CSE 573: Artificial Intelligence

Hanna Hajishirzi
Reinforcement Learning

slides adapted from
Dan Klein, Pieter Abbeel ai.berkeley.edu
And Dan Weld, Luke Zettlemoyer
Reinforcement Learning
Double Bandits
Double-Bandit MDP

- Actions: Blue, Red
- States: Win, Lose

No discount
10 time steps
Both states have the same value
Solving MDPs is offline planning

- You determine all quantities through computation
- You need to know the details of the MDP
- You do not actually play the game!
Let’s Play!
Online Planning

- Rules changed! Red’s win chance is different.
Let’s Play!

$0 $0 $2 $0
$0 $2 $2 $0 $0
$0
What Just Happened?

- That wasn’t planning, it was learning!
  - Specifically, reinforcement learning
  - There was an MDP, but you couldn’t solve it with just computation
  - You needed to actually act to figure it out

- Important ideas in reinforcement learning that came up
  - Exploration: you have to try unknown actions to get information
  - Exploitation: eventually, you have to use what you know
  - Regret: even if you learn intelligently, you make mistakes
  - Sampling: because of chance, you have to try things repeatedly
  - Difficulty: learning can be much harder than solving a known MDP
Reinforcement Learning

- Still assume a Markov decision process (MDP):
  - A set of states \( s \in S \)
  - A set of actions (per state) \( A \)
  - A model \( T(s,a,s') \)
  - A reward function \( R(s,a,s') \)

- Still looking for a policy \( \pi(s) \)

- New twist: don’t know \( T \) or \( R \)
  - I.e. we don’t know which states are good or what the actions do
  - Must actually try actions and states out to learn
Basic idea:
- Receive feedback in the form of rewards
- Agent’s utility is defined by the reward function
- Must (learn to) act so as to maximize expected rewards
- All learning is based on observed samples of outcomes!
Example: Learning to Walk

Initial

A Learning Trial

After Learning [1K Trials]

[Kohl and Stone, ICRA 2004]
Example: Toddler Robot

[Video: TODDLER – 40s]
Robotics Rubik Cube

- [https://www.youtube.com/watch?v=x4O8pojMF0w](https://www.youtube.com/watch?v=x4O8pojMF0w)

Solving Rubik’s Cube with a Robot Hand
ChatGPT: Optimizing Language Models for Dialogue

We’ve trained a model called ChatGPT which interacts in a conversational way. The dialogue format makes it possible for ChatGPT to answer follow up questions, admit its mistakes, challenge incorrect premises, and reject inappropriate requests. ChatGPT is a sibling model to InstructGPT, which is trained to follow an instruction in a prompt and provide a detailed response.

We are excited to introduce ChatGPT to get users’ feedback and learn about its strengths and weaknesses. During the research preview, usage of ChatGPT is free. Try it now at chat.openai.com.
The Crawler!

[Demo: Crawler Bot (L10D1)] [You, in Project 3]
Video of Demo Crawler Bot
Reinforcement Learning

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- A set of states \( s \in S \)
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New twist: don’t know \( T \) or \( R \)

- I.e. we don’t know which states are good or what the actions do
- Must actually try actions and states out to learn
Offline (MDPs) vs. Online (RL)

- Offline Solution
- Online Learning
Model-Based Learning
Model-Based Learning

- Model-Based Idea:
  - Learn an approximate model based on experiences
  - Solve for values as if the learned model were correct

- Step 1: Learn empirical MDP model
  - Count outcomes \( s' \) for each \( s, a \)
  - Normalize to give an estimate \( \hat{T}(s, a, s') \)
  - Discover each \( \hat{R}(s, a, s') \) when we experience \( (s, a, s') \)

- Step 2: Solve the learned MDP
  - For example, use value iteration, as before
### Example: Model-Based Learning

**Input Policy** $\pi$

```
A
B
C
D
E

Assume: $\gamma = 1$
```

**Observed Episodes (Training)**

<table>
<thead>
<tr>
<th>Episode</th>
<th>Actions</th>
<th>Rewards</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Episode 1</strong></td>
<td>B, east, C, -1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C, east, D, -1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>D, exit, x, +10</td>
<td></td>
</tr>
<tr>
<td><strong>Episode 2</strong></td>
<td>B, east, C, -1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C, east, D, -1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>D, exit, x, +10</td>
<td></td>
</tr>
<tr>
<td><strong>Episode 3</strong></td>
<td>E, north, C, -1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C, east, D, -1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>D, exit, x, +10</td>
<td></td>
</tr>
<tr>
<td><strong>Episode 4</strong></td>
<td>E, north, C, -1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C, east, A, -1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>A, exit, x, -10</td>
<td></td>
</tr>
</tbody>
</table>

### Learned Model

\[
\hat{T}(s, a, s') =
\begin{align*}
T(B, \text{east}, C) &= 1.00 \\
T(C, \text{east}, D) &= 0.75 \\
T(C, \text{east}, A) &= 0.25 \\
\end{align*}
\]

\[
\hat{R}(s, a, s') =
\begin{align*}
R(B, \text{east}, C) &= -1 \\
R(C, \text{east}, D) &= -1 \\
R(D, \text{exit}, x) &= +10 \\
\end{align*}
\]
Model-Free Learning
Direct Evaluation

- Goal: Compute values for each state under $\pi$
- Idea: Average together observed sample values
  - Act according to $\pi$
  - Every time you visit a state, write down what the sum of discounted rewards turned out to be
  - Average those samples
- This is called direct evaluation
Example: Direct Evaluation

Input Policy $\pi$

Assume: $\gamma = 1$

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

Output Values

If B and E both go to C under this policy, how can their values be different?
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 wastes information about state connections
  - Each state must be learned separately
  - 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?
Passive Reinforcement Learning

- **Simplified 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:**
  - Learner is “along for the ride”
  - 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.
Why Not Use Policy Evaluation?

- Simplified Bellman updates calculate $V$ for a fixed policy:
  - Each round, replace $V$ with a one-step-look-ahead layer over $V$
    
    $V_0^\pi(s) = 0$
    
    $V_{k+1}^\pi(s) \leftarrow \sum_{s'} T(s, \pi(s), s') [R(s, \pi(s), s') + \gamma V_k^\pi(s')]$

    - This approach fully exploited the connections between the states
    - Unfortunately, we need $T$ and $R$ to do it!

- Key question: how can we do this update to $V$ without knowing $T$ and $R$?
  - In other words, how to we take a weighted average without knowing the weights?
Sample-Based Policy Evaluation?

- We want to improve our estimate of $V$ by computing these averages:

$$V_{k+1}^\pi(s) \leftarrow \sum_{s'} T(s, \pi(s), s') [R(s, \pi(s), s') + \gamma V_k^\pi(s')]$$

- Idea: Take samples of outcomes $s'$ (by doing the action!) and average

$$\text{sample}_1 = R(s, \pi(s), s'_1) + \gamma V_k^\pi(s'_1)$$
$$\text{sample}_2 = R(s, \pi(s), s'_2) + \gamma V_k^\pi(s'_2)$$
$$\ldots$$
$$\text{sample}_n = R(s, \pi(s), s'_n) + \gamma V_k^\pi(s'_n)$$

$$V_{k+1}^\pi(s) \leftarrow \frac{1}{n} \sum_i \text{sample}_i$$
Temporal Difference Learning

- Big idea: learn from every experience!
  - Update $V(s)$ each time we experience a transition $(s, a, s', r)$
  - Likely outcomes $s'$ will contribute updates more often

- Temporal difference learning of values
  - Policy still fixed, still doing evaluation!
  - Move values toward value of whatever successor occurs: running average

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

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

Same update:
\[
V^\pi(s) \leftarrow V^\pi(s) + \alpha(\text{sample} - V^\pi(s))
\]
Exponential Moving Average

- Exponential moving average
  - The running interpolation update: \( \bar{x}_n = (1 - \alpha) \cdot \bar{x}_{n-1} + \alpha \cdot x_n \)
  - Makes recent samples more important
  - Forgets about the past (distant past values were wrong anyway)

- Decreasing learning rate (alpha) can give converging averages
Example: Temporal Difference Learning

States

Assume: \( \gamma = 1, \alpha = 1/2 \)

Observed Transitions

\[
V^\pi(s) \leftarrow (1 - \alpha)V^\pi(s) + \alpha \left[ R(s, \pi(s), s') + \gamma V^\pi(s') \right]
\]
Problems with TD Value Learning

- TD value leaning is a model-free way to do policy evaluation, mimicking Bellman updates with running sample averages.
- However, if we want to turn values into a (new) policy, we’re sunk:

\[ \pi(s) = \arg \max_a Q(s, a) \]

\[ Q(s, a) = \sum_{s'} T(s, a, s') \left[ R(s, a, s') + \gamma V(s') \right] \]

- Idea: learn Q-values, not values.
- Makes action selection model-free too!
Active Reinforcement Learning
Active Reinforcement Learning

- Full reinforcement learning: optimal policies (like value iteration)
  - 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!
  - Fundamental tradeoff: exploration vs. exploitation
  - This is NOT offline planning! You actually take actions in the world and find out what happens…
Detour: Q-Value Iteration

- Value iteration: find successive (depth-limited) values
  - Start with $V_0(s) = 0$, which we know is right
  - Given $V_k$, calculate the depth $k+1$ values for all states:
    $$V_{k+1}(s) \leftarrow \max_a \sum_{s'} T(s, a, s') \left[ R(s, a, s') + \gamma V_k(s') \right]$$

- But Q-values are more useful, so compute them instead
  - Start with $Q_0(s,a) = 0$, which we know is right
  - Given $Q_k$, calculate the depth $k+1$ q-values for all q-states:
    $$Q_{k+1}(s, a) \leftarrow \sum_{s'} T(s, a, s') \left[ R(s, a, s') + \gamma \max_{a'} Q_k(s', a') \right]$$
Q-Learning

- Q-Learning: sample-based Q-value iteration
  \[ Q_{k+1}(s, a) \leftarrow \sum_{s'} T(s, a, s') \left[ R(s, a, s') + \gamma \max_{a'} Q_k(s', a') \right] \]

- Learn Q(s,a) values as you go
  - Receive a sample (s,a,s',r)
  - Consider your old estimate: \( Q(s, a) \)
  - Consider your new sample estimate:
    \[ \text{sample} = R(s, a, s') + \gamma \max_{a'} Q(s', a') \]
    no longer policy evaluation!
  - Incorporate the new estimate into a running average:
    \[ Q(s, a) \leftarrow (1 - \alpha)Q(s, a) + (\alpha) [\text{sample}] \]
Q-Learning Demo
Video of Demo Q-Learning -- Gridworld
Video of Demo Q-Learning -- Crawler
Q-Learning: act according to current optimal (and also explore…)

- Full reinforcement learning: optimal policies (like value iteration)
  - 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!
  - Fundamental tradeoff: exploration vs. exploitation
  - This is NOT offline planning! You actually take actions in the world and find out what happens…
Q-Learning Properties

- Amazing result: Q-learning converges to optimal policy -- even if you’re acting suboptimally!

- 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
  - Basically, in the limit, it doesn’t matter how you select actions
Discussion: Model-Based vs Model-Free RL

- Model-Based vs. Model Free
- Active vs. Passive
Recap: Reinforcement Learning

- Still assume a Markov decision process (MDP):
  - A set of states \( s \in S \)
  - A set of actions (per state) \( A \)
  - A model \( T(s,a,s') \)
  - A reward function \( R(s,a,s') \)
- Still looking for a policy \( \pi(s) \)
- New twist: don’t know \( T \) or \( R \)
  - I.e. we don’t know which states are good or what the actions do
  - Must actually try actions and states out to learn
- Big Idea: Compute all averages over \( T \) using sample outcomes
## The Story So Far: MDPs and RL

### Known MDP: Offline Solution

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<thead>
<tr>
<th>Goal</th>
<th>Technique</th>
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<tbody>
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<td>Compute $V^<em>, Q^</em>, \pi^*$</td>
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<td>Evaluate a fixed policy $\pi$</td>
<td>Policy evaluation</td>
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### Unknown MDP: Model-Based

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<tr>
<td>Compute $V^<em>, Q^</em>, \pi^*$</td>
<td>VI/PI on approx. MDP</td>
</tr>
<tr>
<td>Evaluate a fixed policy $\pi$</td>
<td>PE on approx. MDP</td>
</tr>
</tbody>
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### Unknown MDP: Model-Free

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<tbody>
<tr>
<td>Compute $V^<em>, Q^</em>, \pi^*$</td>
<td>Q-learning</td>
</tr>
<tr>
<td>Evaluate a fixed policy $\pi$</td>
<td>Value Learning</td>
</tr>
</tbody>
</table>
Model-Free Learning

- act according to current optimal (based on Q-Values)
- but also explore…
Q-Learning

- Q-Learning: sample-based Q-value iteration
  \[ Q_{k+1}(s, a) \leftarrow \sum_{s'} T(s, a, s') \left[ R(s, a, s') + \gamma \max_{a'} Q_k(s', a') \right] \]

- Learn Q(s,a) values as you go
  - Receive a sample (s,a,s',r)
  - Consider your old estimate \( Q(s, a) \)
  - Consider your new sample estimate:
    \[ \text{sample} = R(s, a, s') + \gamma \max_{a'} Q(s', a') \]
    no longer policy evaluation!
  - Incorporate the new estimate into a running average:
    \[ Q(s, a) \leftarrow (1 - \alpha)Q(s, a) + (\alpha)\text{[sample]} \]
Q-Learning:
act according to current optimal (and also explore…)

- Full reinforcement learning: optimal policies (like value iteration)
  - 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!
  - Fundamental tradeoff: exploration vs. exploitation
  - This is NOT offline planning! You actually take actions in the world and find out what happens…
Q-Learning Properties

- Amazing result: Q-learning converges to optimal policy -- even if you’re acting suboptimally!

- 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
  - Basically, in the limit, it doesn’t matter how you select actions
Exploration vs. Exploitation
How to Explore?

- Several schemes for forcing exploration
  - Simplest: random actions ($\epsilon$-greedy)
    - Every time step, flip a coin
    - With (small) probability $\epsilon$, act randomly
    - With (large) probability $1-\epsilon$, act on current policy

- Problems with random actions?
  - You do eventually explore the space, but keep thrashing around once learning is done
  - One solution: lower $\epsilon$ over time
  - Another solution: exploration functions
Exploration Functions

- **When to explore?**
  - Random actions: explore a fixed amount
  - Better idea: explore areas whose badness is not (yet) established, eventually stop exploring

- **Exploration function**
  - Takes a value estimate $u$ and a visit count $n$, and returns an optimistic utility, e.g. $f(u, n) = u + k/n$

  Regular Q-Update: $Q(s, a) \leftarrow \alpha R(s, a, s') + \gamma \max_{a'} Q(s', a')$

  Modified Q-Update: $Q(s, a) \leftarrow \alpha R(s, a, s') + \gamma \max_{a'} f(Q(s', a'), N(s', a'))$

  - Note: this propagates the “bonus” back to states that lead to unknown states as well!

[Demo: exploration – Q-learning – crawler – exploration function (L11D4)]
Q-Learn Epsilon Greedy
Video of Demo Q-learning – Epsilon-Greedy – Crawler
Video of Demo Q-learning – Exploration Function – Crawler
Regret

- Even if you learn the optimal policy you still make mistakes along the way!
- Regret is a measure of your total mistake cost: the difference between your (expected) rewards and optimal (expected) rewards.
- Minimizing regret goes beyond learning to be optimal – it requires optimally learning to be optimal.
- Example: random exploration and exploration functions both end up optimal, but random exploration has higher regret.
Approximate Q-Learning
Generalizing Across States

- Basic Q-Learning keeps a table of all q-values

- In realistic situations, we cannot possibly learn about every single state!
  - Too many states to visit them all in training
  - Too many states to hold the q-tables in memory

- Instead, we want to generalize:
  - Learn about some small number of training states from experience
  - Generalize that experience to new, similar situations
  - This is a fundamental idea in machine learning, and we'll see it over and over again
Video of Demo Q-Learning Pacman – Tiny – Watch All
Video of Demo Q-Learning Pacman – Tiny – Silent Train
Video of Demo Q-Learning Pacman – Tricky – Watch All
Example: Pacman

Let’s say we discover through experience that this state is bad:

In naïve q-learning, we know nothing about this state:

Or even this one!
Feature-Based Representations

- **Solution:** describe a state using a vector of features (properties)
  - Features are functions from states to real numbers (often 0/1) that capture important properties of the state
  - Example features:
    - Distance to closest ghost
    - Distance to closest dot
    - Number of ghosts
    - $\frac{1}{\text{dist to dot}^2}$
    - Is Pacman in a tunnel? (0/1)
    - ...... etc.
    - Is it the exact state on this slide?
  - Can also describe a q-state $(s, a)$ with features (e.g. action moves closer to food)
Linear Value Functions

- Using a feature representation, we can write a q function (or value function) for any state using a few weights:

  \[ V(s) = w_1 f_1(s) + w_2 f_2(s) + \ldots + w_n f_n(s) \]

  \[ Q(s, a) = w_1 f_1(s, a) + w_2 f_2(s, a) + \ldots + w_n f_n(s, a) \]

- Advantage: our experience is summed up in a few powerful numbers

- Disadvantage: states may share features but actually be very different in value!
Approximate Q-Learning

\[ Q(s, a) = w_1 f_1(s, a) + w_2 f_2(s, a) + \ldots + w_n f_n(s, a) \]

- Q-learning with linear Q-functions:
  
  \[
  \text{transition} = (s, a, r, s') \\
  \text{difference} = \left[ r + \gamma \max_{a'} Q(s', a') \right] - Q(s, a) \\
  Q(s, a) \leftarrow Q(s, a) + \alpha \text{ [difference]} \\
  w_i \leftarrow w_i + \alpha \text{ [difference]} f_i(s, a)
  \]

- Intuitive interpretation:
  - Adjust weights of active features
  - E.g., if something unexpectedly bad happens, blame the features that were on: disprefer all states with that state’s features

- Formal justification: online least squares
Example: Q-Pacman

\[ Q(s, a) = 4.0 \cdot f_{\text{DOT}}(s, a) - 1.0 \cdot f_{\text{GST}}(s, a) \]

\[ f_{\text{DOT}}(s, \text{NORTH}) = 0.5 \]
\[ f_{\text{GST}}(s, \text{NORTH}) = 1.0 \]

\[ Q(s, \text{NORTH}) = +1 \]
\[ r + \gamma \max_{a'} Q(s', a') = -500 + 0 \]

\[ \text{difference} = -501 \]

\[ w_{\text{DOT}} \leftarrow 4.0 + \alpha [-501] 0.5 \]
\[ w_{\text{GST}} \leftarrow -1.0 + \alpha [-501] 1.0 \]

\[ Q(s, a) = 3.0 \cdot f_{\text{DOT}}(s, a) - 3.0 \cdot f_{\text{GST}}(s, a) \]
Video of Demo Approximate Q-Learning -- Pacman
Q-Learning and Least Squares
Linear Approximation: Regression

Prediction:
\[ \hat{y} = w_0 + w_1 f_1(x) \]

Prediction:
\[ \hat{y}_i = w_0 + w_1 f_1(x) + w_2 f_2(x) \]
Optimization: Least Squares

\[
\text{total error} = \sum_i (y_i - \hat{y}_i)^2 = \sum_i \left( y_i - \sum_k w_k f_k(x_i) \right)^2
\]
Minimizing Error

Imagine we had only one point \( x \), with features \( f(x) \), target value \( y \), and weights \( w \):

\[
\text{error}(w) = \frac{1}{2} \left( y - \sum_k w_k f_k(x) \right)^2
\]

\[
\frac{\partial \text{error}(w)}{\partial w_m} = - \left( y - \sum_k w_k f_k(x) \right) f_m(x)
\]

\[
w_m \leftarrow w_m + \alpha \left( y - \sum_k w_k f_k(x) \right) f_m(x)
\]

Approximate q update explained:

\[
w_m \leftarrow w_m + \alpha \left[ r + \gamma \max_a Q(s', a') - Q(s, a) \right] f_m(s, a)
\]

“target” \hspace{1cm} “prediction”
Overfitting: Why Limiting Capacity Can Help
New in Model-Free RL
Playing Atari Games
Policy Search
Policy Search

- Problem: often the feature-based policies that work well (win games, maximize utilities) aren’t the ones that approximate $V / Q$ best
  - E.g. your value functions from project 2 were probably horrible estimates of future rewards, but they still produced good decisions
  - Q-learning’s priority: get Q-values close (modeling)
  - Action selection priority: get ordering of Q-values right (prediction)

- Solution: learn policies that maximize rewards, not the values that predict them

- Policy search: start with an ok solution (e.g. Q-learning) then fine-tune by hill climbing on feature weights
Policy Search

- Simplest policy search:
  - Start with an initial linear value function or Q-function
  - Nudge each feature weight up and down and see if your policy is better than before

- Problems:
  - How do we tell the policy got better?
  - Need to run many sample episodes!
  - If there are a lot of features, this can be impractical

- Better methods exploit lookahead structure, sample wisely, change multiple parameters…
RL: Learning Soccer

[Bansal et al, 2017]
## Summary: MDPs and RL

### Known MDP: Offline Solution

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<th>Goal</th>
<th>Technique</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compute $V^<em>$, $Q^</em>$, $\pi^*$</td>
<td>VI/PI on approx. MDP</td>
</tr>
<tr>
<td>Evaluate a fixed policy $\pi$</td>
<td>PE on approx. MDP</td>
</tr>
</tbody>
</table>

### Unknown MDP: Model-Free

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<tbody>
<tr>
<td>Compute $V^<em>$, $Q^</em>$, $\pi^*$</td>
<td>Q-learning</td>
</tr>
<tr>
<td>Evaluate a fixed policy $\pi$</td>
<td>Value Learning</td>
</tr>
</tbody>
</table>
Conclusion

- We’ve seen how AI methods can solve problems in:
  - Search
  - Games
  - Markov Decision Problems
  - Reinforcement Learning

- Next up: Uncertainty and Learning!