CSC 665: Artificial Intelligence

Reinforcement Learning

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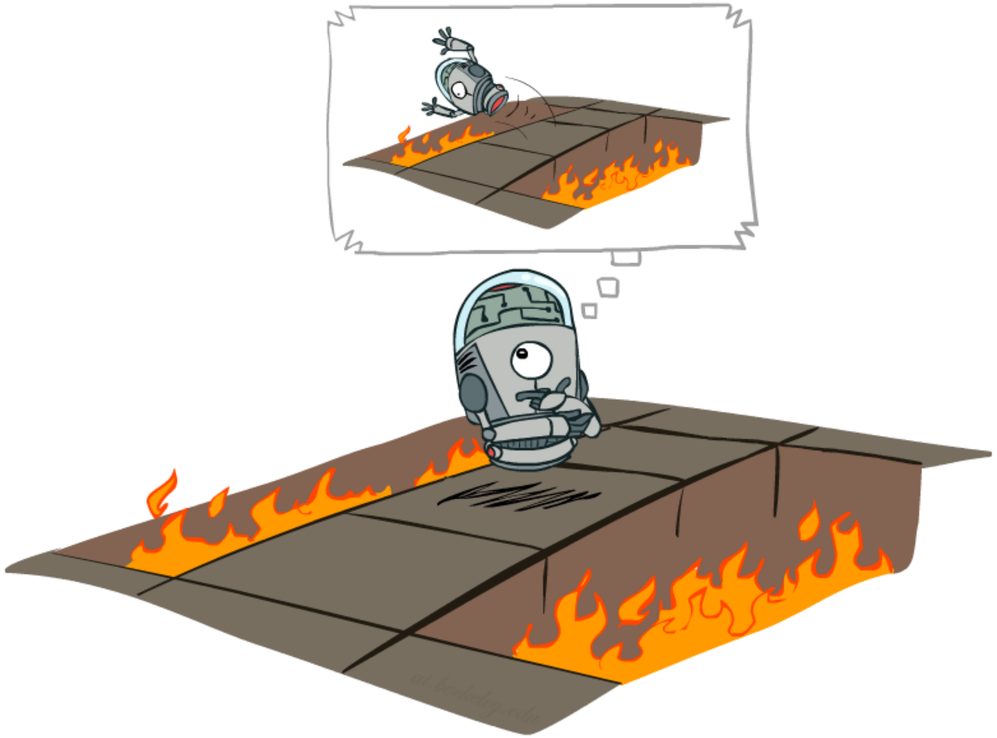
Reinforcement Learning

- Still assume a Markov decision process (MDP):
  - A set of states $s \in S$
  - A set of actions (per state) A
  - A transition function T(s,a,s')
  - A reward function R(s,a,s')
- Still looking for an optimal policy $\pi^*(s)$
- New twist: don't know T or R (model of MDP)
  - I.e. we don't know which states are good or what the actions do

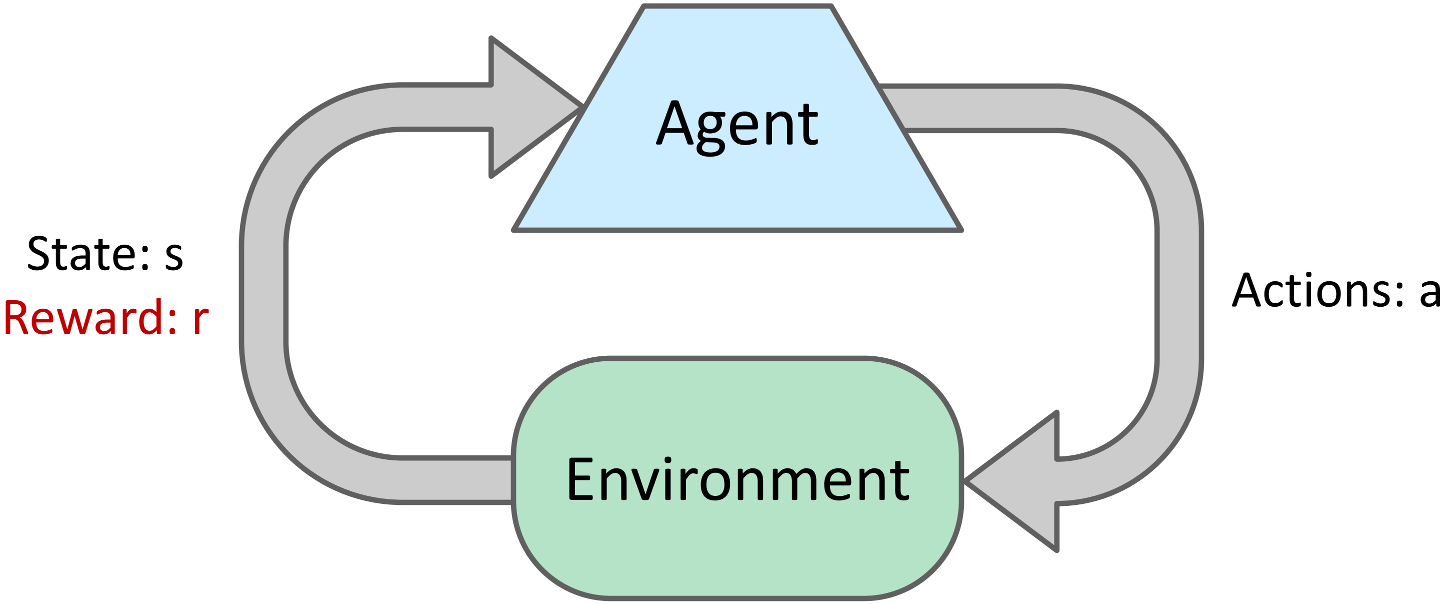
Reinforcement Learning

MDP computes an optimal policy (offline)



RL learns an optimal policy (online)

Reinforcement Learning



- Basic idea:
  - Receive feedback in the form of rewards
  - Must (learn to) act to maximize expected rewards based on observed samples of outcomes!

Example: Learning to Walk

Initial

After Learning [1K Trials]

[Kohl and Stone, ICRA 2004]

Example: Learning to Walk

Initial

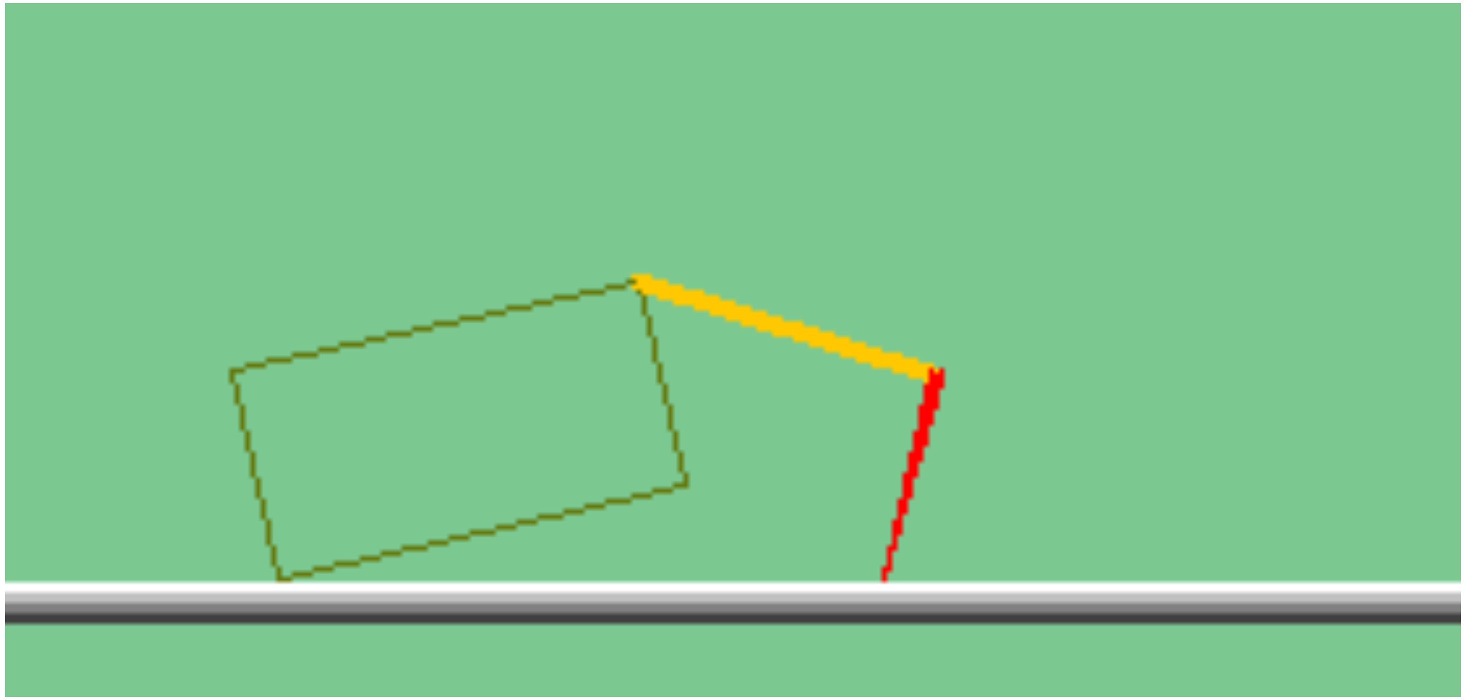
[Kohl and Stone, ICRA 2004]

Example: Learning to Walk

Finished

[Kohl and Stone, ICRA 2004]

The Crawler!



Video of Demo Crawler Bot

Passive vs Active Reinforcement Learning

- Passive RL Learning
  - The agent acts based on a fixed policy π and tries to learn how good the policy is by observing the world go by

- Active RL Learning
  - The agent attempts to find an optimal policy by exploring different actions in the world

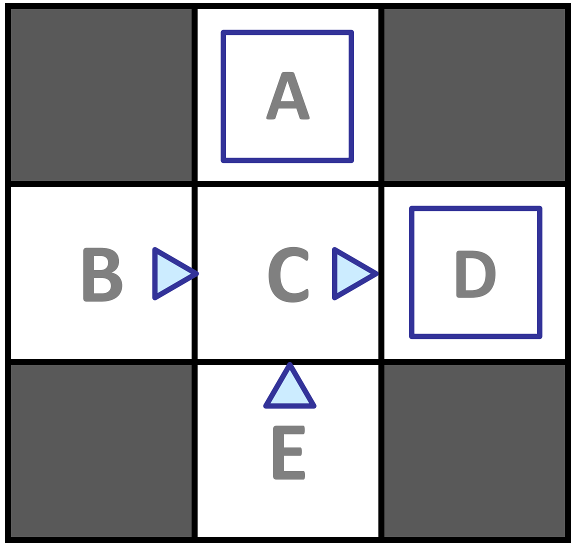
Model-Based vs Model-Free Learning

- Model-Based approach to RL:
  - Learn the MDP model (T and R), or an approximation of it
    - Use it to evaluate the fixed policy (Passive RL Learning)
    - Use it to find the optimal policy (Active RL Learning)

- Model-Free approach to RL:
  - Without explicitly learning the model (T and R)
    - Evaluate the fixed policy (Passive RL Learning)
    - Find the optimal policy (Active RL Learning)

Example: Model-Based Learning

Input Policy π



Assume: γ = 1

Observed Episodes (Training)

Episode 1

B, east, C, -1
C, east, D, -1
D, exit, x, +10

Episode 2

B, east, C, -1
C, east, D, -1
D, exit, x, +10

Episode 3

E, north, C, -1
C, east, D, -1
D, exit, x, +10

Episode 4

E, north, C, -1
C, east, A, -1
A, exit, x, -10

Learned Model

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

T(B, east, C) = 1.00
T(C, east, D) = 0.75
T(C, east, A) = 0.25
…

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

R(B, east, C) = -1
R(C, east, D) = -1
R(D, exit, x) = +10
…

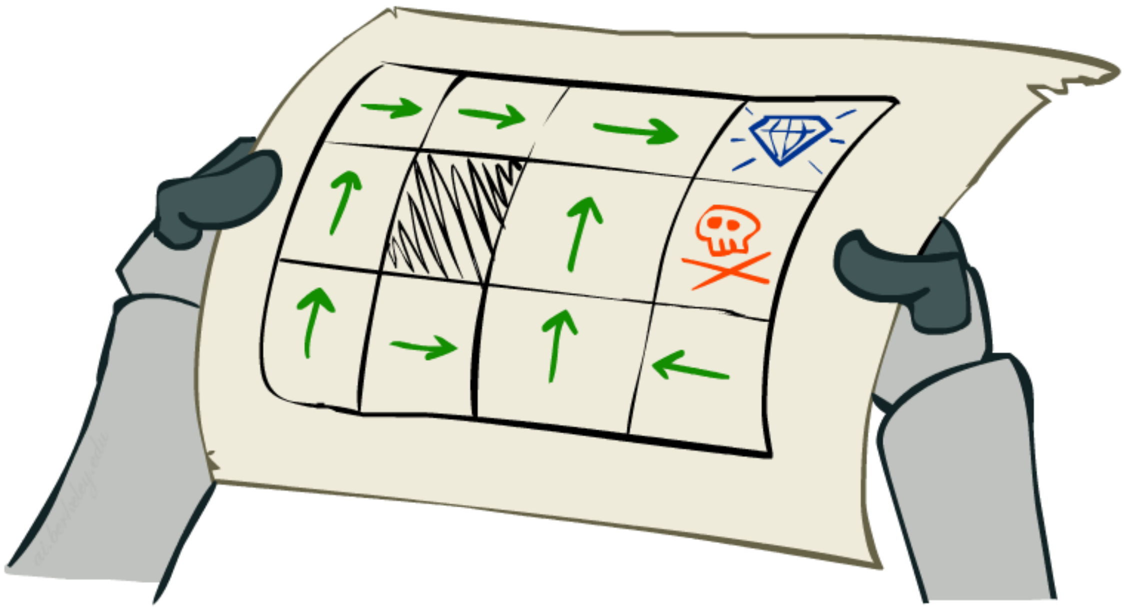
Model-Based Learning

- Step 1: Learn the MDP model (T and R)
  - Count outcomes s' for each s, a
  - Normalize to give an estimate of $\widehat{T}(s,a,s')$
  - Discover each $\widehat{R}(s,a,s')$ when we experience (s, a, s')
- Step 2: Solve the learned MDP
  - Use Policy Evaluation to evaluate the fixed policy (Passive RL Learning)
  - Use Value Iteration to find the optimal policy (Active RL Learning)

Model-Free Learning

Passive Reinforcement Learning

- Task: Policy Evaluation
  - Input: a fixed policy $\pi(s)$
  - You don't know the transitions T(s,a,s')
  - You don't know the rewards R(s,a,s')
  - Goal: learn the state values

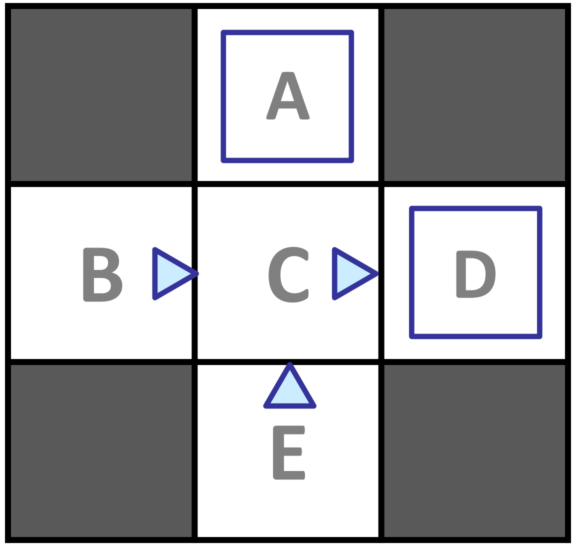


- In this case:
  - No choice about what actions to take
  - Just execute the policy and learn from experience
  - This is NOT offline planning! You actually take actions in the world.

Direct Evaluation

Example: Direct Evaluation

Input Policy π



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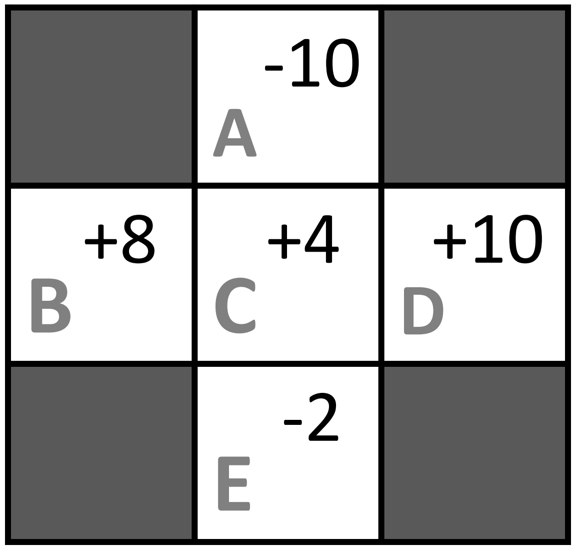
Episode 3

E, north, C, -1
C, east, D, -1
D, exit, x, +10

Episode 4

E, north, C, -1
C, east, A, -1
A, exit, x, -10

Output Values



Direct Evaluation

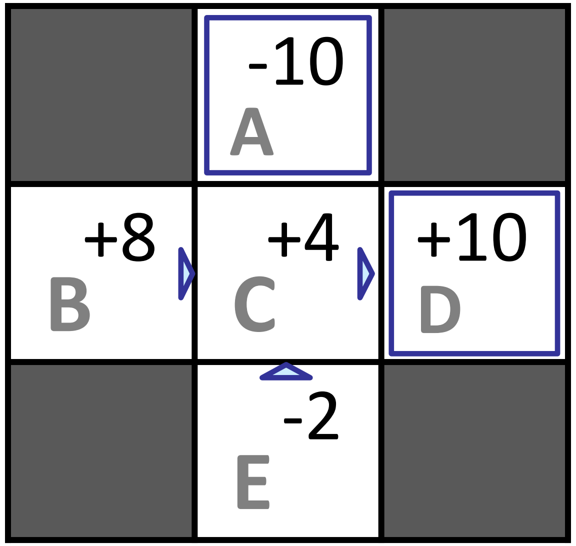
- Goal: Compute values for each state under π
- Idea:
  - Act according to π
  - Use the actual sum of discounted rewards from s
  - Average over multiple trials and visits to s
- This is called Direct Evaluation

Problems with Direct Evaluation

- What's good about Direct Evaluation?
  - It's easy to understand
  - It doesn't require any knowledge of T, R
  - It eventually computes the correct average values, using just sample transitions

- What bad about it?
  - It ignores information about state connections
  - So, it takes a long time to learn

Output Values



If B and E both go to C under this policy, how can their values be different?

Question?

Direct Evaluation is a ……. Approach

Model-Free ✓

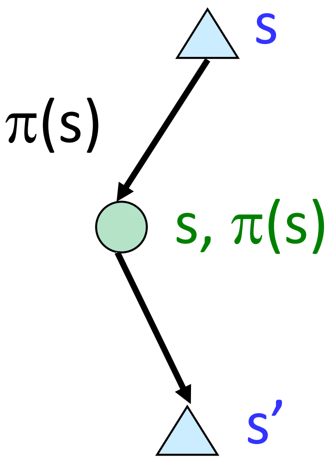
Model-Based

Temporal Difference Learning

Temporal Difference Learning

- Idea: learn from every experience!
  - Update V(s) each time we experience a transition (s, a, s', r)

- Temporal Difference Learning of values
  - Policy still fixed, still doing evaluation!



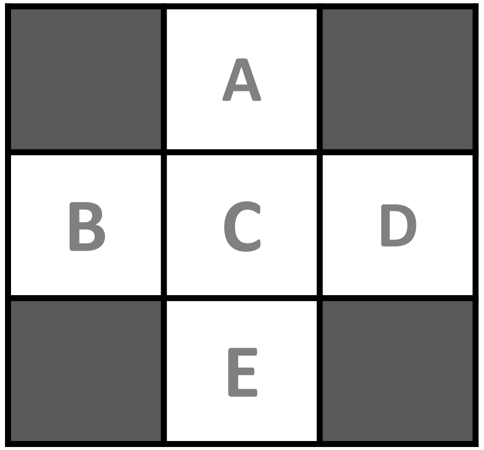
Sample of V(s): $sample = R(s, \pi(s), s') + \gamma V^{\pi}(s')$

Update to V(s): $V^{\pi}(s) \leftarrow (1 - \alpha)V^{\pi}(s) + (\alpha) sample$

- **α is the learning rate:** determines to what extent the newly acquired information will override the old information.

Example: Temporal Difference Learning

States

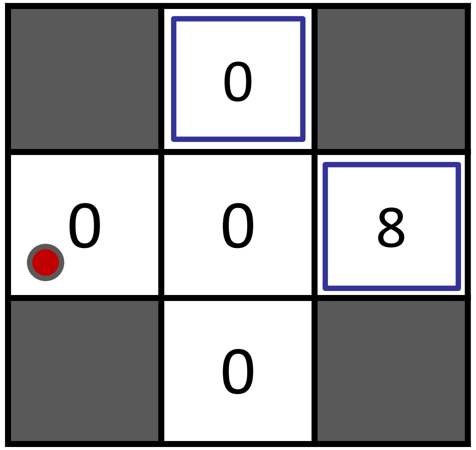


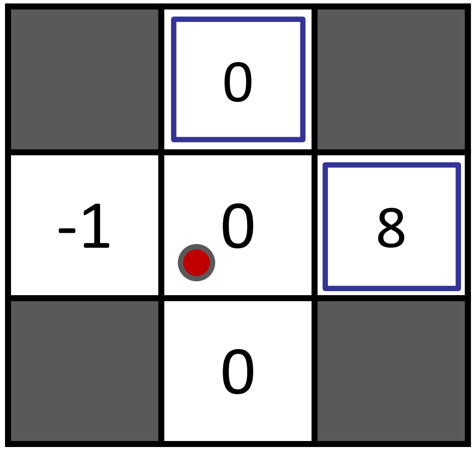
Assume: $\gamma = 1$, $\alpha = 1/2$

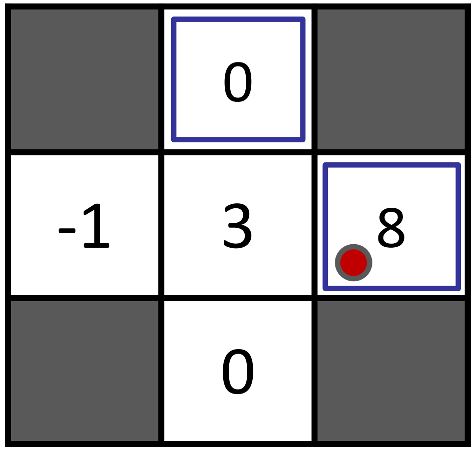
Observed Transitions

B, east, C, -2

C, east, D, -2







$$V^{\pi}(s) \leftarrow (1-\alpha)V^{\pi}(s) + \alpha\left[R(s,\pi(s),s') + \gamma V^{\pi}(s')\right]$$

Question?

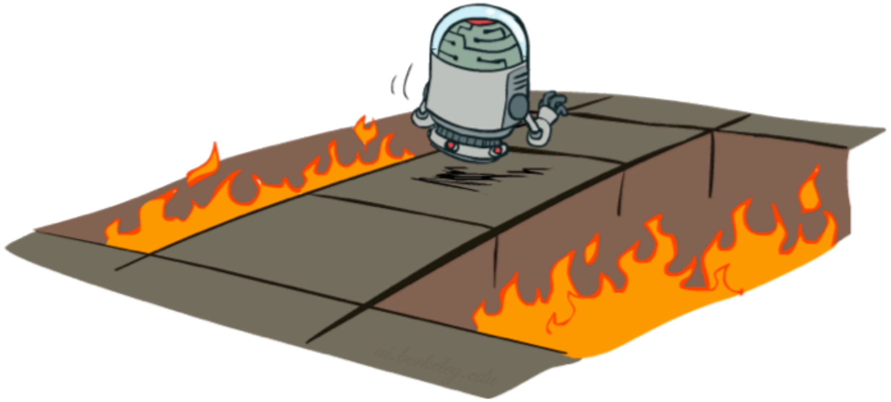
TD Learning is a ……. Approach.

Model-Free

Model-Based

Active Reinforcement Learning

- Full reinforcement learning: optimal policies
  - You don’t know the transitions T(s,a,s’)
  - You don’t know the rewards R(s,a,s’)
  - You choose the actions now
  - Goal: learn the optimal policy / values



- In this case:
  - Learner makes choices!
  - This is NOT offline planning! You actually take actions in the world and find out what happens…

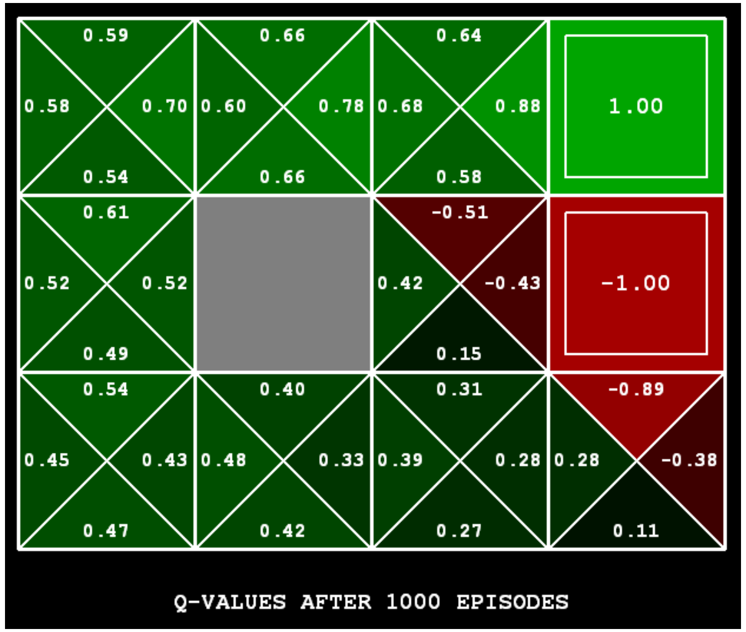
Q-Learning

Q-Learning

- Learn Q(s,a) values as you go
  - Receive a sample (s,a,s',r)
  - Consider your new sample estimate:

$$sample = R(s,a,s') + \gamma \max_{a'} Q(s',a')$$

  - Incorporate the new estimate:



$$Q(s,a) \leftarrow (1-\alpha)Q(s,a) + (\alpha)\,[sample]$$

or

$$Q(s,a) \leftarrow (1-\alpha)Q(s,a) + (\alpha)\left[r + \gamma \max_{a'} Q(s',a')\right]$$

Q-Learning – Manual Grid

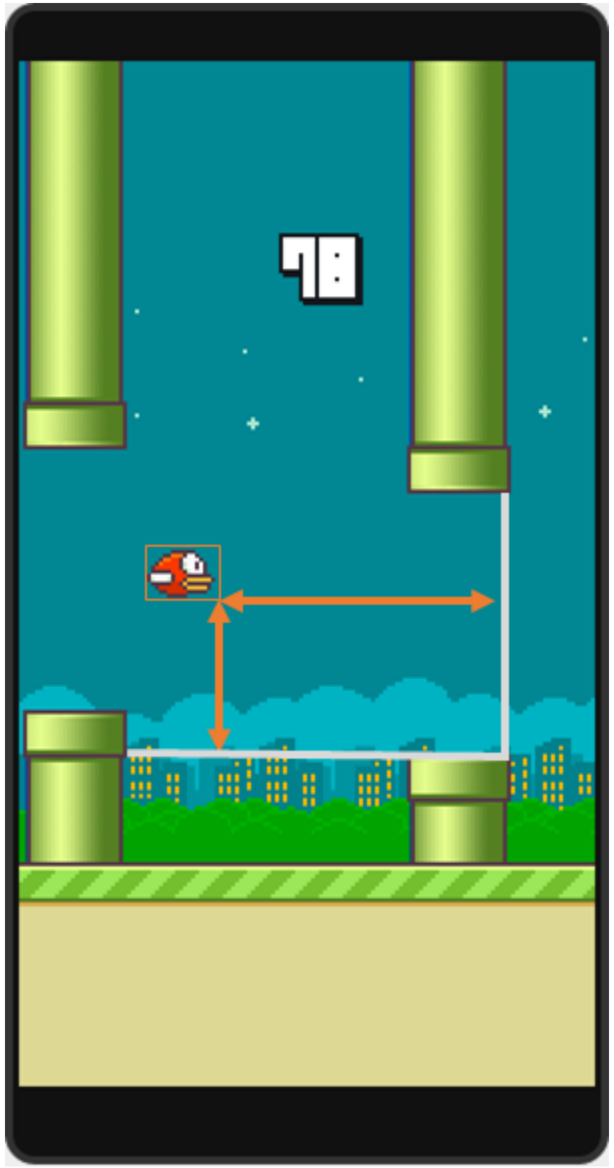
Q-Learning – Auto Grid

Q-Learning Properties

- Amazing result: Q-learning converges to optimal policy!
- This is called off-policy learning
- Caveats:
  - You have to explore enough
  - You have to eventually make the learning rate small enough
  - … but not decrease it too quickly

Flappy Bird RL

- State space
  - Discretized vertical distance from lower pipe
  - Discretized horizontal distance from next pair of pipes
  - Life: Dead or Living
- Actions
  - Click
  - Do nothing
- Rewards
  - +1 if Flappy Bird still alive
  - -1000 if Flappy Bird is dead
- 6-7 hours of Q-learning



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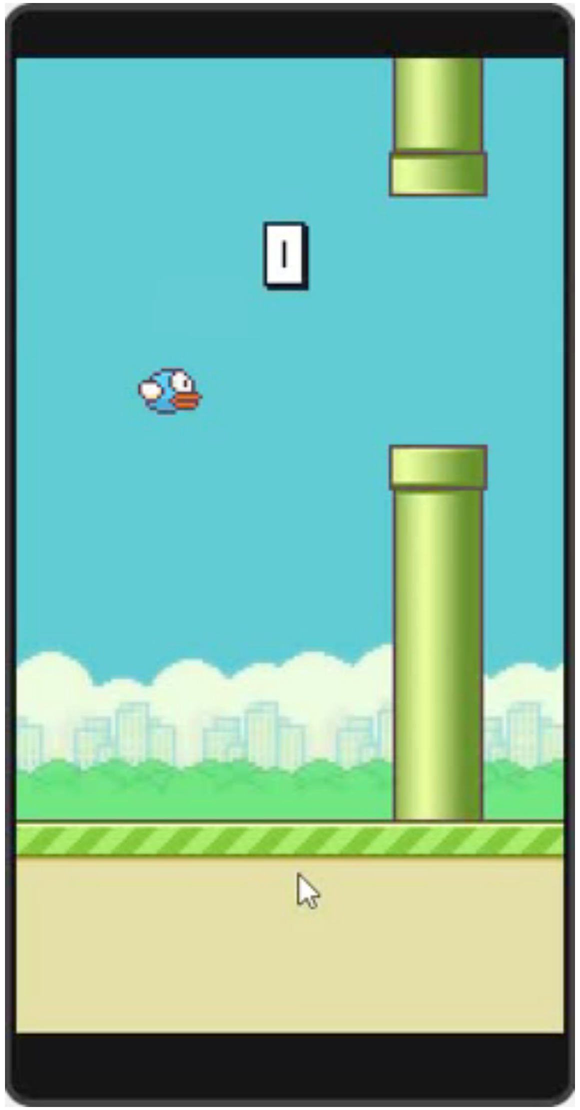

Summary: Passive vs Active Reinforcement Learning

- Passive RL Learning
  - Policy Evaluation on Approx. MDP (Model-Based)
  - Direct Evaluation (Model-Free)
  - Temporal Difference (TD) Learning (Model-Free)

- Active RL Learning
  - Value Iteration on Approx. MDP (Model-Based)
  - Q-learning (Model-Free)

The Story So Far: MDPs and RL

Known MDP: Offline Solution

Goal	Technique
Compute V*, Q*, π*	
Evaluate a fixed policy π	

Unknown MDP: Model-Based

Goal	Technique
Compute V*, Q*, π*	
Evaluate a fixed policy π	

Unknown MDP: Model-Free

Goal	Technique
Compute V*, Q*, π*	
Evaluate a fixed policy π	

The Story So Far: MDPs and RL

Known MDP: Offline Solution

Goal	Technique
Compute V*, Q*, π*	Value Iteration
Evaluate a fixed policy π	Policy Evaluation

Unknown MDP: Model-Based

Goal	Technique
Compute V*, Q*, π*	VI on approx. MDP
Evaluate a fixed policy π	PE on approx. MDP

Unknown MDP: Model-Free

Goal	Technique
Compute V*, Q*, π*	Q-learning
Evaluate a fixed policy π	TD Learning/Direct Eval

Reading

- Read Sections 22.1, 22.2, and 22.3 in the AIMA textbook