Reinforcement Learning

Last Time

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

Course Map

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

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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

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Unknown!

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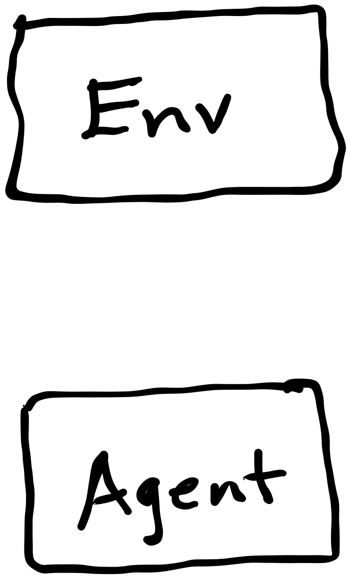
Now: Episodic Simulator



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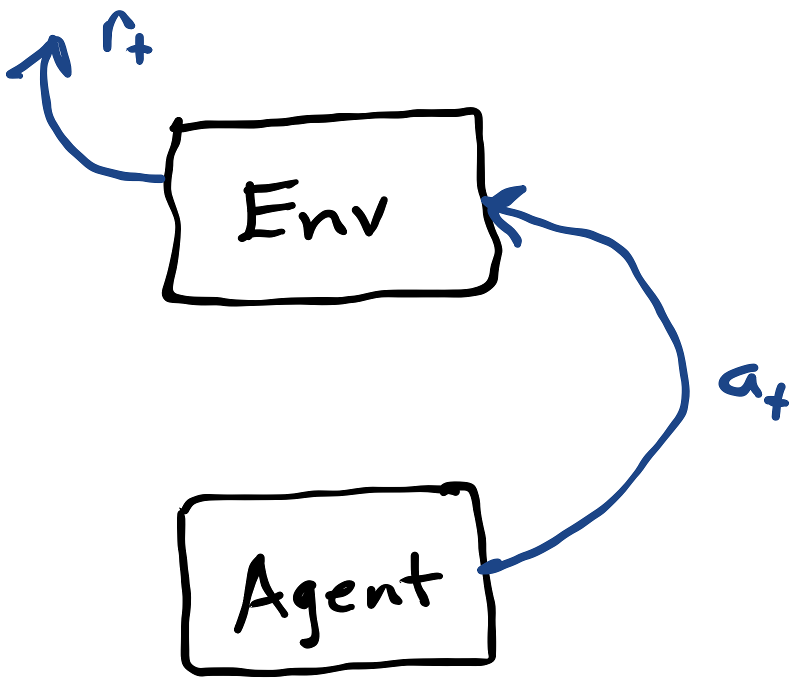


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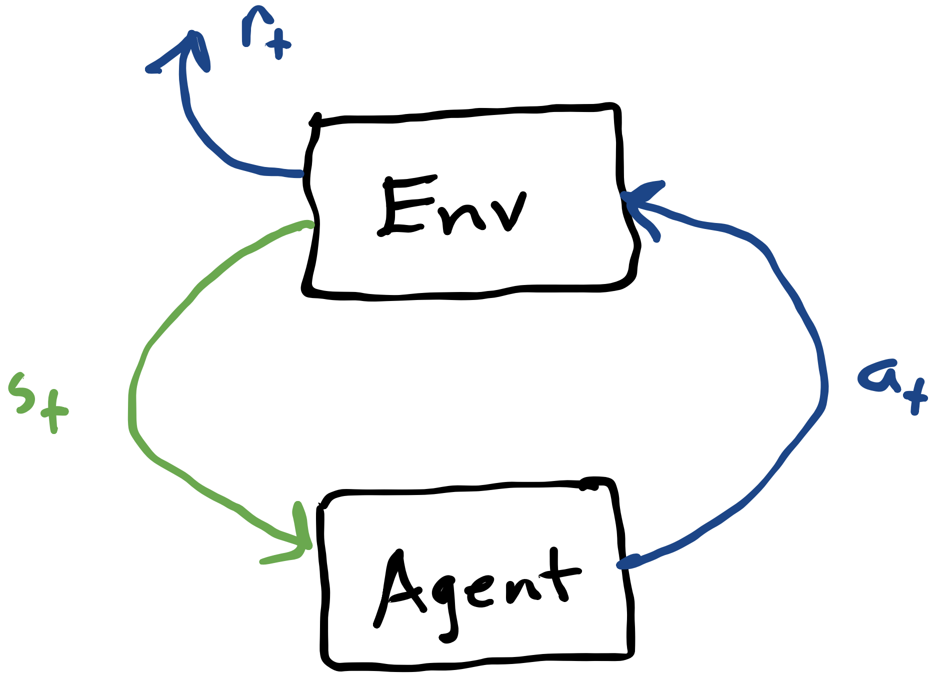


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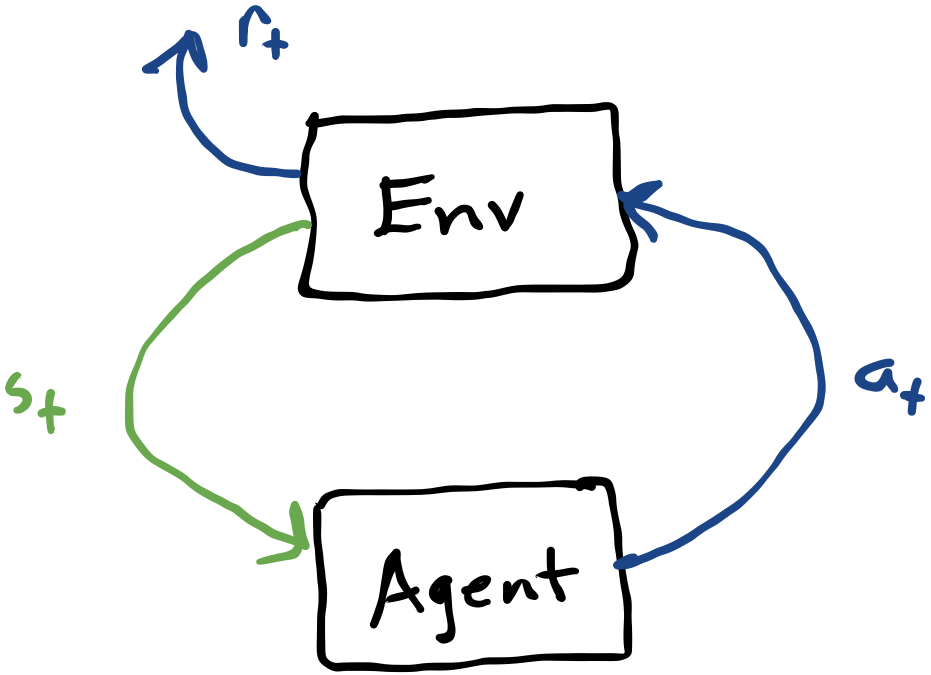


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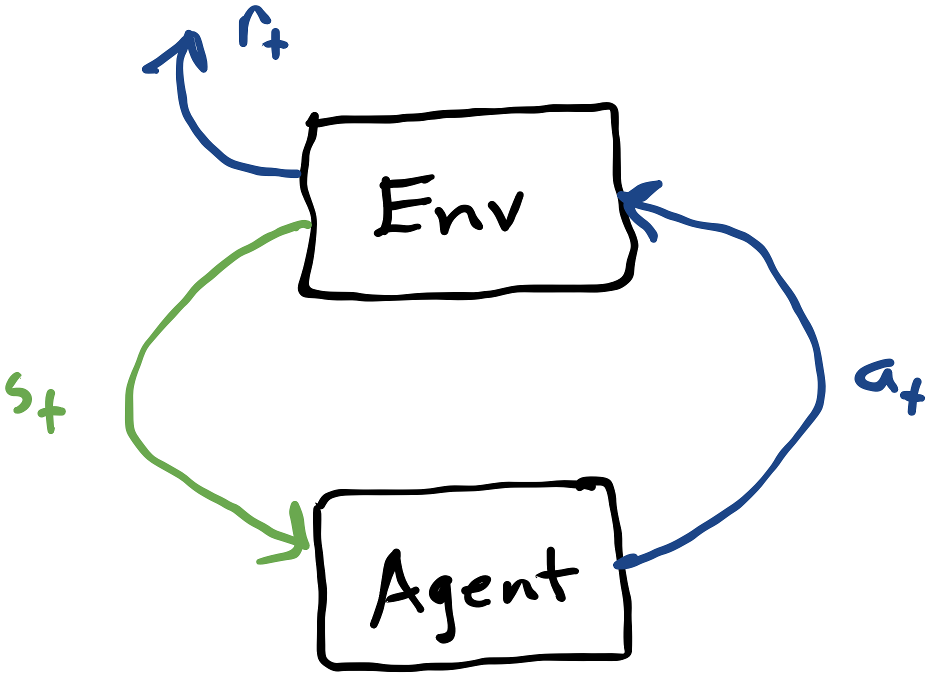


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Note: Different from $s', r = G(s, a)$

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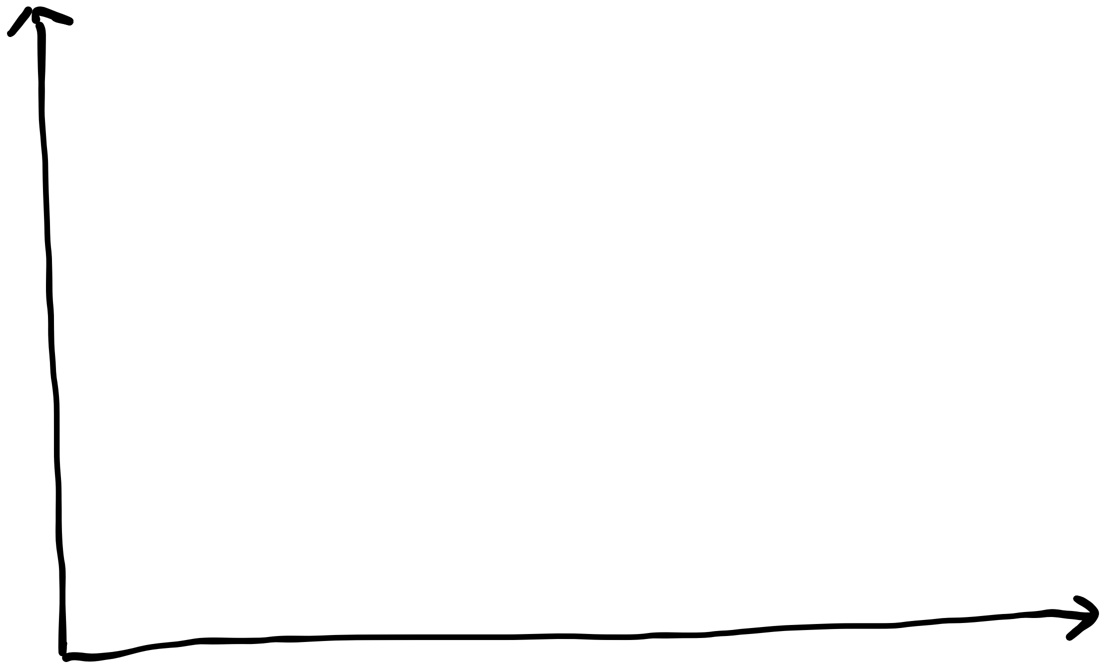

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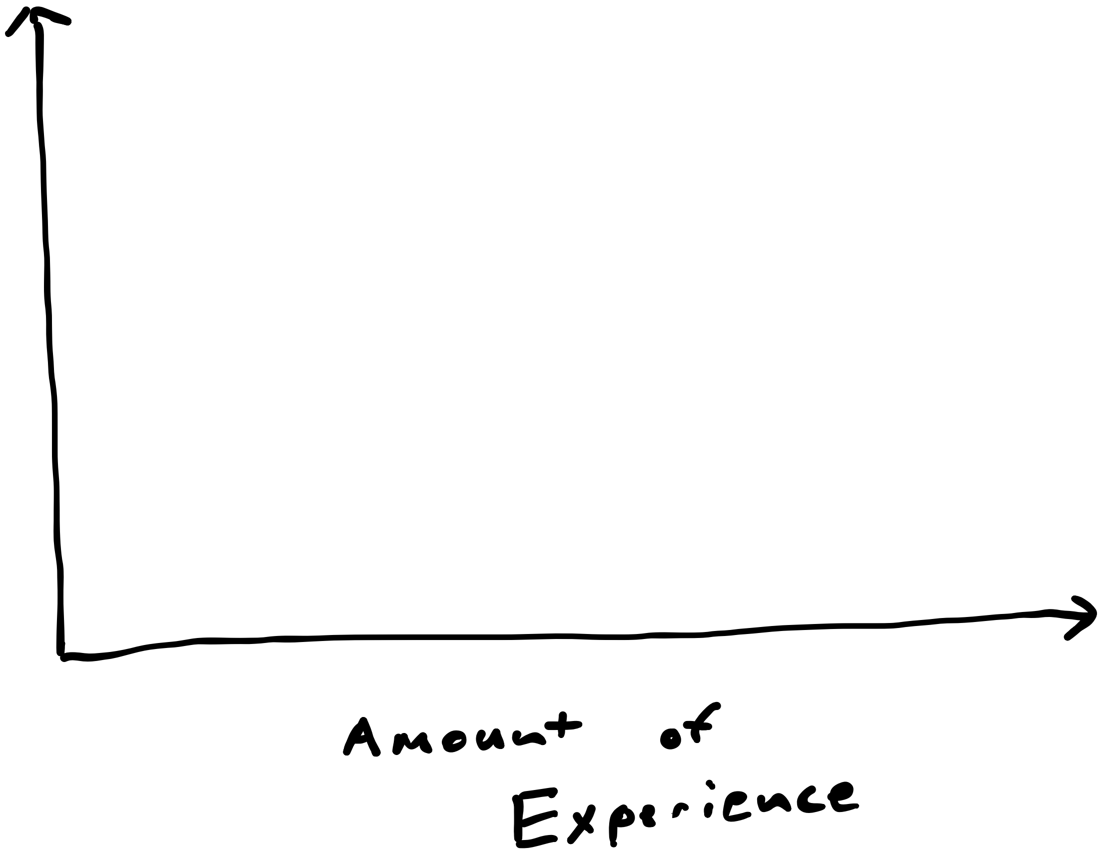

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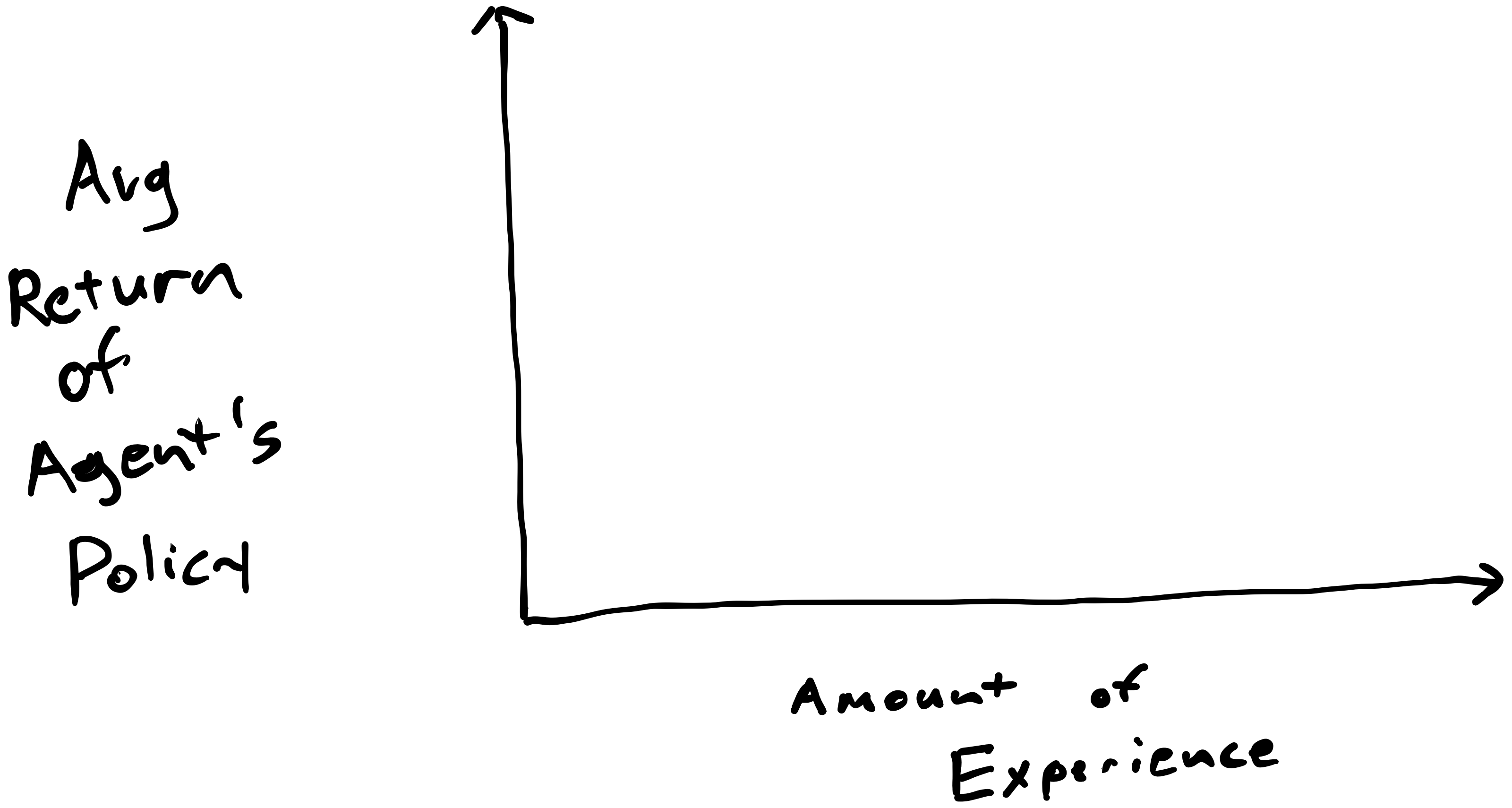

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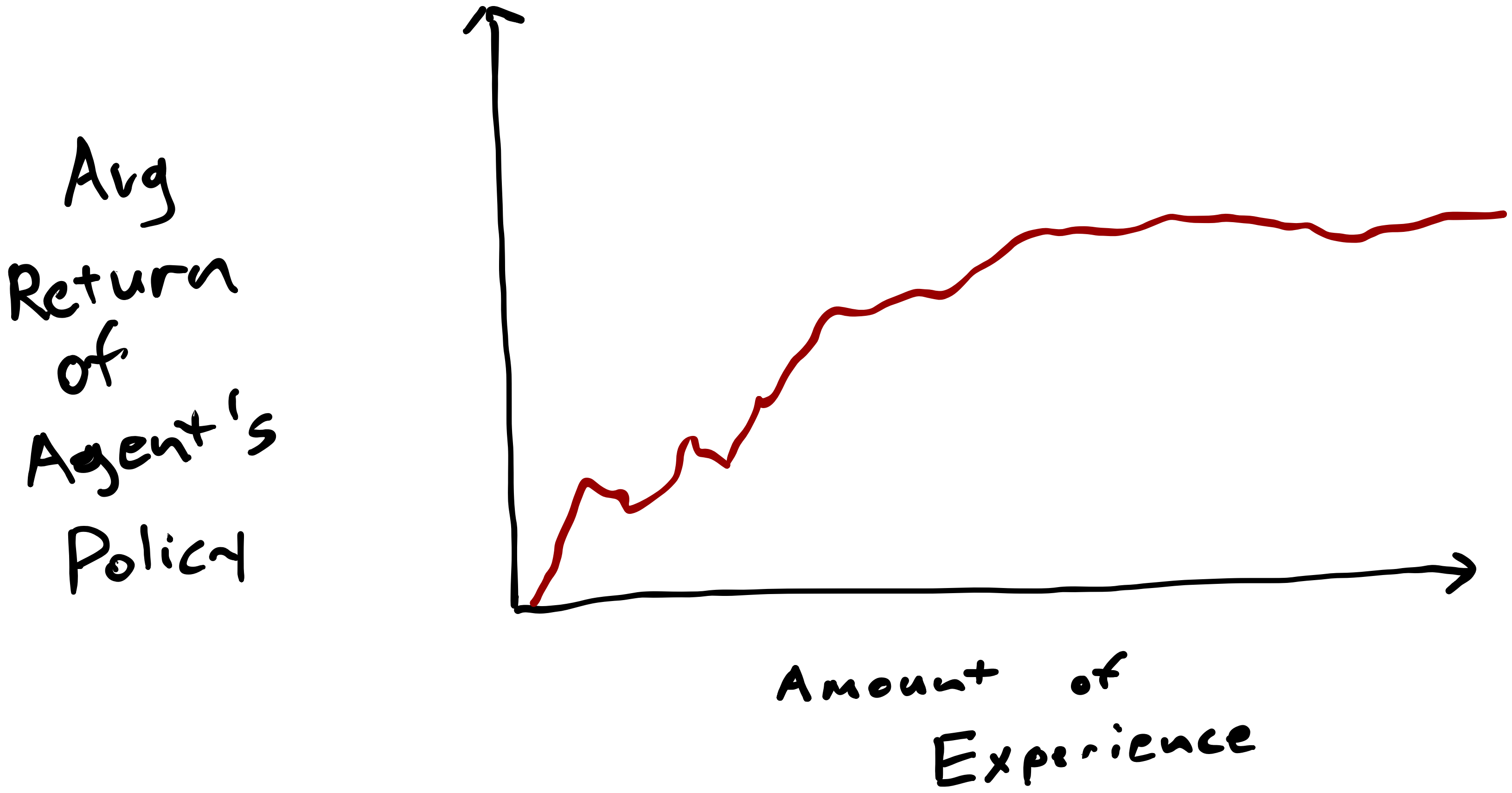

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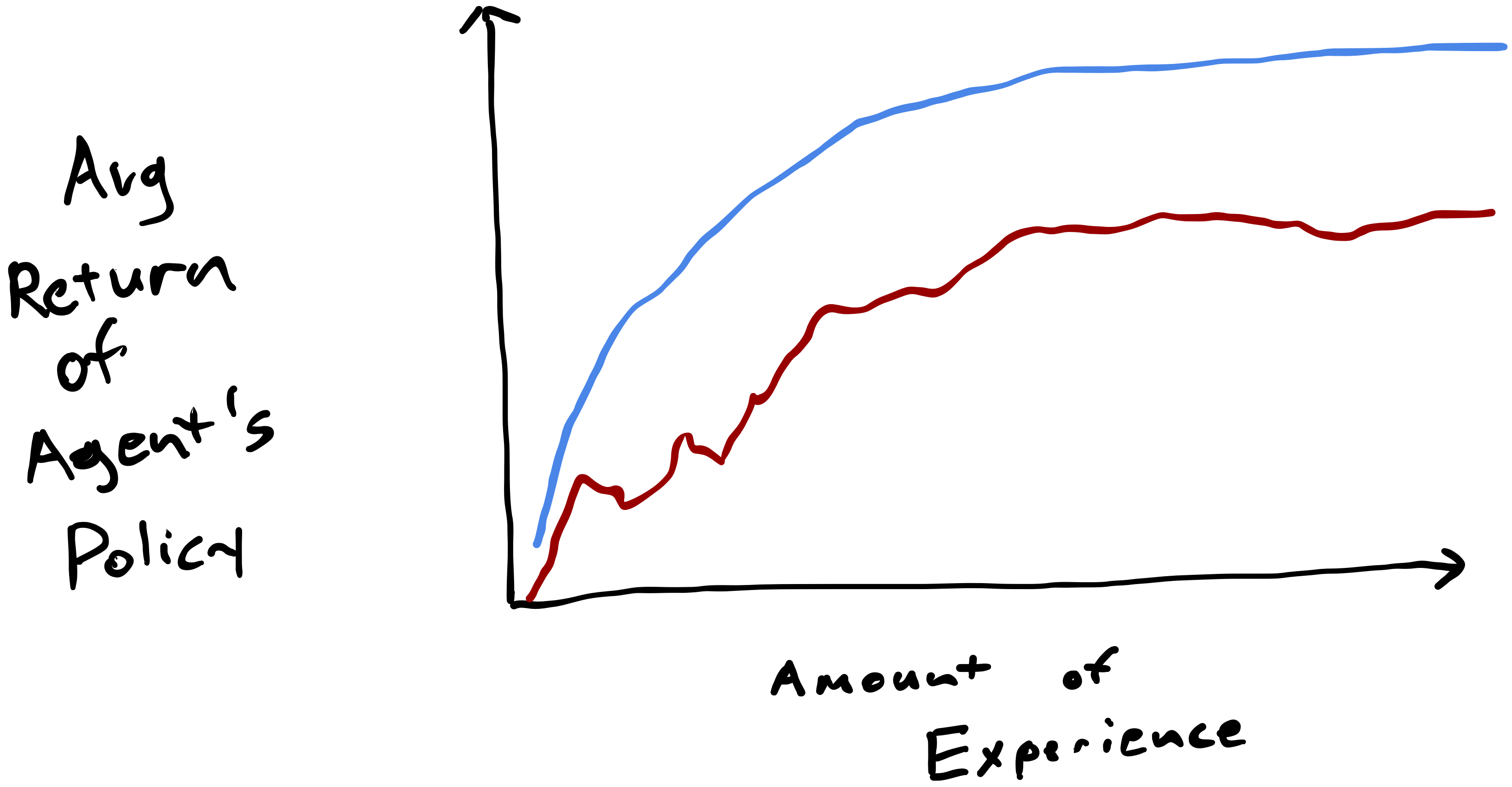

Break

Challenges

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1. Exploration vs Exploitation

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2. Credit Assignment

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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

$N[s, a, s'] \leftarrow 0 \quad \forall s, a, s'$

$\rho[s, a] \leftarrow 0 \quad \forall s, a$

$s \leftarrow \text{observe(env)}$

$\pi \leftarrow \text{random policy}$

loop

  reset!(env)

  while not terminated(env)

    $a \leftarrow \begin{cases} \text{rand}(A) & \text{w.p. } \varepsilon \\ \pi(s) & \text{w.p. } 1 - \varepsilon \end{cases}$

    $r \leftarrow \text{act!}(\text{env}, a)$

    $s' \leftarrow \text{observe(env)}$

    $N[s, a, s'] \mathrel{+}= 1$

    $\rho[s, a] \mathrel{+}= r$

    $s \leftarrow s'$

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

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

  $\pi \leftarrow \text{solve}((S, A, T, R, \gamma))$

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