Last Time

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

Value Iteration – Function Approximation
LQR
Policy Search – Cross Entropy
Model Predictive Control

Course Map

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Value Function

- Outcome Uncertainty, Immediate vs Future Rewards (MDP)

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- Model Uncertainty (Reinforcement Learning)

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Guiding Questions

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- What is Reinforcement Learning?
- What are the main challenges in Reinforcement Learning?

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- What is Reinforcement Learning?
- What are the main challenges in Reinforcement Learning?
- How do we categorize RL approaches?

Reinforcement Learning

~~In python, typically~~

~~`s, r = step(env, a)`~~

Reinforcement Learning

Previously: (S, A, T, R, γ)

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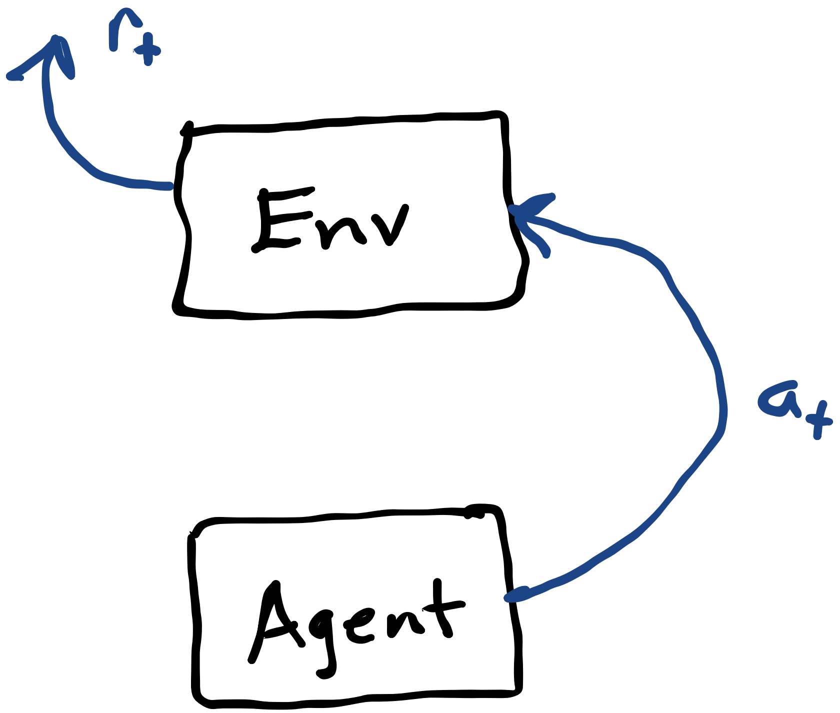

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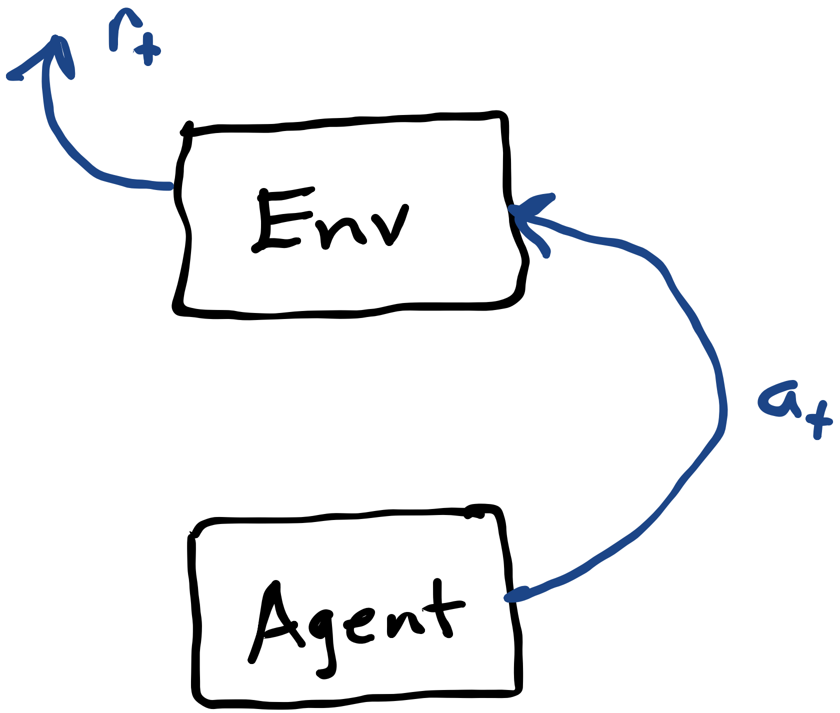


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r = act!(env, a)
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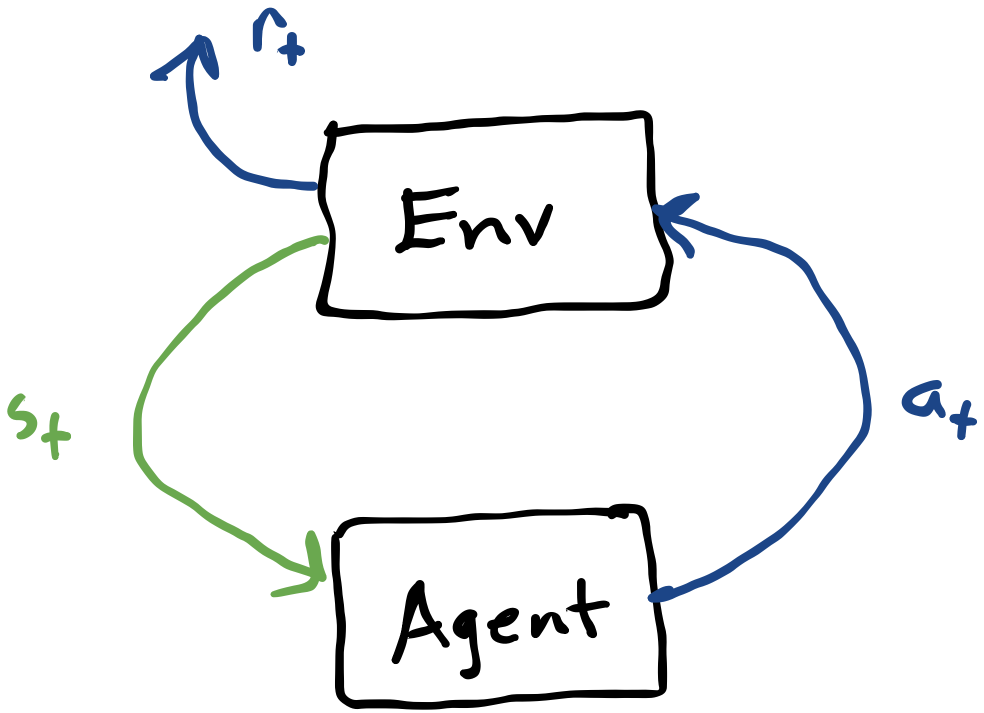


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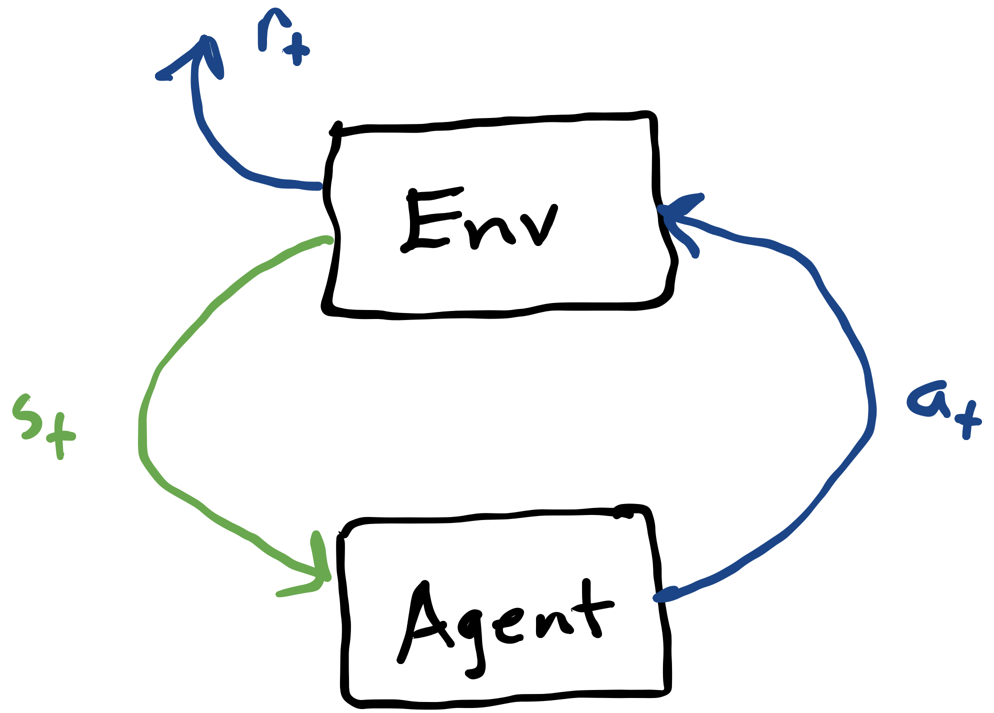


```
r = act!(env, a)

s = observe(env)
```

In python, typically

~~s, r = step(env, a)~~

s, r = env.step(a)

Reinforcement Learning

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

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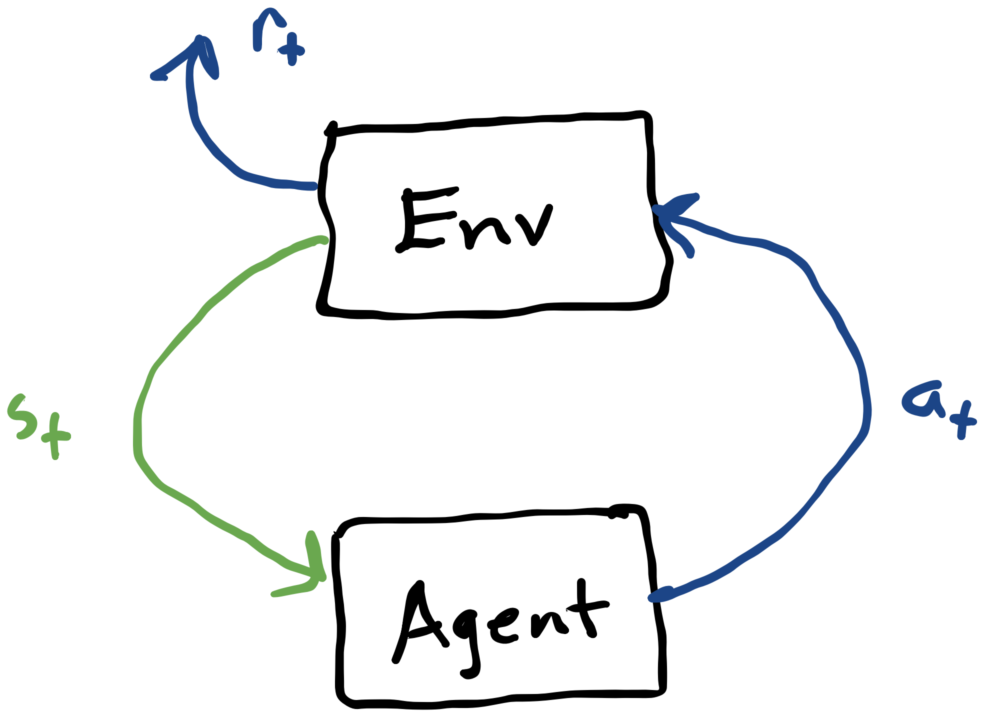


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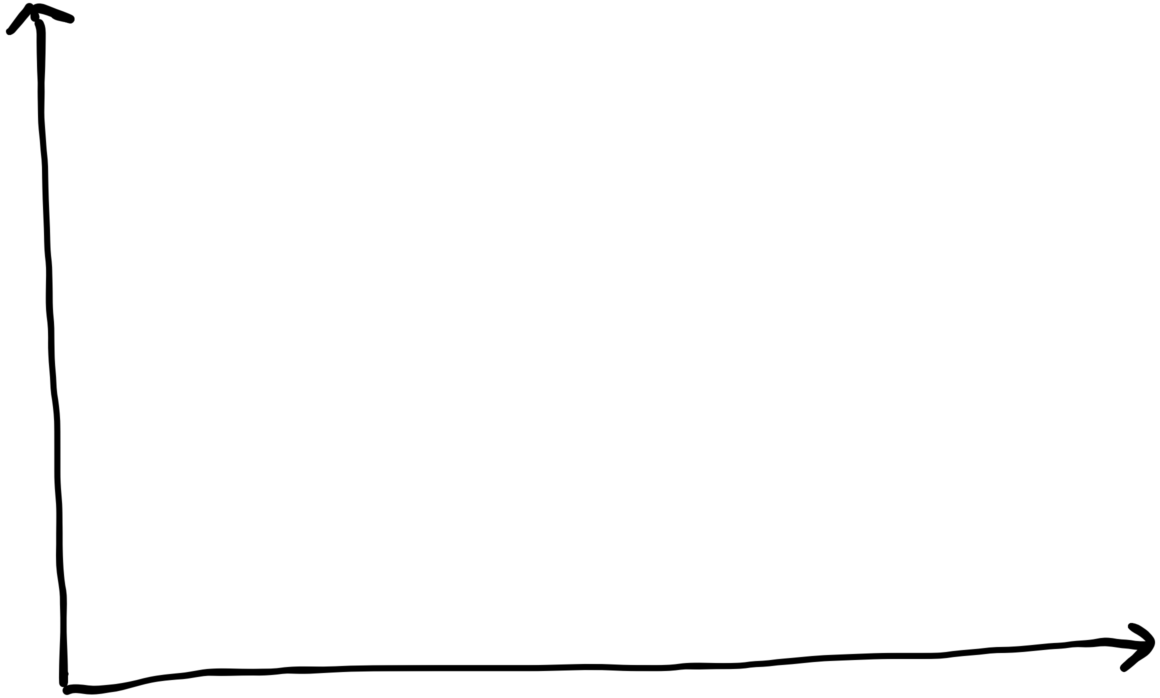
Note: Different from $s', r = G(s, a)$

Learning Curve

Learning Curve



Learning Curve

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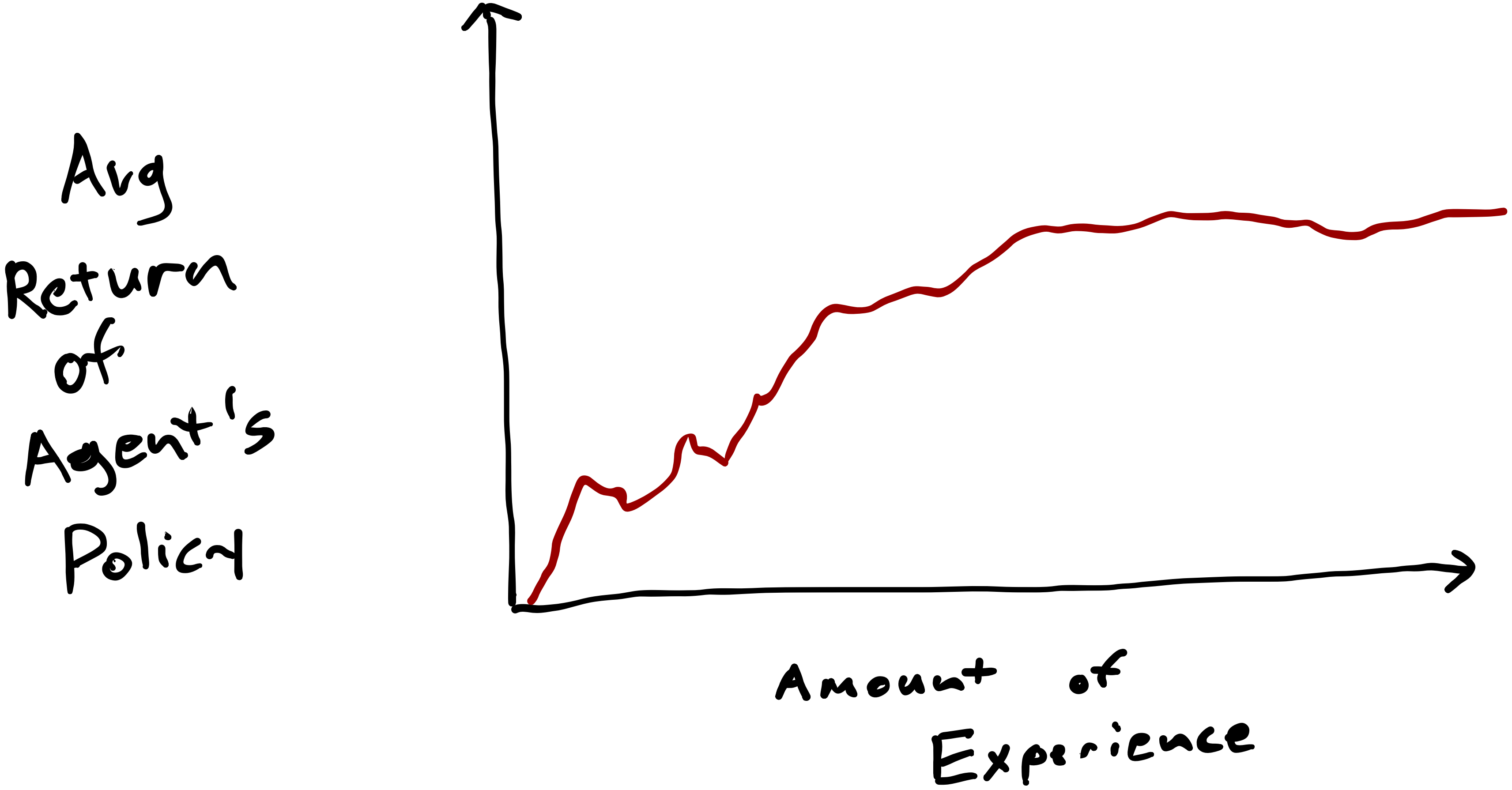

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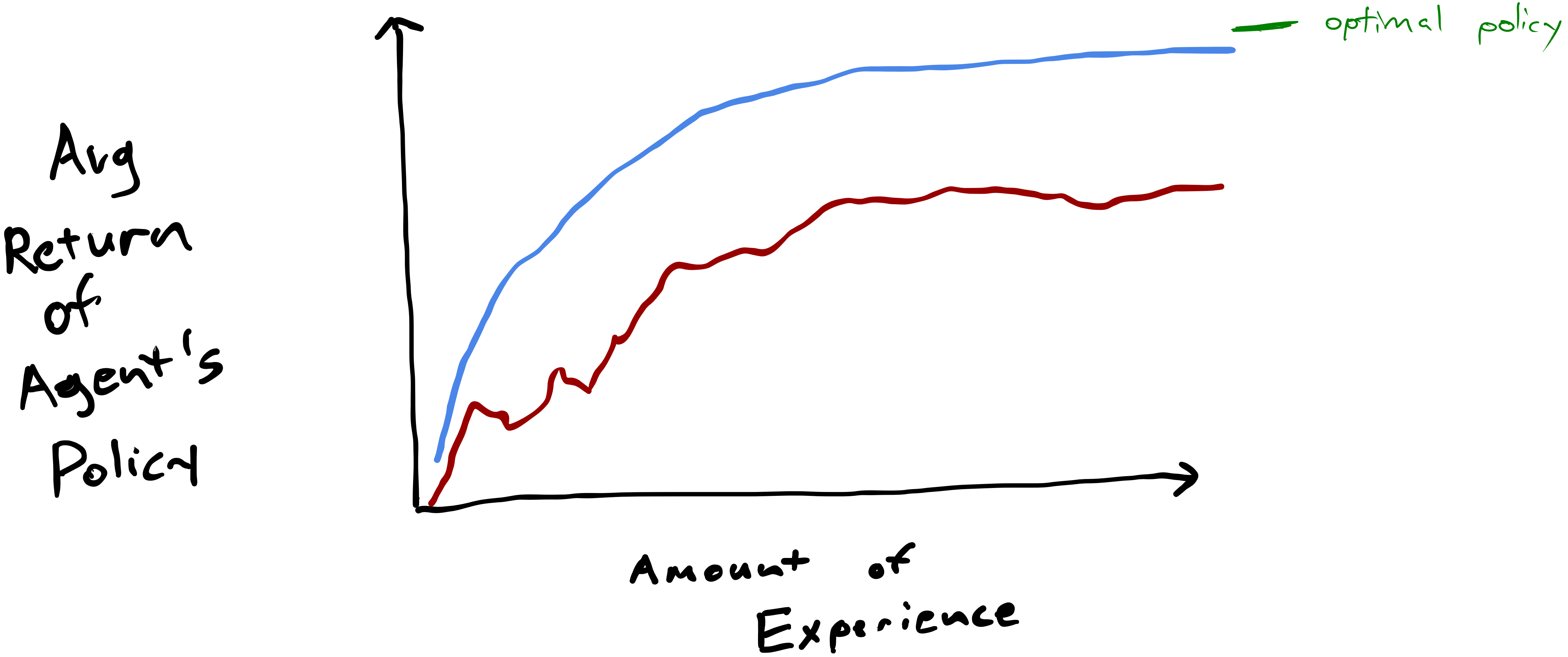
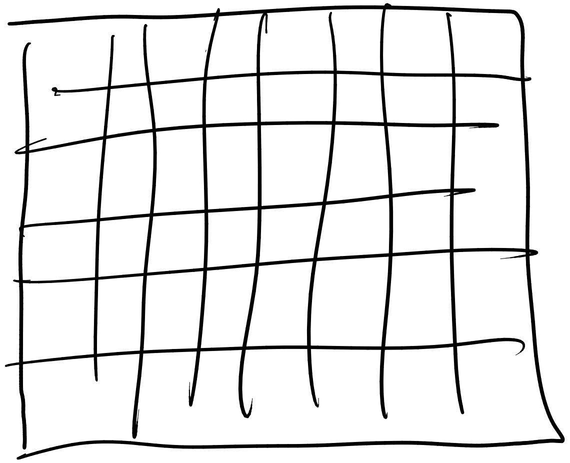


Breakout Rooms



T ?

R ?

$-10 \le R(s,a) \le 10$

How should we approach this?

What are challenges?

Exploration

Exploitation

1) MC-based equal prob actions
   log rewards, transition
   value iteration

2) ~~try all actions~~, estimate rewards + transitions, update policy every 100 steps

3) Cross Entropy Policy Search

Challenges

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1. Exploration vs Exploitation

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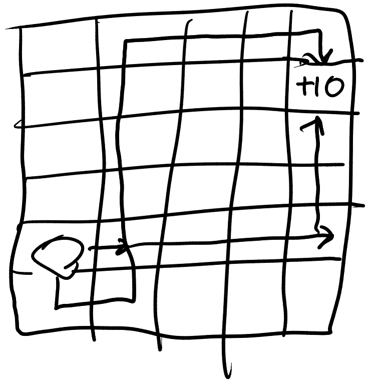
1. Exploration vs Exploitation
2. Credit Assignment



Challenges

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

Classifications

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- **Model Based**: Attempt to learn T and R, then find π^* by solving MDP

Classifications

1 2

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- **Model Free**: Attempt to find Q^* or π^* directly without estimating T or R

3

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$\pi_\theta \xrightarrow{\theta} \pi_{\theta'}$

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$\pi_{\theta_t} \xrightarrow{\theta_{t-1,t-2,\dots}} \pi_{\theta_{t+1}}$

- **Batch**: Learn only from previously-generated experience.

- **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, $|S|$, $|A|$

$N \in \mathbb{N}^{|S| \times |A| \times |S|}$

$\rho \in \mathbb{R}^{|S| \times |A|}$

$N[s, a, s']$

$\rho[s, a]$ = cumulative reward

$N \leftarrow 0$
$\rho \leftarrow 0$
$s \leftarrow$ observe(env)
$\pi \leftarrow$ random policy
loop

$a \leftarrow \begin{cases} \text{rand}(A) & \text{w.p. } \varepsilon \\ \pi(s) & \text{otherwise} \end{cases}$ ← exploration ε-greedy

$r \leftarrow$ act!(env, a)
$s' \leftarrow$ observe(env)
$N[s, a, s']$ += 1
$\rho[s, a]$ += r

$T[a][s, s'] \leftarrow \dfrac{N[s, a, s']}{\sum_{s'} N[s, a, s']}$ $\forall$ s, a, s'

$R[s, a] \leftarrow \dfrac{\rho[s, a]}{\sum_{s'} N[s, a, s']}$ $\forall$ s, a

$\pi \leftarrow$ solve(T, R) ← expensive
$s \leftarrow s'$

SARSA

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