Reinforcement Learning

Last Time

- What tools do we have to solve MDPs with continuous S and A?

1. LQR $\qquad$ $\pi^*(s) = -Ks$
2. Sparse sampling / prog. widening
3. Value Function Approx.
4. MPC

Course Map

- Outcome Uncertainty, Immediate vs Future Rewards (MDP)
- Model Uncertainty (Reinforcement Learning)
- State Uncertainty (POMDP)
- Interaction Uncertainty (Game)

Course Map

$R(s,a)$ $U(s')$

- Outcome Uncertainty, Immediate vs Future Rewards (MDP) ✓
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Course Map

- Outcome Uncertainty, Immediate vs Future Rewards (MDP) ✅
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Guiding Questions

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- How do we categorize RL approaches?

Problem from HW2

Question 2. (25 pts) Consider a game with 3 squares in a horizontal line drawn on paper, a token, and a die. Each turn, the player can either reset or roll the die. If the player rolls and the die shows an odd number, the token is moved one square to the right, and if an even number is rolled, the token is moved two squares to the right (in both cases stopping at the rightmost square[1]). If the player resets, the token is always moved to the leftmost square. If the reset occurs when the token is in the middle square, two points are added; if the player resets when the token is on the right square, a point is subtracted.

c) Suppose you are not sure that the die is fair (i.e. whether it will yield odd and even with equal probability). Give finite upper and lower bounds for the accumulated discounted score that you can expect to receive with discount $\gamma = 0.95$.

Reinforcement Learning

Reinforcement Learning

Previously: (S, A, T, R, γ)

Reinforcement Learning

Previously: $(S, A, \cancel{T}, \cancel{R}, \gamma)$

Unknown!

Reinforcement Learning

Previously: $(S, A, \cancel{T}, \cancel{R}, \gamma)$
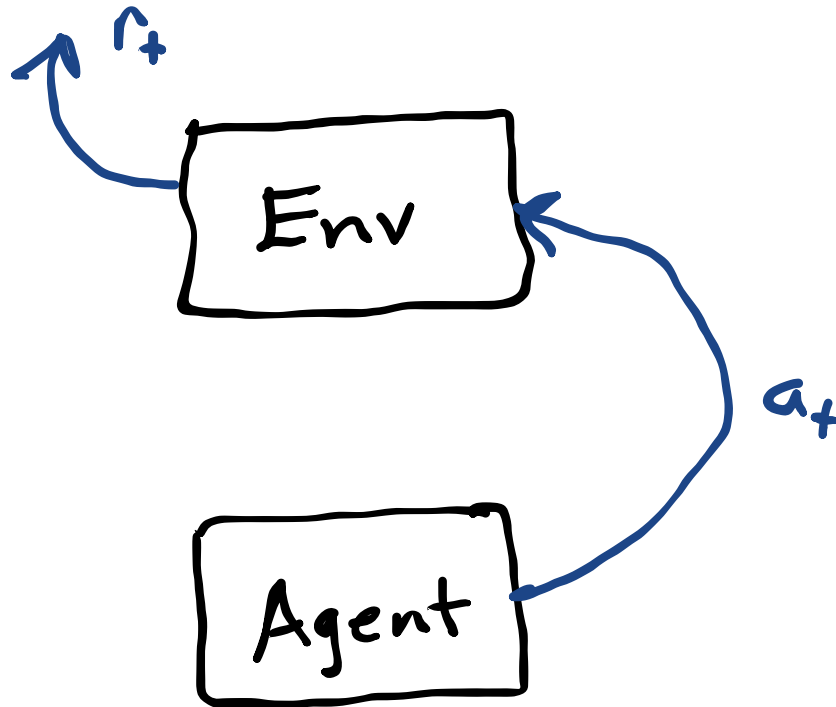
Unknown!

Now: Episodic Simulator

Env

Agent

Reinforcement Learning

Previously: $(S, A, \cancel{T}, \cancel{R}, \gamma)$

Unknown!
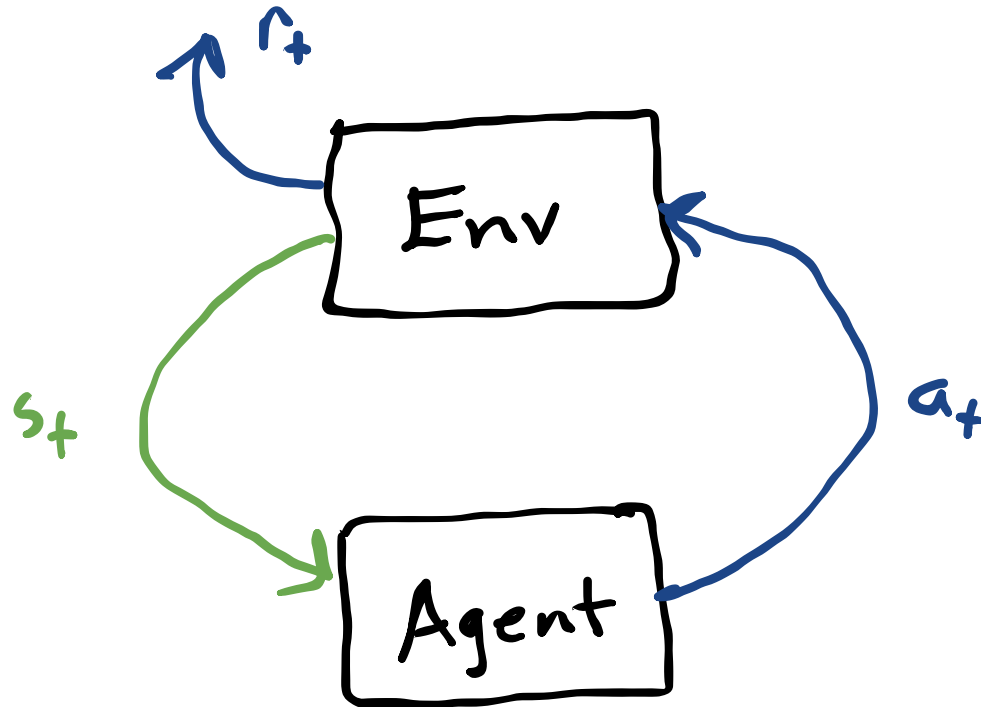
Now: Episodic Simulator

```
r = act!(env, a)
```

r_t

Env

a_t

Agent

Reinforcement Learning

Previously: $(S, A, \cancel{T}, \cancel{R}, \gamma)$

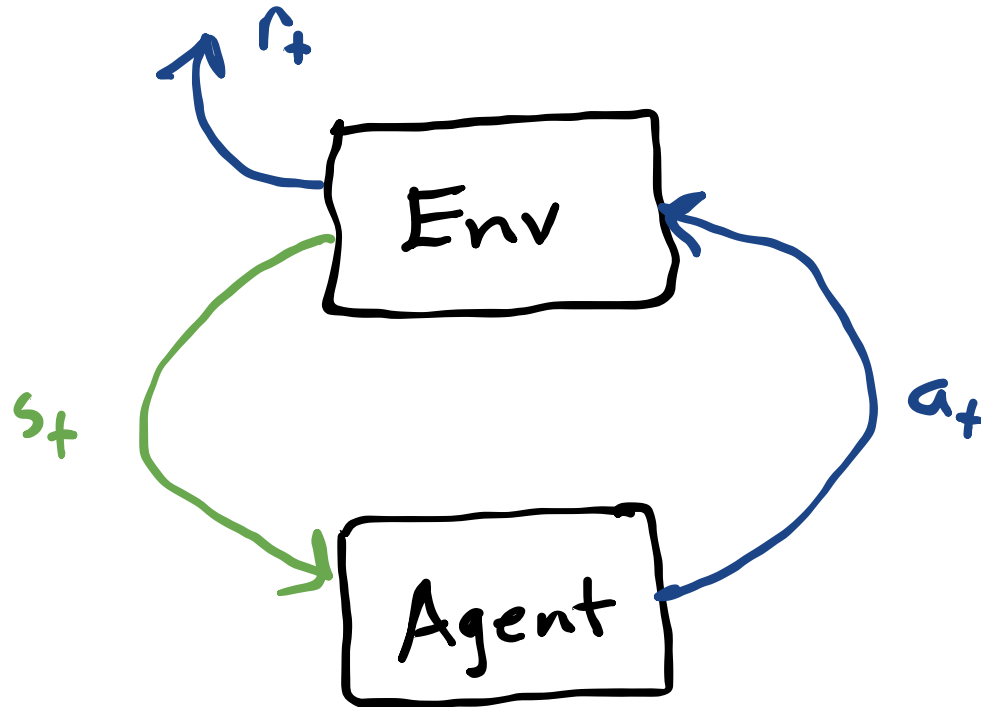Unknown!

Now: Episodic Simulator


```
r = act!(env, a)

s = observe(env)
```

Reinforcement Learning

Previously: $(S, A, \cancel{T}, \cancel{R}, \gamma)$

Unknown!

Now: Episodic Simulator


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r = act!(env, a)

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In python, typically

```
s, r = env.step(a)
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Reinforcement Learning

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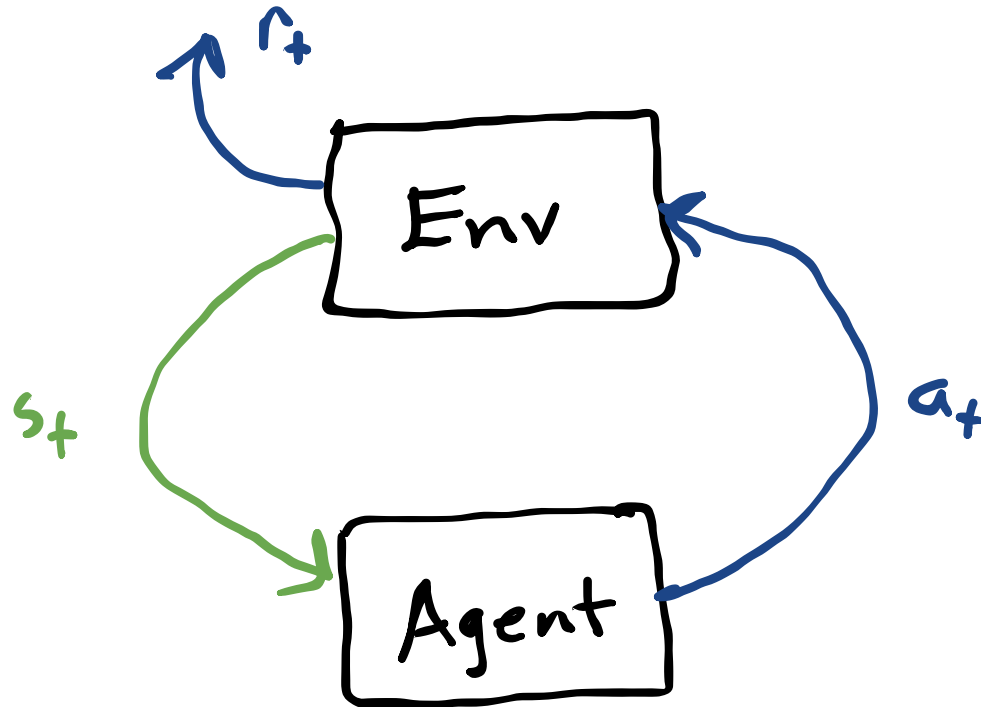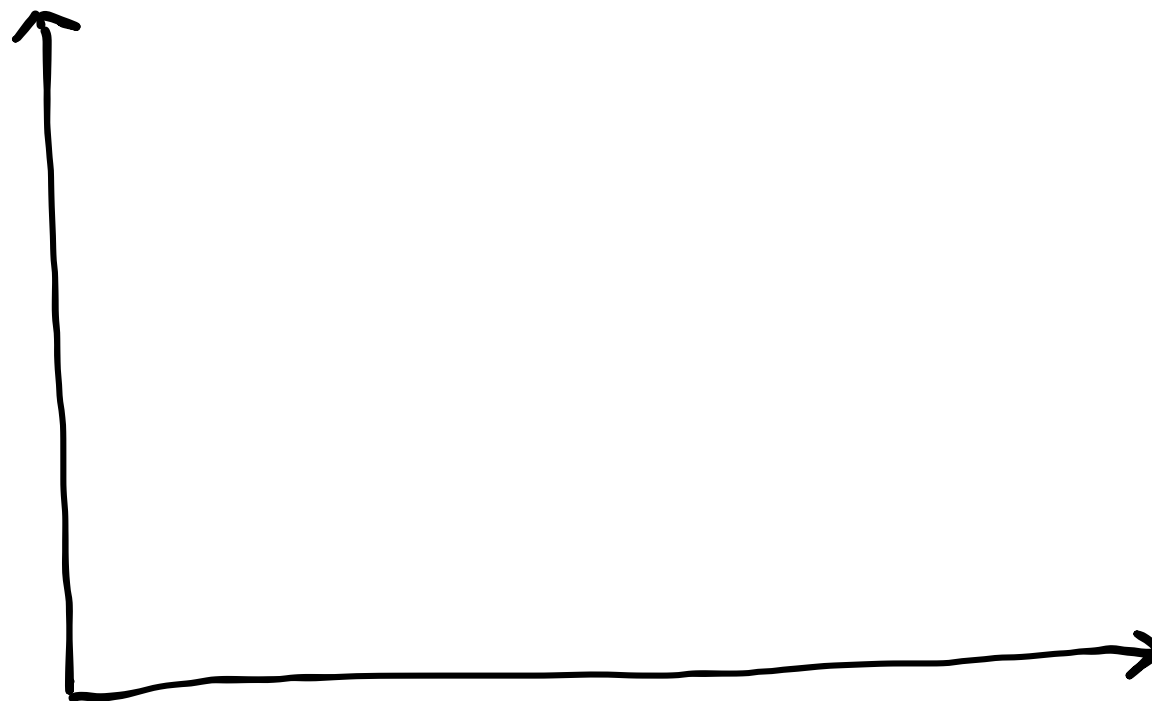
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```

Note: Different from $s', r = G(s, a)$

Learning Curve

Learning Curve
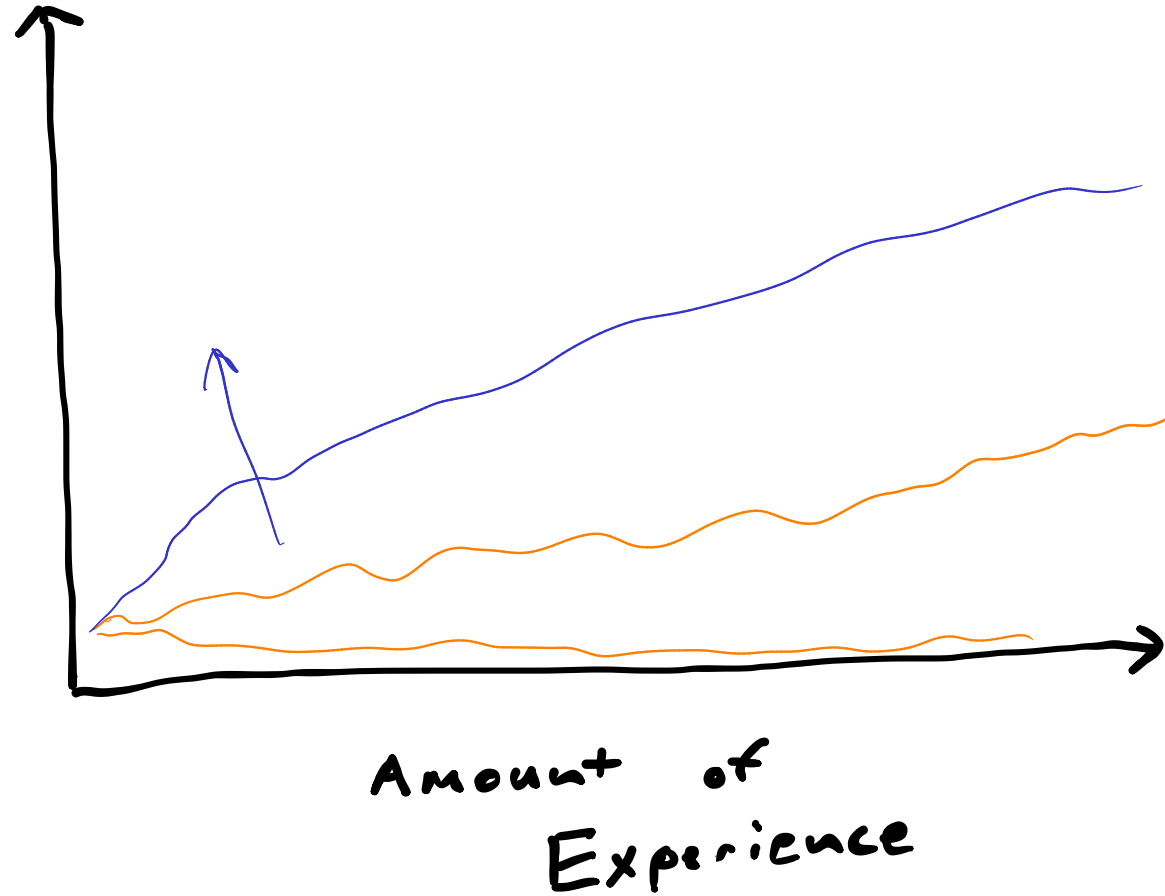
Learning Curve

Amount of Experience

Learning Curve

$$\sum_{t=0}^{\infty} r_t \stackrel{.}{=} R(\tau)$$

$$U(\pi) = E\Big[R(\tau)\Big]$$

$$\tau = \Big(s_0, a_0, r_0, s_1$$

Avg Return of Agent's Policy

Amount of Experience

Learning Curve

Learning Curve

Avg Return of Agent's Policy
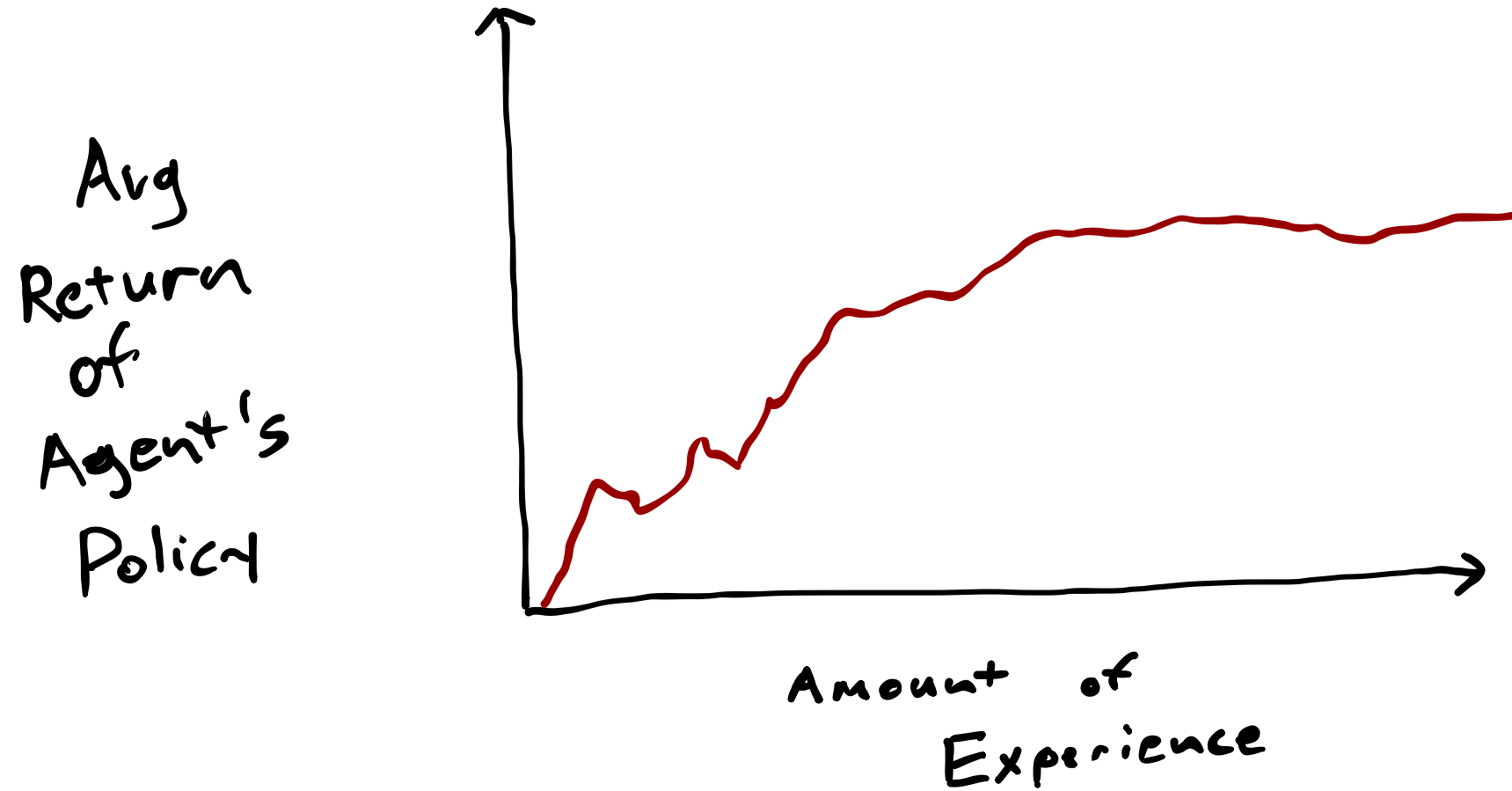
Amount of Experience

Break

$$\hat{R}(s,a)$$

$$\rightarrow \hat{T}(s'|s,a)$$

$$\hat{Q}(s,a)$$

$$Q^{*}(s,a)$$

$$\pi^{*}(s) = \underset{a}{\arg\max}\ Q^{*}(s,a)$$

$$\pi(a|s) \propto \hat{R}(s,a)$$
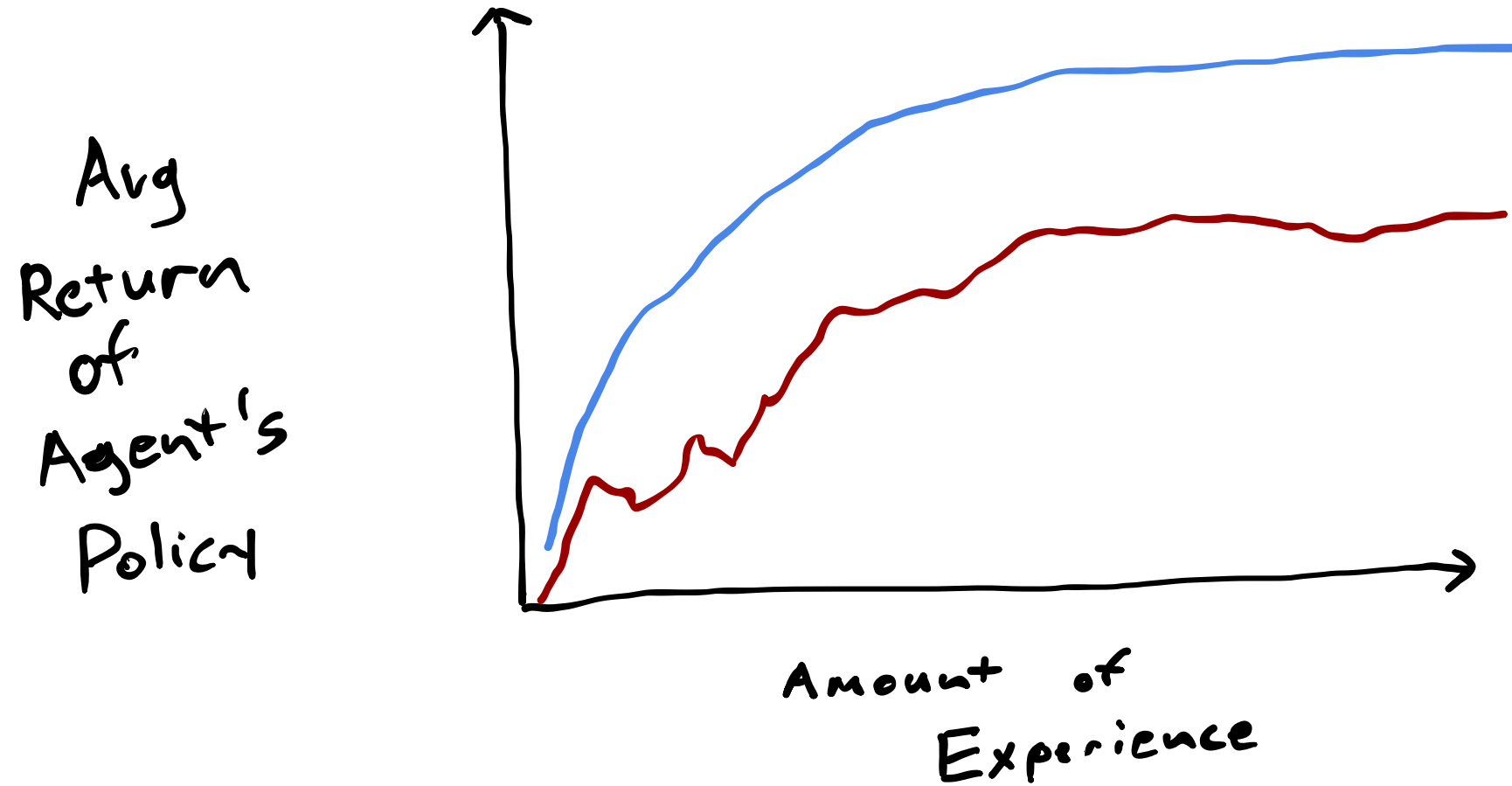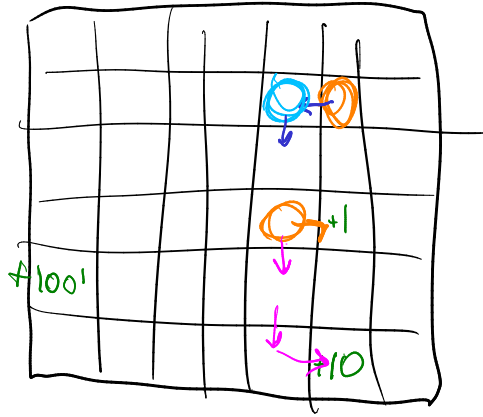
$$Q(s,a) + c$$

$$\hat{\pi}_{\theta}(s)$$

Challenges

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1. Exploration vs Exploitation

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2. Credit Assignment

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1. Exploration vs Exploitation
2. Credit Assignment
3. Generalization

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- **Tabular**: Keep track of learned values for each state in a table
- **Deep**: Use a neural network to approximate learned values

Tabular Maximum Likelihood
Model-Based RL

Given env, S, A

$N[s,a,s'] \leftarrow 0 \quad \forall s,a,s'$
$\rho[s,a] \leftarrow 0 \quad \forall s,a$
$s \leftarrow observe(env)$
$\pi \leftarrow$ random policy
loop
    reset!(env)
    while not terminated(env)
        $a \leftarrow \begin{cases} rand(A) & w.p. \; \varepsilon \\ \pi(s) & w.p. \; 1-\varepsilon \end{cases}$
        $r \leftarrow act!(env,a)$
        $s' \leftarrow observe(env)$
        $N[s,a,s'] \; += 1$
        $\rho[s,a] \; += \rho$
        $s \leftarrow s'$
    $T^a[s,s'] \leftarrow \dfrac{N[s,a,s']}{\sum\limits_{s'} N[s,a,s']} \quad \forall s,a,s'$
    $R^a[s] \leftarrow \dfrac{\rho[s,a]}{\sum\limits_{s'} N[s,a,s']}$
    $\pi \leftarrow solve((S,A,T,R,\gamma))$

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