LMU LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN

Praktikum Autonome Systeme

Reinforcement Learning

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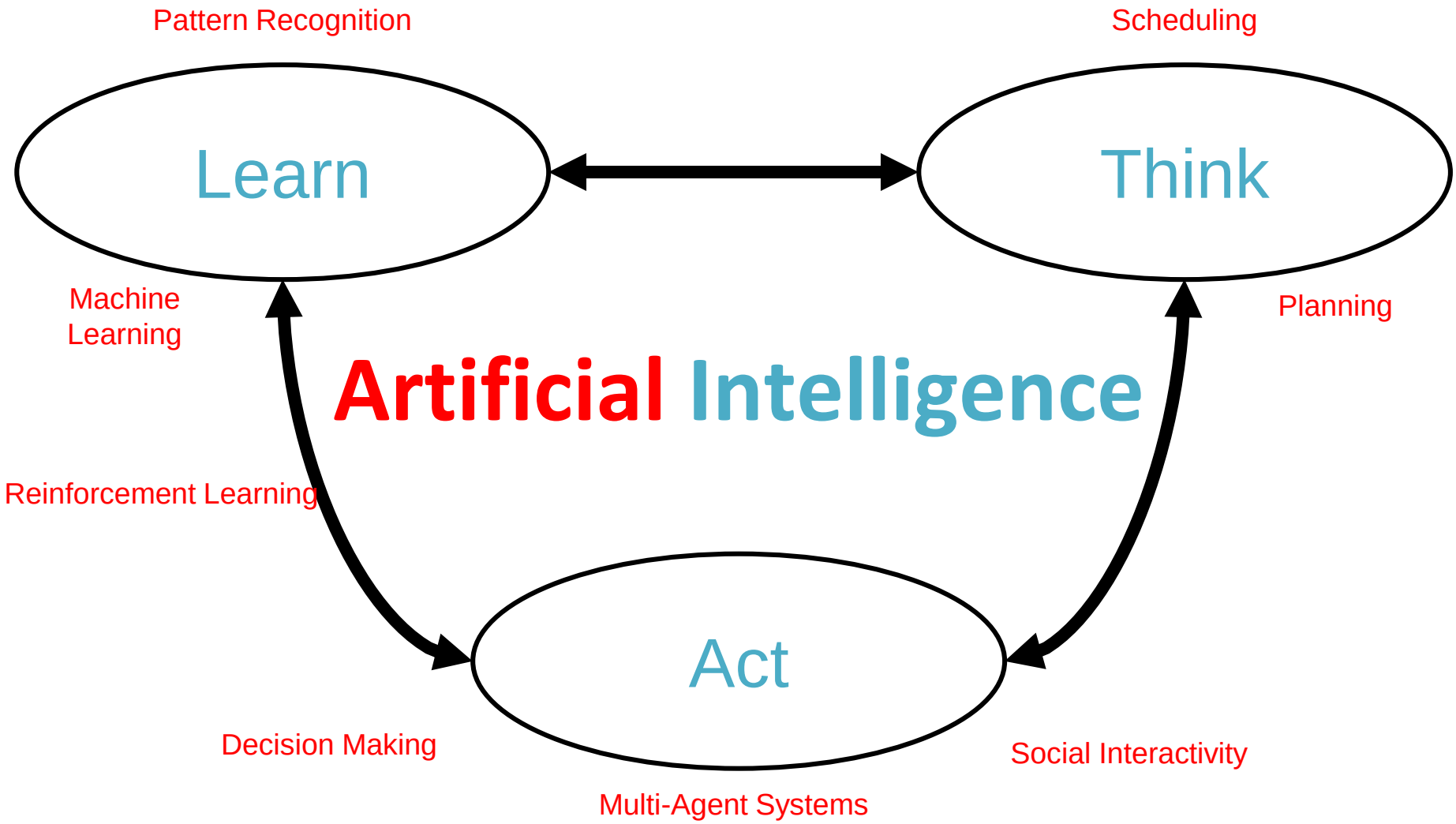
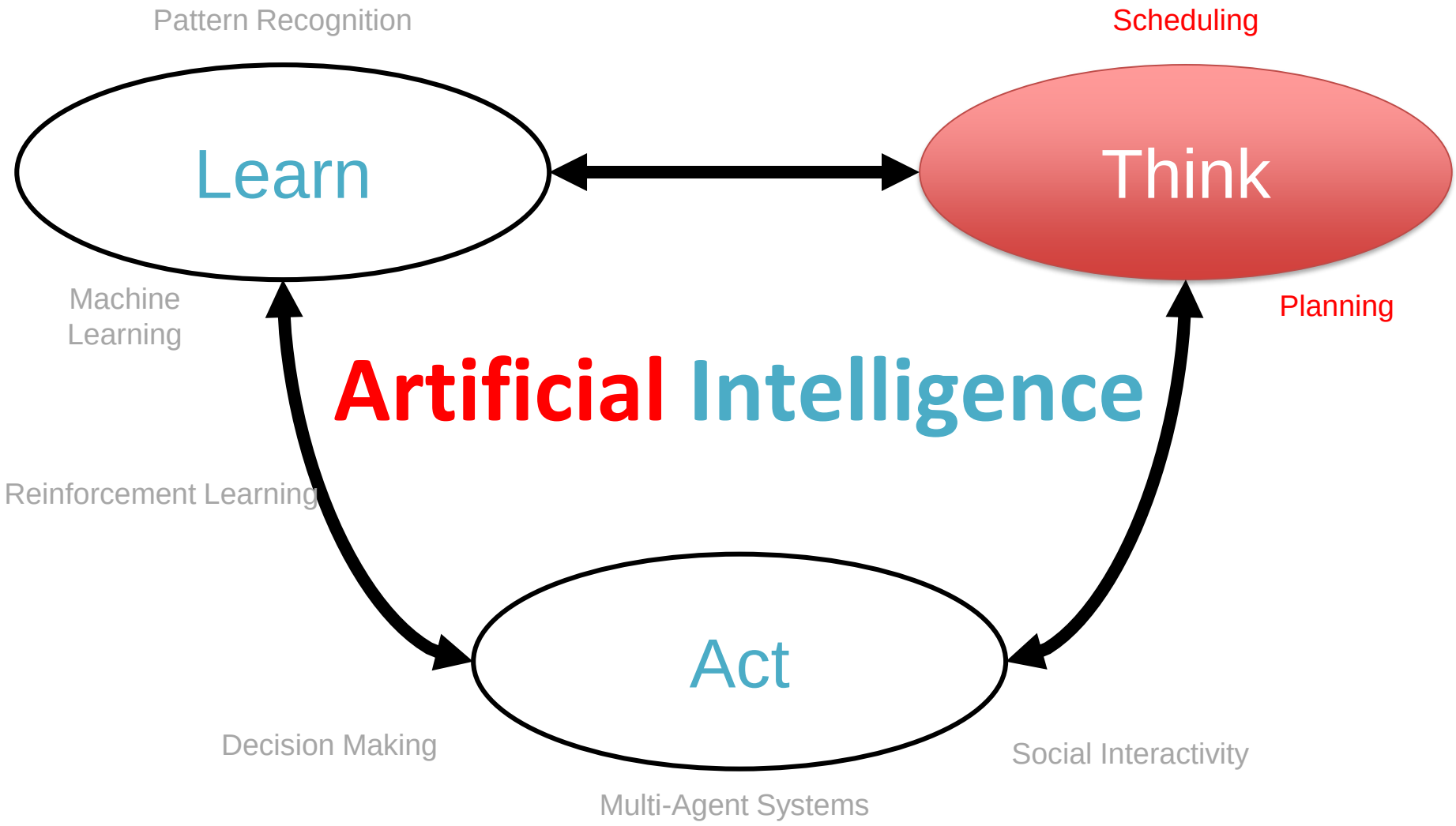
WiSe 2019/20

Recap: Automated Planning


Pattern Recognition
Scheduling
Learn
Think
Machine Learning
Planning
Artificial Intelligence
Reinforcement Learning
Act
Decision Making
Social Interactivity
Multi-Agent Systems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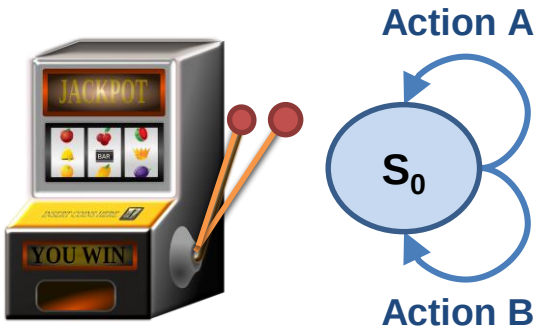
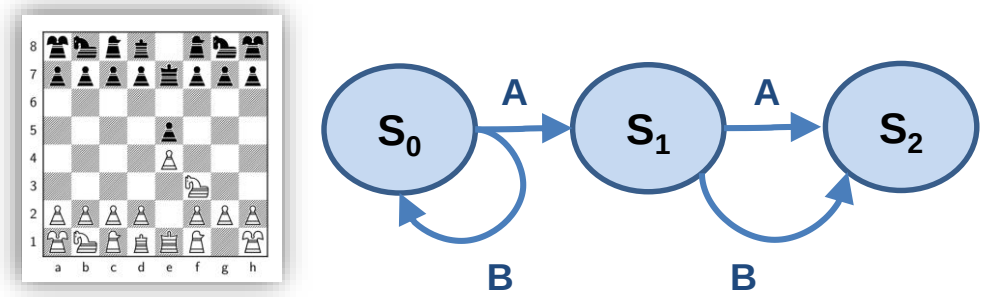
Overview

Multi-Armed Bandits



- Only a single state
- Multiple actions
  with possibly different reward

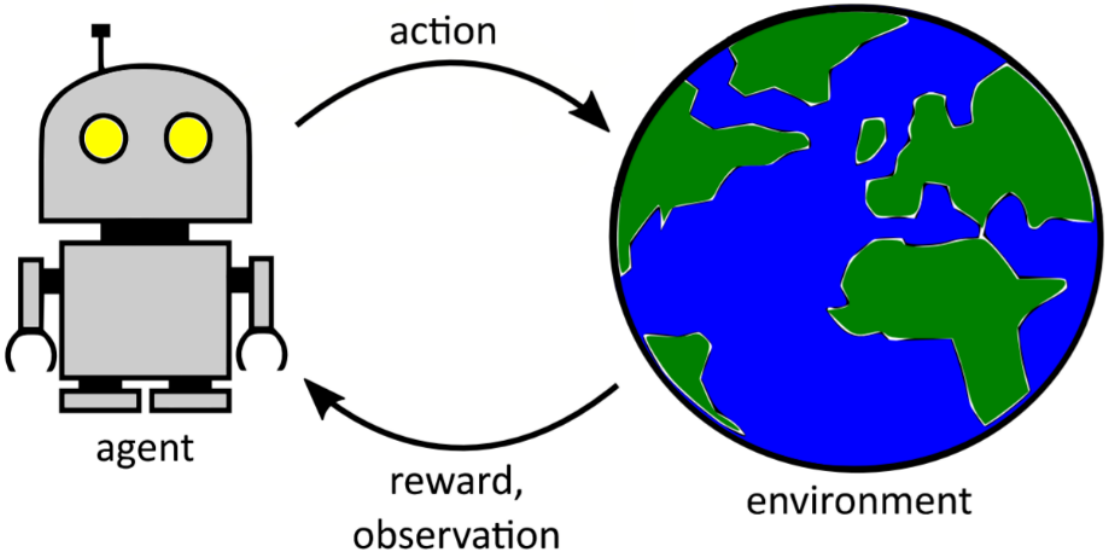
Sequential Decision Making



- Multiple states
- Multiple actions
  - with different rewards
  - and different transitions

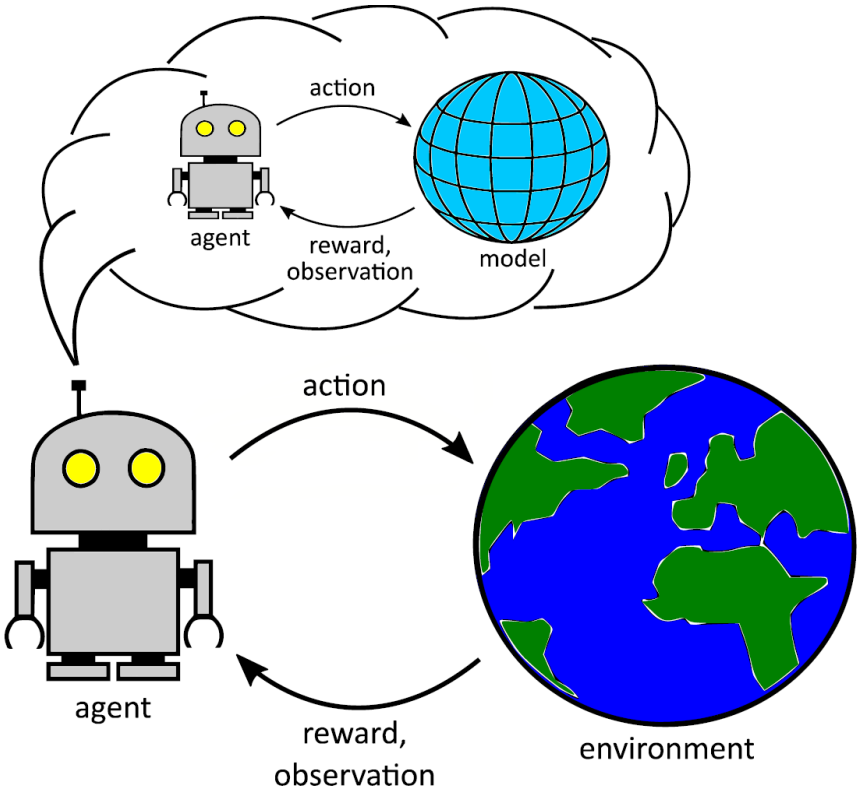
Sequential Decision Making

- **Goal:** Autonomously select actions to solve a (complex) task
  - time is important (actions might have **long term** consequences)
  - maximize the **expected cumulative reward** for each state

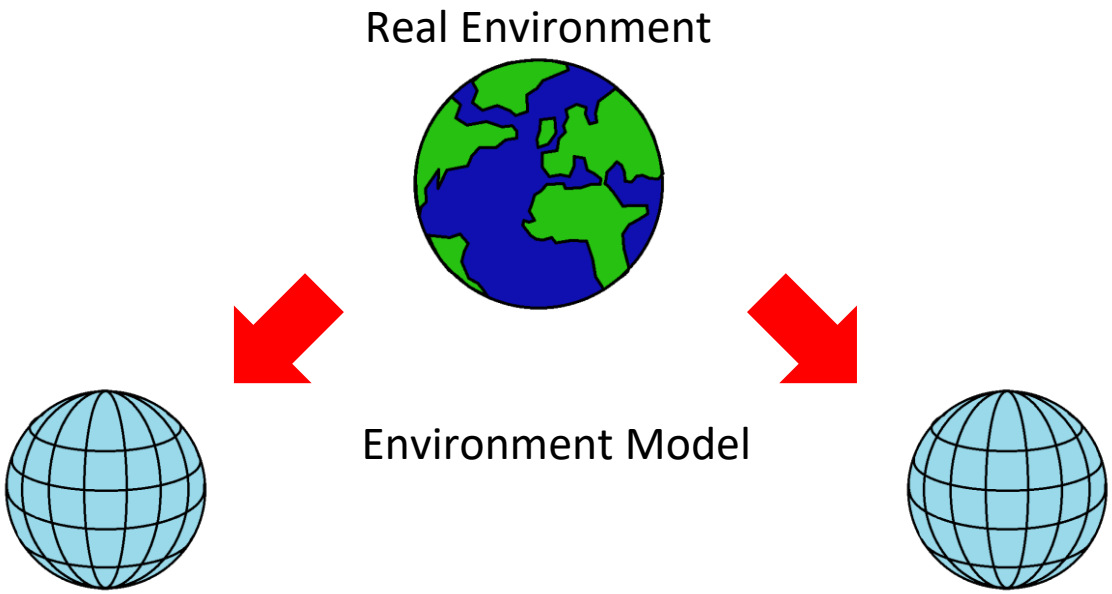


Automated Planning

- **Goal:** Find (near-)**optimal policies** π^* to solve complex problems
- Use (heuristic) lookahead search on a **given model** $\widehat{M} \approx M$ of the problem



Explicit Model vs. Generative Model

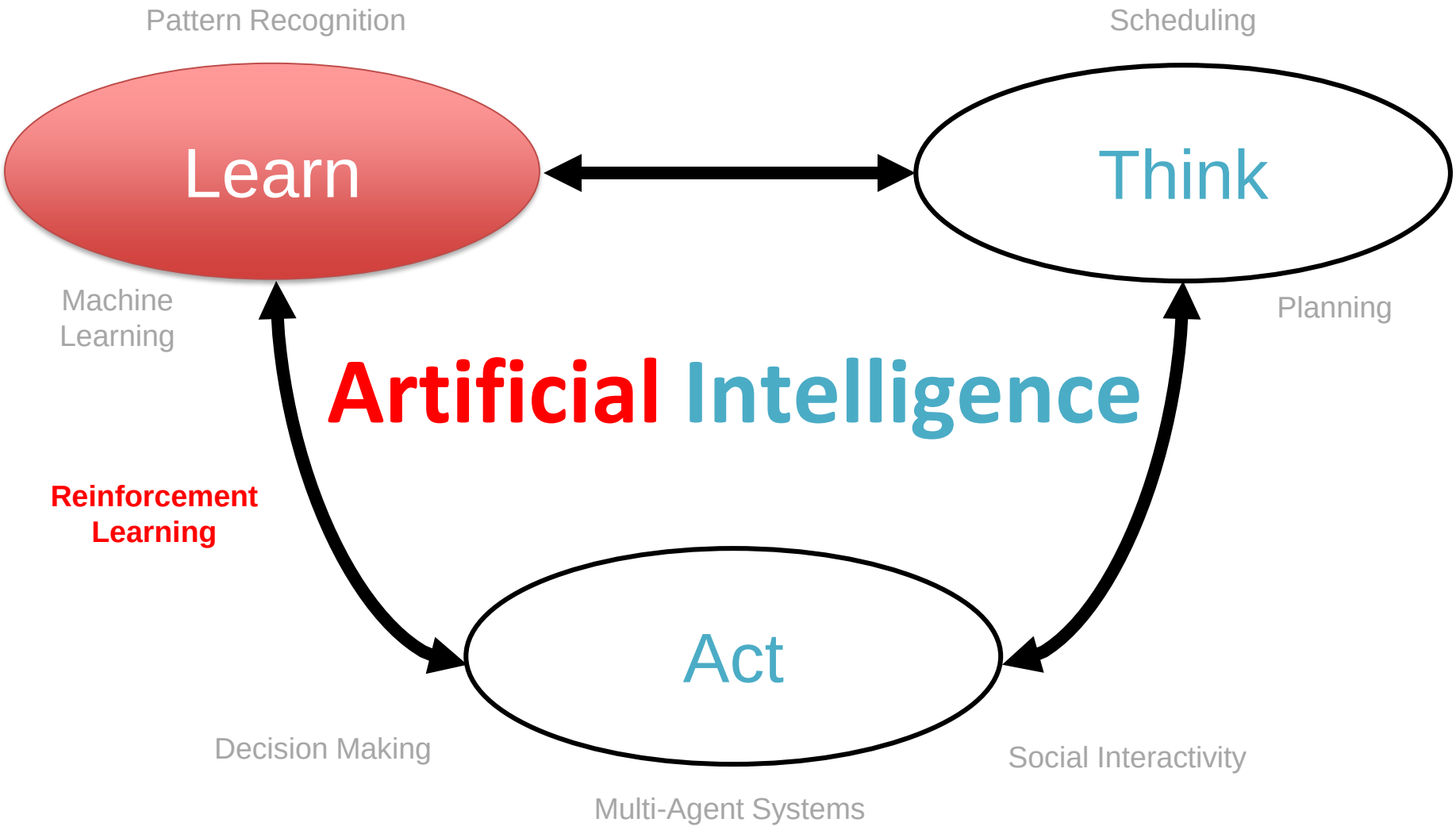


Dynamic Programming

- Uses Transition Probabilities $P(s_{t+1}|s_t, a_t)$
- Policy Iteration / Value Iteration

Monte Carlo Planning

- Uses Samples from the Model to approximate V* / Q*
- MC Rollout / MCTS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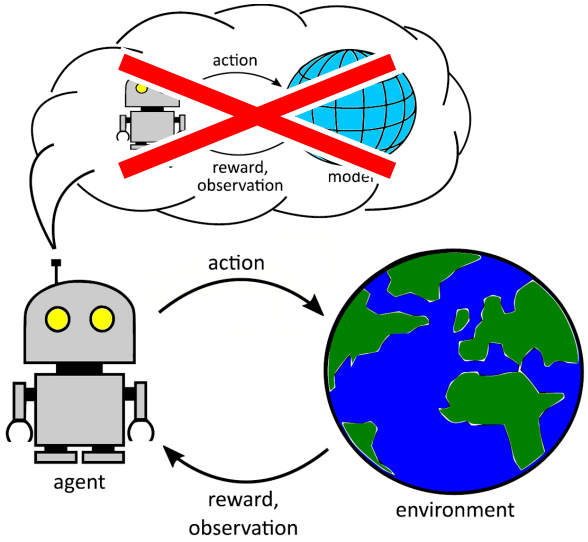
Model Free Reinforcement Learning

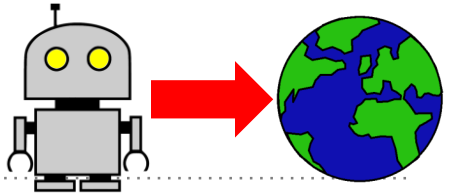


What if we don’t have a model?

Step1: Model Free Prediction

Step2: Model Free Control

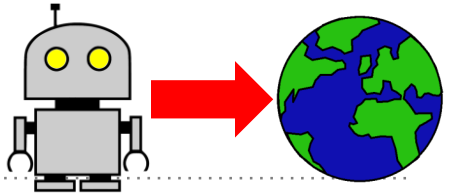
Model Free Reinforcement Learning



What if we don't have a model?
Step1: Model Free Prediction

"How good is the policy π?"
"What is the value of state s (when using π)"?

- We have a policy π and want to evaluate it, i.e.:
- Estimate the Value Function V_π of an unknown MDP
- **Note: we don't yet try to improve the policy!**
  This will be done later in "model free control"



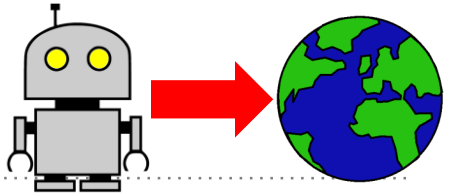
Evaluation Method 1: Monte Carlo (MC)

- **Simply perform MC rollouts directly in the real world**
  - Complete some episodes (i.e. use policy π)
  - Calculate the value as the mean of the returns

- **First-Visit Monte-Carlo Policy Evaluation**
  Goal: evaluate a state s
  - The **first** time a state is visiten in an episode
  - Increment a counter N(s)++
  - Increment the total return $S(s) \leftarrow S(s) + G_t$
    Recall: G_t is the total discounted reward:
    $$G_t = R_{t+1} + \gamma R_{t+2} + \cdots + \gamma^{T-1} R_T$$
  - Value is then estimated as $V(s) = \frac{S(s)}{N(s)}$

Model Free Reinforcement Learning

Model Free Prediction



- **First-Visit Monte-Carlo Policy Evaluation**
  - Value is then estimated as $V(s) = \frac{S(s)}{N(s)}$

Note: This is not iterative!

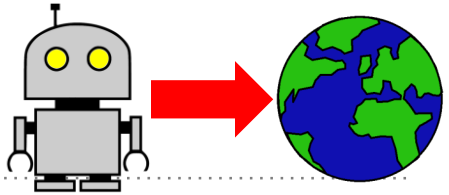
If we want to update V(s) after every episode, the mean can also be calculated incrementally:

- use the **incremental mean**

$$V(s_t) \leftarrow V(s_t) + \frac{1}{N(S_t)}(G_t - V(S_t))$$

- or the **running mean** (forgets old episodes)

$$V(s_t) \leftarrow V(s_t) + \propto (G_t - V(S_t))$$



Evaluation Method 2: Temporal difference learning (TD)

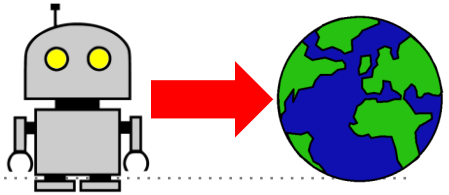
“Why learn only after the end of episodes?”

- TD learns from incomplete episodes (i.e. it *bootstraps*)
- Simplest TD: TD(0)
- Every step: Update the Value $V(S_t)$ toward the estimated return:
  - $R_{t+1} + \gamma V(S_{t+1})$
  - $V(S_t) \leftarrow V(S_t) + \alpha(R_{t+1} + \gamma V(S_{t+1}) - V(S_t))$

- $V(s_t) \leftarrow V(s_t) + \propto (G_t - V(S_t))$ [Monte-Carlo]

Model Free Reinforcement Learning

Model Free Prediction



What is better - MC or TD learning?

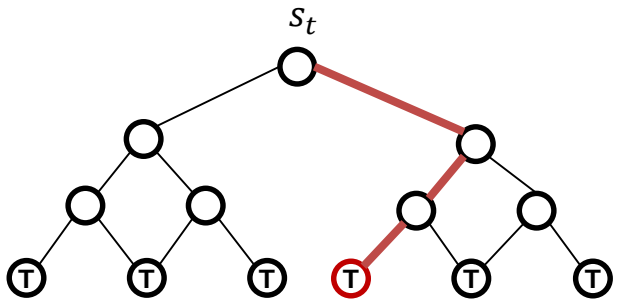
- No clear winner

- TD can learn before the end of episodes
- … or if there never are final ends!

- MC has high variance, but NO bias
  - good convergence
- TD has low variance, but is biased
  - converges, but not always when using function approximation

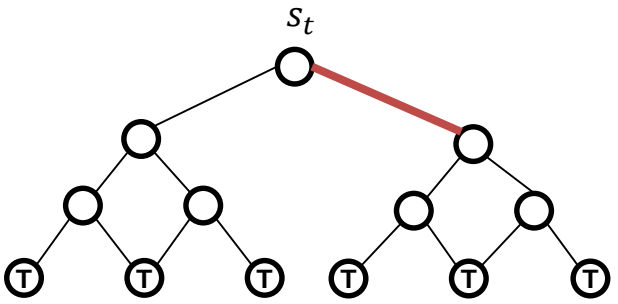
Model Free Reinforcement Learning

Model Free Prediction



Monte-Carlo

$$V(s_t) \leftarrow V(s_t) + \propto (G_t - V(S_t))$$

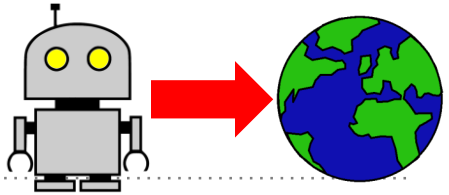


Temporal-Difference

$$V(S_t) \leftarrow V(S_t) + \alpha(R_{t+1} + \gamma V(S_{t+1}) - V(S_t))$$

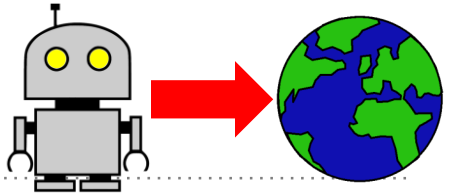
Model Free Reinforcement Learning

Can we improve the policy without a model?



Step2: Model Free Control

- **We want to improve a policy π**
- Optimize the value function of an unknown MDP



Recap: Model-Free VS Model-Based Policy Iteration

- **Computing improvements using V(s) requires the transition probabilities of the MDP:**

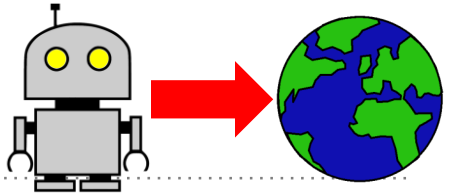
$$\pi'(s) = \underset{a \in A}{\operatorname{argmax}}\, R_s^a + P_{ss'}^a V(s')$$

- **No model needed when using the Action-Value function Q:**

$$\pi'(s) = \underset{a \in A}{\operatorname{argmax}}\, Q(s,a)$$

Model Free Reinforcement Learning

Improve the policy after rollouts



ε-greedy Monte-Carlo Control

Pull Arm 1: Reward 0 | V(A1) = 0
Pull Arm 2: Reward +1 | V(A2) = +1
Pull Arm 2: Reward +3 | V(A2) = +2
Pull Arm 2: Reward +2 | V(A2) = +2

„Certain that Arm 2 (A2) is the best arm?“

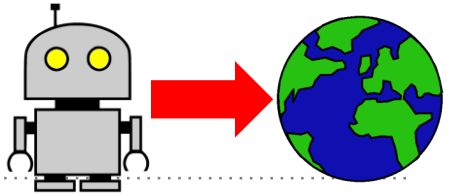
What is ε-greedy?

- Simplest idea to ensure ongoing exploration
- All actions are tried with probability > 0

- Algorithm:
  - Choose greedy action with probability $1 - \varepsilon$
  - Choose a random action with probability ε
  - With $\varepsilon \in [0,1]$

Model Free Reinforcement Learning

Improve the policy after rollouts



ε-greedy Monte-Carlo Control

- Same idea as before, perform some rollouts
- **Evaluate**, i.e. calculate $Q(S_t, A_t)$:

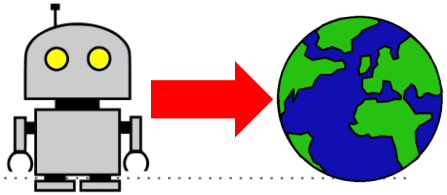
$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \frac{1}{N(S_t, A_t)}(G_t - Q(S_t, A_t))$$

- **Improve** using the new Q:

$$\pi \leftarrow \varepsilon\text{−}greedy(Q)$$

Model Free Reinforcement Learning

Improve the policy every step



Why not use TD instead and update every step?

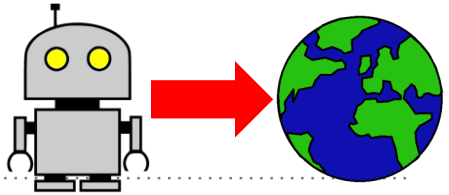
→ **Sarsa** (**S**tate, **A**ction, **R**eward, **S**tate', **A**ction')

$$Q(S,A) \leftarrow Q(S,A) + \propto (R + \gamma Q(S',A') - Q(S,A))$$

MC VS Sarsa: Empirical G_t was replaced by current reward R + discount * estimated return from the next step (taking action a')

Model Free Reinforcement Learning

Improve the policy every step



N-Step Sarsa

- We can also consider more than the last reward:

n=1 (Sarsa) $q_t^{(1)} = R_{t+1} + \gamma Q(S_{t+1})$

n=2 $q_t^{(2)} = R_{t+1} + \gamma R_{t+2} + \gamma^2 Q(S_{t+2})$

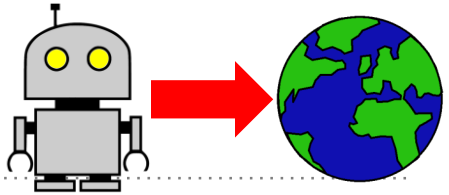
…

n=∞ (MC) $q_t^{(\infty)} = R_{t+1} + \gamma R_{t+2} + \cdots + \gamma^n Q(S_{t+n})$

$$Q(S,A) \leftarrow Q(S,A) + \propto (q_t^{(n)} - Q(S,A))$$

Model Free Reinforcement Learning

Improve the policy every step



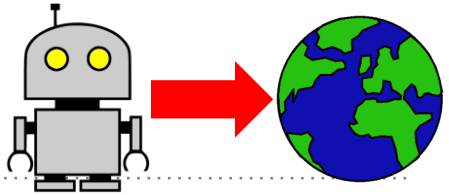
Sarsa: Pseudo Code (Tabular)

$$Q(S,A) \leftarrow Q(S,A) + \propto (R + \gamma Q(S',A') - Q(S,A))$$

```
Repeat n_episode times:
        s = reset environment
        a = policy(s)
        For t in max_step_times:
                s‘,r,done = environment.step(a)
                a‘ = policy(s‘)
                td_target = r + discount*Q(s‘,a‘)
                td_error = td_target – Q(s,a)
                Q[s,a] = Q(s,a) + ∝ * td_error
                s = s‘;
                a = a‘
                if done or t == max_step_times:
                        break
```

Model Free Reinforcement Learning

Can we act A and learn B?



On-Policy VS Off-Policy Learning

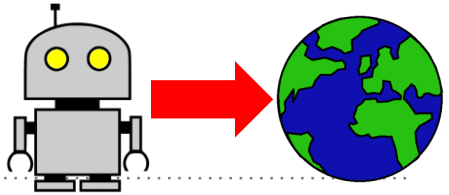
- Notice how both MC Control and Sarsa used the current policy to choose the next action

- We can also learn off-policy:
  - Choose the next action using one policy $\mu(a|s)$
  - But evaluate using a different policy π and it‘s $q_\pi(s,a)$

- This way, we can learn from observing others
- Or re-use experience collected using an old policy

Model Free Reinforcement Learning

Q Learning



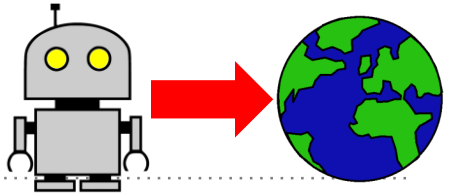
Sarsa:

$$Q(S,A) \leftarrow Q(S,A) + \propto (R + \gamma Q(S',A') - Q(S,A))$$

Off-Policy learning of the action-value function: Q-Learning

$$Q(S,A) \leftarrow Q(S,A) + \propto (R + \underbrace{\gamma \max_{a'} Q(S',a')} - Q(S,A))$$

Sarsa VS Q-Learning: The successor action a‘ is not ‚taken‘ based on the behaviour policy but greedy (→ max)



Q-Learning: Pseudo Code (Tabular)

$$Q(S,A) \leftarrow Q(S,A) + \propto (R + \gamma \max_{a'} Q(S',a') - Q(S,A))$$

```
Repeat n_episode times:
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        For t in max_step_times:
                a = policy(s)
                s‘,r,done = environment.step(a)
                td_target = r + discount*max(Q(s‘))
                td_error = td_target – Q(s,a)
                Q[s,a] = Q(s,a) + ∝ * td_error
                s = s‘
                if done or t == max_step_times:
                        break
```

Thank you!