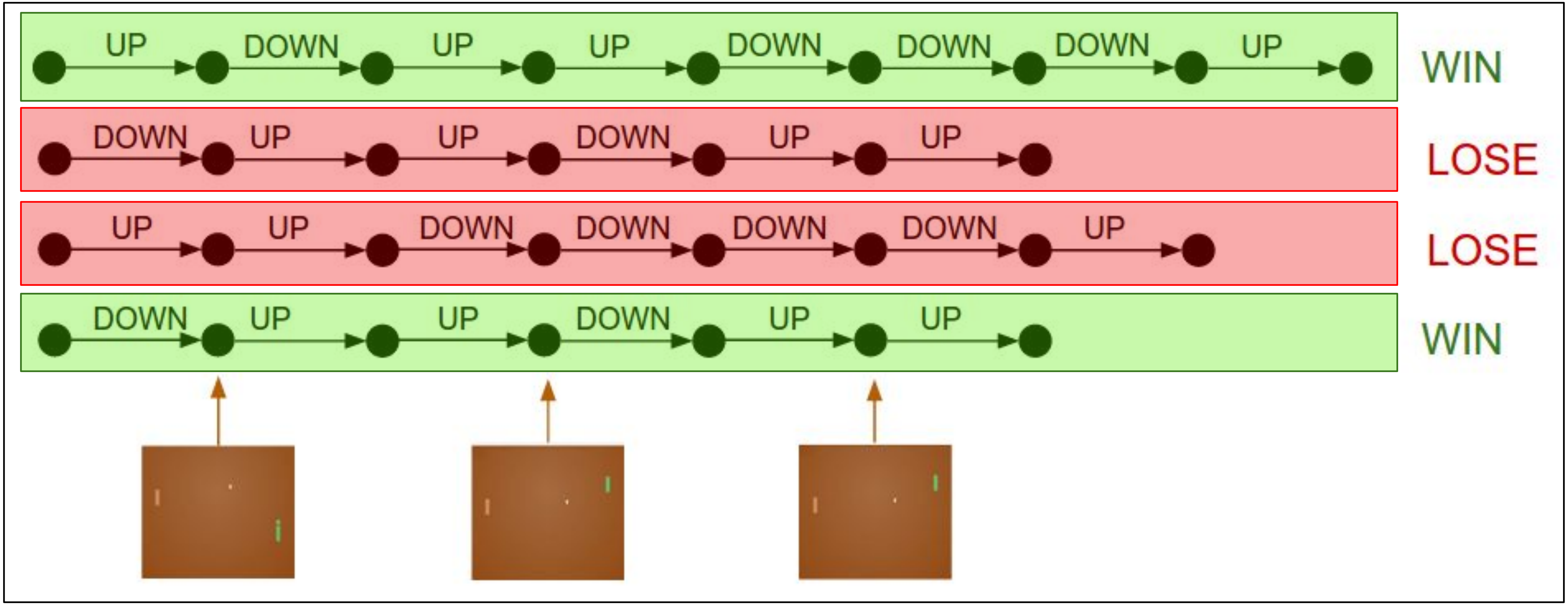


Pretend every action we took here was the correct label.

maximize: $\log p(y_i \mid x_i)$

Pretend every action we took here was the wrong label.

maximize: $(-1) * \log p(y_i \mid x_i)$



Supervised Learning

maximize:

$$\boxed{\sum_i \log p(y_i | x_i)}$$

For images x_i and their labels y_i.

Reinforcement Learning

1) we have no labels so we sample:

$$\boxed{y_i \sim p(\cdot | x_i)}$$

2) once we collect a batch of rollouts:
maximize:

$$\boxed{\sum_i A_i * \log p(y_i | x_i)}$$

We call this the **advantage**, it's a number, like +1.0 or -1.0 based on how this action eventually turned out.

Supervised Learning

maximize:

$$\boxed{\sum_i \log p(y_i \mid x_i)}$$

For images x_i and their labels y_i.

Reinforcement Learning

1) we have no labels so we sample:

$$\boxed{y_i \sim p(\cdot \mid x_i)}$$

2) once we collect a batch of rollouts:
maximize:

$$\boxed{\sum_i A_i * \log p(y_i \mid x_i)}$$

+ve advantage will make that action more likely in the future, for that state.
-ve advantage will make that action less likely in the future, for that state.

Vanilla Policy Optimization Algorithm

Initialize the policy

For iterations=1,2,…

Collect a set of trajectories by executing the current policy

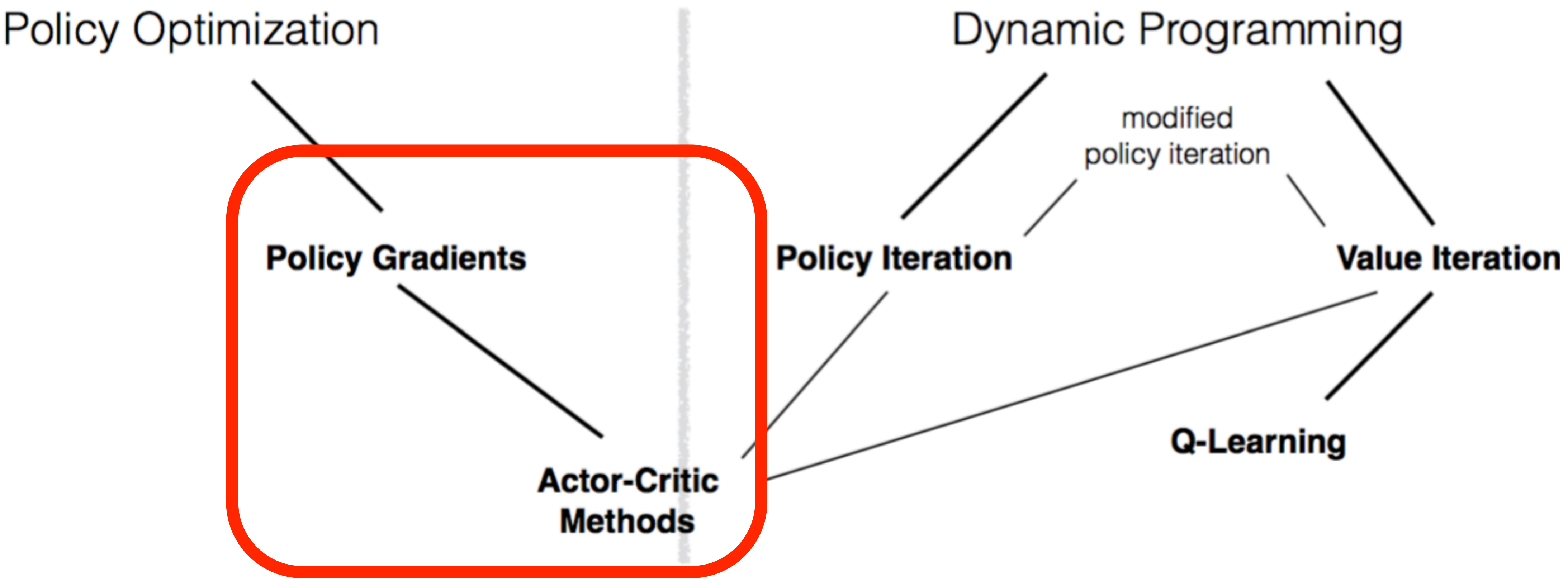
At each time step of the trajectory, compute the advantage A_i

Update the policy using a policy gradient estimate, which is

$\nabla_\theta A_i . logP(y_i|x_i, \theta)$

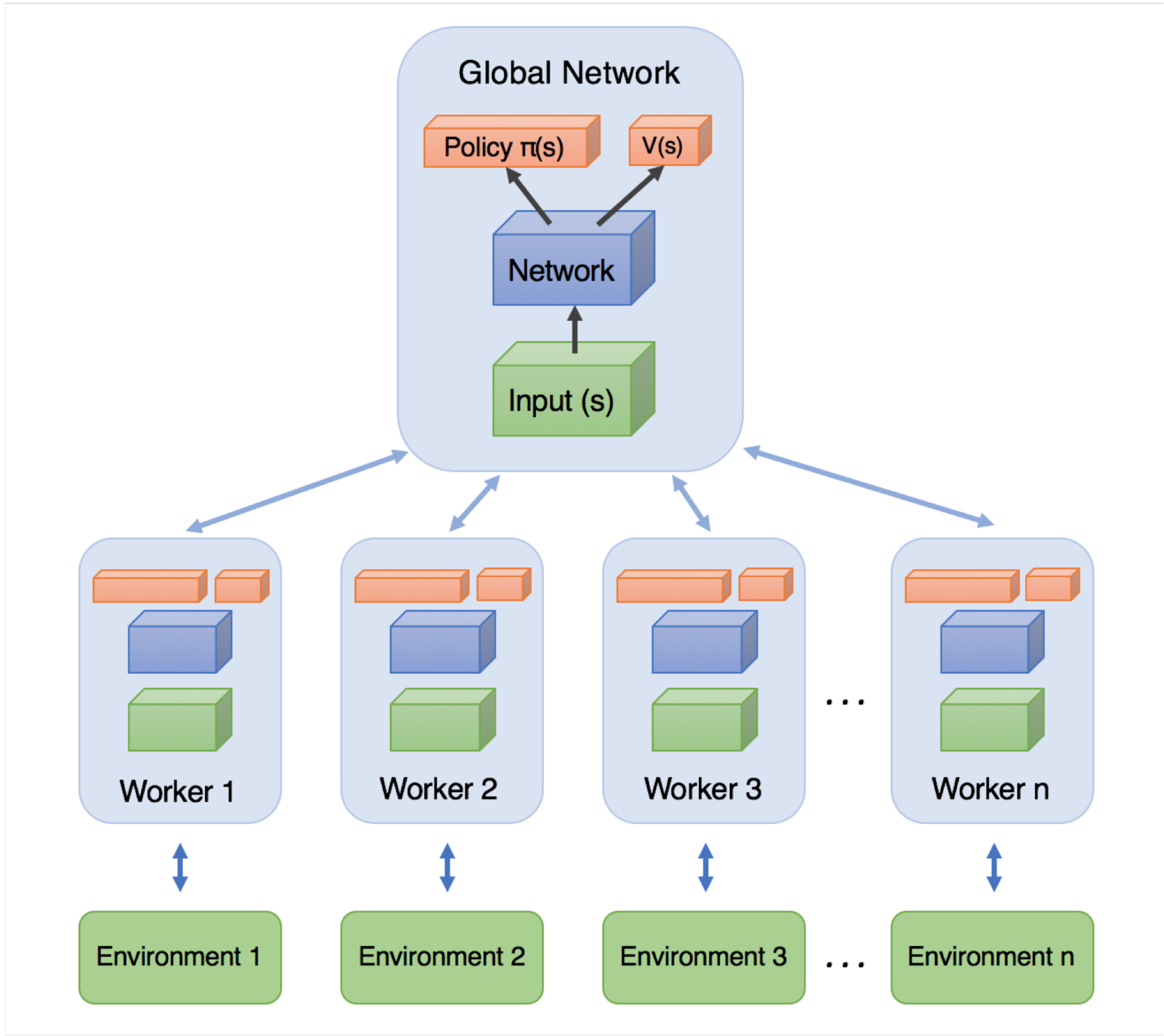
End for

Policy Optimization vs. Dynamic Programming



Asynchronous Advantage Actor-Critic (A3C)

- Asynchronous:
  - Multiple workers (agents)
- Actor-Critic:
  - Policy optimization + Value Iteration
  - Networks for Policy and V function

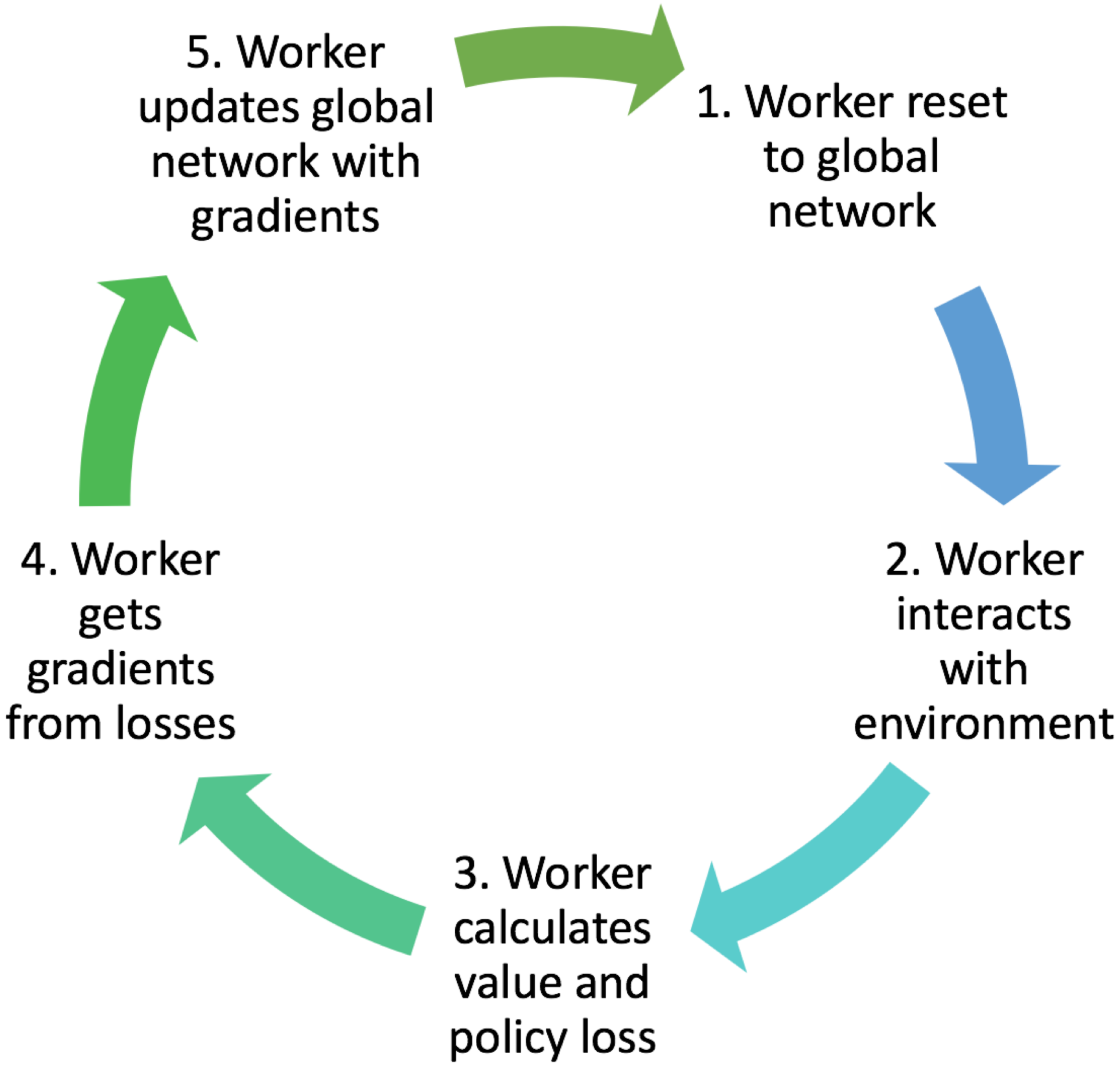


A3C Actor-Critic

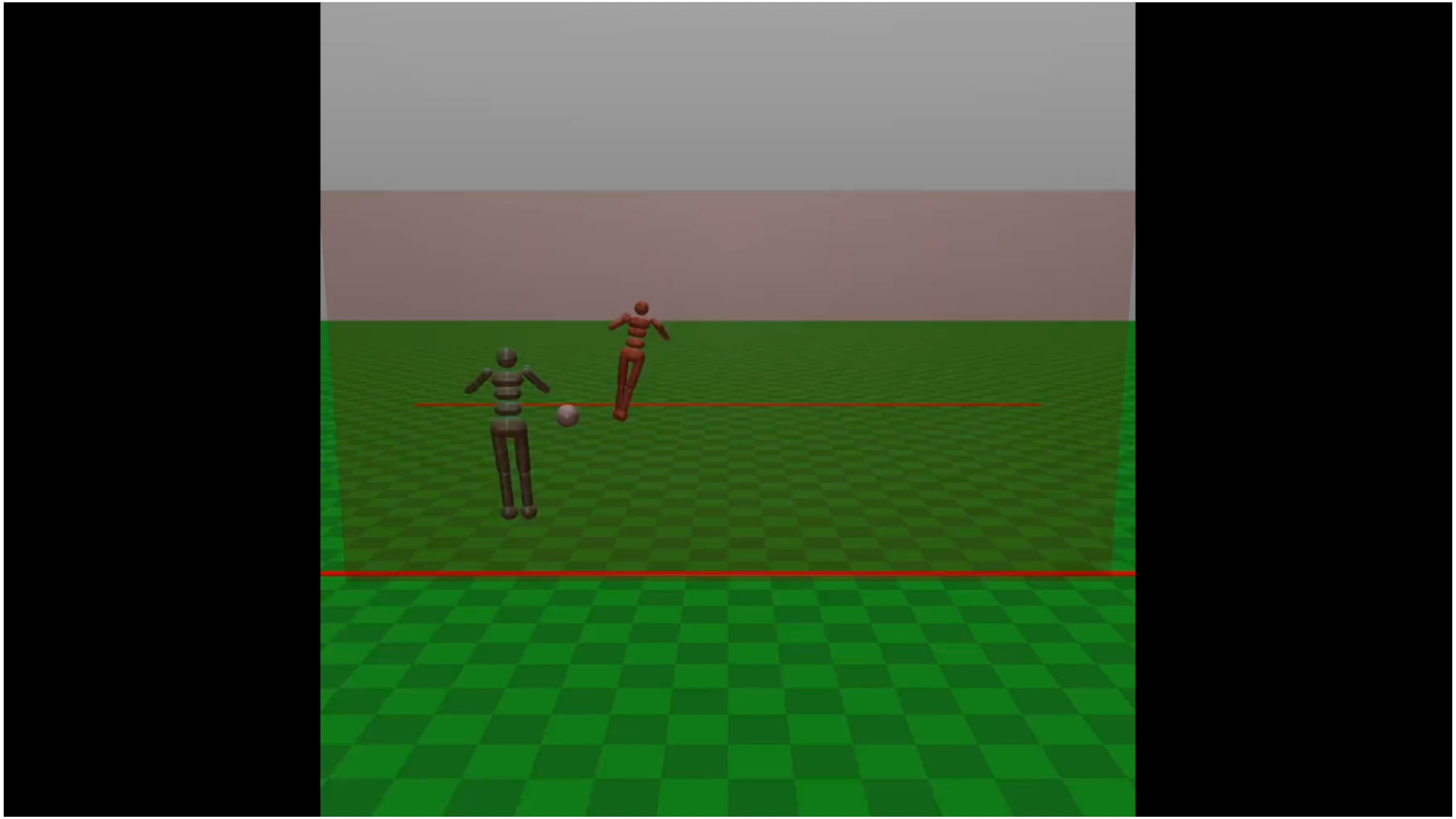
- Asynchronous:
  - Multiple workers to increase efficiency and diversity
    - Unlike Q-Learning and Policy gradient with single agent
  - Global Network for policy
    - Independent local networks for each worker
- Actor-Critic:
  - Actor: computes policy(s): probability over actions
  - Critic: Computes V(s): how good a certain state is to be in

A3C

- Constructing the global network
  - convolutional layers to process spatial dependencies
  - LSTM layer to process temporal dependencies
  - value and policy output layers.



[Video: GAE]



Conclusion

- Done with Search and Control
- Move on to Probabilistic Inference