AI Planning for Autonomy

11. Reinforcement Learning

How to learn without a model

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Planning and Learning

So far, the AI Plannning course:

- Planning required a **complete** description of the world/problem/environment.
- If we allow **stochasticity** but still **fully known** environments (e.g. Backgammon), we arrive at a Stochastic Planning problem (MDP).
- If we deal with an **unknown** environment, which can only be **learned through experience**, we get a machine learning problem.

Reinforcement Learning $\approx$ Learning + Planning

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Intuition

With value & policy iteration, we know the MDP model; that is, we know what happens when actions are performed and what rewards are received.

In reinforcement learning, there is an MDP model that dictates what happens when actions are performed and what the rewards are (that is, the world behaves like an MDP), **BUT**, the we do not know this information. We must *learn* it.

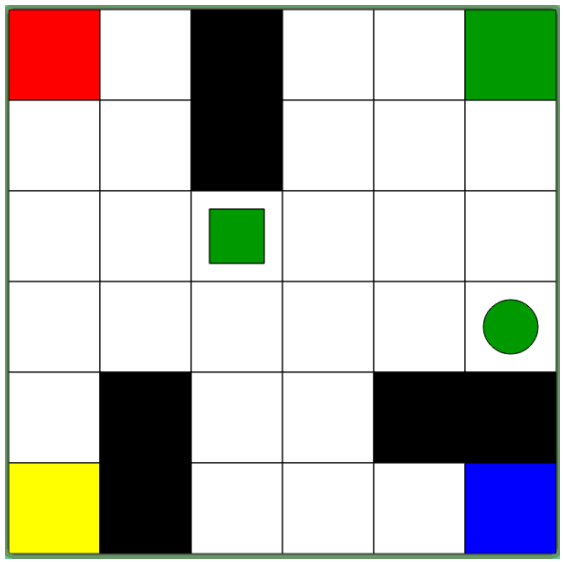
Assumptions:

- The agent does **not** know the environment (which is an MDP).
- The agent **experiences** the environment by **interacting** with it.
- The environment is **revealed** to agent in the form of a **state** s.
- The agent **influences** the environment by applying actions and then receiving **rewards**.

In short, all we know is what actions the agent can do, how to read/see see the state, and how to receive rewards.

Example: The Mystery Game

https://programmingheroes.blogspot.com/2016/02/udacity-reinforcement-learning-mystery-game.html



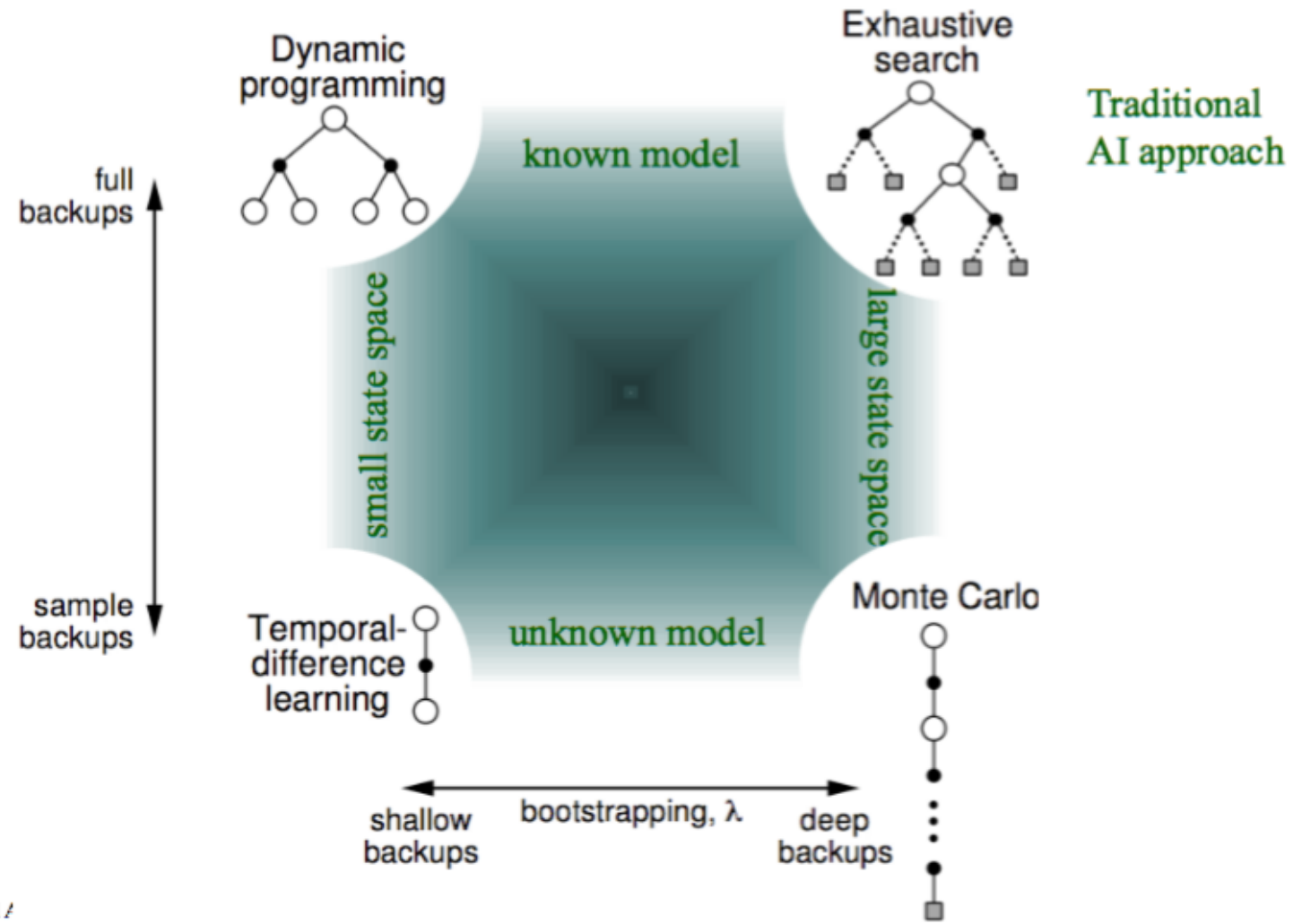
From the website (in Spanish): The aim of this game is to experiment how computers learn. Press keys from 1 to 6 to do actions. You need to learn what the actions produce and how to win the game.
Some rewards values appears when you do the things very well or very bad. When you finish the game the phrase "You Win :)" appears in the board. Good luck!

Example: Mystery Game (continued)

- What was the process you took?
- What did you learn?
- What assumptions did you use?

$\rightarrow$ Imagine how hard it is for a computer that doesn't have any assumptions or intuition!

Approaches to AI Planning and Learning



Reinforcement Learning: The Basics

There are many different models of reinforcement learning, all with the same basis:

- We execute many different *episodes* of the problem we want to solve, and from that we learnt a *policy*.
- During learning, we try to learn the value of applying particular actions in particular states.
- During each episode, we need to execute some actions. After each action, we get a reward (which may be 0) and we can see the new state.
- From this, we *reinforce* our estimates of applying the previous action in the previous state.
- We terminate when: (1) we run out of training time; (2) we think our policy has converged to the optimal policy (for each new episode we see no improvement); or (3) our policy is 'good enough' (for each new episode we see minimal improvement).

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Q-Learning

Q-Learning is perhaps the simplest of reinforcement learning methods, and is based on how animals learn from their environment. The intuition is quite straightforward. Maintain a Q-function that records $Q(s, a)$ for every state-action pair. At each step: (1) choose an action using a multi-armed bandit algorithm; (2) apply that action and receive the reward; and (3) update $Q(s, a)$ based on that reward. Repeat over a number of episodes until . . . when?

Initialize $Q(s, a)$ arbitrarily
Repeat (for each episode):
  Initialize s
  Repeat (for each step of episode):
    Choose a from s using policy derived from Q (e.g., ε-greedy)
    Take action a, observe r, s'
    $Q(s, a) \leftarrow Q(s, a) + \alpha\left[r + \gamma \max_{a'} Q(s', a') - Q(s, a)\right]$
    $s \leftarrow s'$;
  until s is terminal

Figure: Q-Learning Algorithm (from Sutton and Barto)

Updating the Q-function

Updating the Q-function (line 7) is where the learning happens:

$$Q(s,a) \leftarrow \underbrace{Q(s,a)}_{\text{old value}} + \overbrace{\alpha}^{\text{learning rate}} \cdot [\underbrace{r}_{\text{reward}} + \overbrace{\gamma}^{\text{discount factor}} \cdot \underbrace{\max_{a'} Q(s',a')}_{\text{estimate of optimal future value}} \overbrace{-Q(s,a)}^{\text{do not count extra } Q(s,a)}]$$

A higher learning rate α will weight more recent information higher than older information ($Q(s,a)$).

Note that we estimate the future value using $\max_{a'} Q(s',a')$, which means it *ignores* the action chosen by the policy, and instead updates based on the estimate of the best action for the update. This is known as *off policy* learning – more later.

Q-functions using Q-Tables

Q-tables are the simplest way to maintain a Q-function. They are a table with an entry for every $Q(s, a)$. Thus, like value functions in value iteration, they do not scale to large state-spaces. (More on scaling in the next lecture).

Initially

State	Action			
	North	South	East	West
(0,0)	0	0	0	0
(0,1)	0	0	0	0
...				
(2,2)	0	0	0	0
(2,3)	0	0	0	0

After some training

State	Action			
	North	South	East	West
(0,0)	0.53	0.36	0.36	0.21
(0,1)	0.61	0.27	0.23	0.23
...				
(2,2)	0.79	0.72	0.90	0.72
(2,3)	0.90	0.78	0.99	0.81

Q-learning: Example

After some training

State	Action			
	North	South	East	West
(0,0)	0.53	0.36	0.36	0.21
(0,1)	0.61	0.27	0.23	0.23
...				
(2,2)	0.79	0.72	0.90	0.72
(2,3)	0.90	0.78	0.99	0.81

In state (2,2), the action 'North' is chosen and executed successfully, which would return to state (2,2) there is no cell above (2,2). Using the Q-table above, we would update the Q-value as follows:

$$
\begin{aligned}
Q((2,2),N) &\leftarrow Q((2,2),N) + \alpha[r + \gamma \max_{a'} Q((2,2),a') - Q((2,2),N)] \\
&\leftarrow 0.79 + 0.1[0 + 0.9 \cdot Q((2,2),East) - Q((2,2),N)] \\
&\leftarrow 0.79 + 0.1[0 + 0.9 \cdot 0.90 - 0.79] \\
&\leftarrow 0.792
\end{aligned}
$$

Using Q-functions

We iterate over as many episodes as possible, or until each episode hardly improves our Q-values. This gives us a (close to) optimal Q-function.

Once we have such a Q-function, we stop exploring and just exploit. We use *policy extraction*, which is exactly as we do for value iteration:

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

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SARSA: On-Policy Reinforcement Learning

SARSA = State-action-reward-state-action

On-Policy: Instead of estimating $Q(s', a')$ for the best estimated future state during update, on-policy uses the actual next action to update:

- On-policy learning estimates $\mathcal{Q}^{\pi}(s, a)$ state action pairs, for the current behaviour policy π, whereas off-policy learning estimates the policy independent of the current behaviour.

Initialize $Q(s, a)$ arbitrarily
Repeat (for each episode):
  Initialize s
  Choose a from s using policy derived from Q (e.g., ε-greedy)
  Repeat (for each step of episode):
    Take action a, observe r, s'
    Choose a' from s' using policy derived from Q (e.g., ε-greedy)
    $Q(s, a) \leftarrow Q(s, a) + \alpha\left[r + \gamma Q(s', a') - Q(s, a)\right]$
    $s \leftarrow s'$; $a \leftarrow a'$;
  until s is terminal

On-Policy: Uses the action chosen by the policy for the update!

Q-learning vs. SARSA

Initialize $Q(s, a)$ arbitrarily
Repeat (for each episode):
  Initialize s
  Repeat (for each step of episode):
    Choose a from s using policy derived from Q (e.g., ε-greedy)
    Take action a, observe r, s'
    $Q(s, a) \leftarrow Q(s, a) + \alpha\left[r + \gamma \max_{a'} Q(s', a') - Q(s, a)\right]$
    $s \leftarrow s'$;
  until s is terminal

Figure: Q-Learning Algorithm

Initialize $Q(s, a)$ arbitrarily
Repeat (for each episode):
  Initialize s
  Choose a from s using policy derived from Q (e.g., ε-greedy)
  Repeat (for each step of episode):
    Take action a, observe r, s'
    Choose a' from s' using policy derived from Q (e.g., ε-greedy)
    $Q(s, a) \leftarrow Q(s, a) + \alpha\left[r + \gamma Q(s', a') - Q(s, a)\right]$
    $s \leftarrow s'$; $a \leftarrow a'$;
  until s is terminal

Figure: Sarsa Algorithm

Off-Policy: Ignores the action chosen by the policy, uses the best action $\text{argmax}_{a'} \mathcal{Q}(s', a')$ for the update!

On-Policy SARSA learns action values relative to the policy it follows, while Off-Policy Q-Learning does it relative to the greedy policy.

On-policy vs. off-policy: What is the difference here?

The difference is all in how the update happens in the loop body.

Q-learning: (1) selects an action a; (2) takes that actions and observes the reward & next state s'; and (3) updates *optimistically* by assuming the future reward is $\max_{a'} Q(s', a')$ – that is, it assumes that future behaviour will be optimal (according to its policy).

SARSA: (1) selects action a' for the *next* loop iteration; (2) in the next iteration, takes that action and observes the reward & next state s'; (3) only then chooses a' for the next iteration; and (4) updates using the estimate for the actual next action chosen – which may not be the greediest one (e.g. it could be selected so that it can explore).

SARSA: Example

After some training

State	Action			
	North	South	East	West
(0,0)	0.53	0.36	0.36	0.21
(0,1)	0.61	0.27	0.23	0.23
...				
(2,2)	0.79	0.72	0.90	0.72
(2,3)	0.90	0.78	0.99	0.81

In state (2,2), the action 'North' is chosen and executed successfully, which would return to state (2,2) there is no cell above (2,2). The next selected action is West. Using the Q-table above, we would update the Q-value using SARSA as follows:

$$\begin{aligned} Q((2,2),N) &\leftarrow Q((2,2),N) + \alpha[r + \gamma Q((2,2),W) - Q((2,2),N)] \\ &\leftarrow 0.79 + 0.1[0 + 0.9 \cdot Q((2,2),W) - Q((2,2),N)] \\ &\leftarrow 0.79 + 0.1[0 + 0.9 \cdot 0.72 - 0.79] \\ &\leftarrow 0.7828 \end{aligned}$$

On-policy vs. off-policy: Who cares??

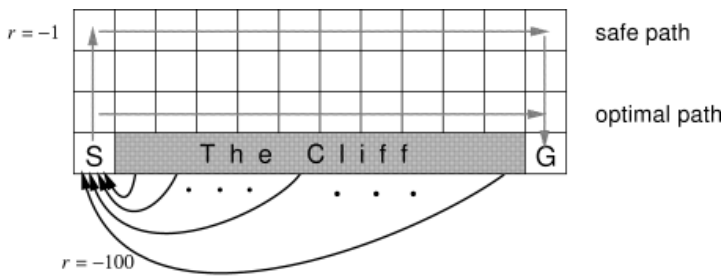
So what difference does this really make? There are two main differences:

- Q-learning will converge to the optimal policy irrelevant of the policy followed, because it is *off-policy*: it uses the greedy reward estimate in its update rather than following the policy such as ϵ-greedy). Using a random policy, Q-learning will still converge to the optimal policy, but SARSA will not (necessarily).
- Q-learning learns an optimal policy, but this can be 'unsafe' or risky *during training*.

SARSA vs. Q-learning: Example

Consider the grid below. S is the start and state G receives a reward of 100. Falling off the cliff receives a reward of -100. Going to the top row receives a -1 reward. Actions are deterministic, but they are not known before learning.

Q-learning leads the optimal path along (along the edge of the cliff), but will fall off sometimes due to the ϵ-greedy action selection. SARSA learns the safe path because it is on-policy and considers the action select method when learning. Here is a graph showing the reward per trial for both Sarsa and Q-Learning:



Rewards during training

SARSA receives a higher average reward *per trial* than Q-Learning, because it falls off the cliff less in later episodes. However, Q-learning learns the *optimal* policy.

Demo of the cliff example: `https://studywolf.wordpress.com/2013/07/01/reinforcement-learning-sarsa-vs-q-learning/`

On-policy vs. off policy: Why do we have both?

- On-policy learning is more appropriate when we want to optimise the behaviour of an agent who learns *while operating in its environment*.

  Imagine if we had 1000 robots that needed to navigate to the other side and each time one fell off the cliff, we lost it; but also we could get each robots Q-function after each episode. Given that the average reward *per trial* is better, this would give us better overall outcomes than Q-learning.
- Off-policy learning is more appropriate when we have the luxury of training our agent offline before it is put into operation.

  That is, imagine if we could run 1000 training episodes on a fake cliff scenario *before* (that is, off-line) we had to move our robots to the other side. In this case, Q-learning would be better because its optimal policy could be followed.

In short: use on-policy reinforcement learning for online learning, and off-policy learning for offline learning.

Example: if we used reinforcement learning for traffic light optimisation, we would use on-policy reinforcement learning, because we could not train it before hand.

Q-learning Examples in Action

In action: solving the cliff example using Q-learning with ϵ-greedy:

`https://www.youtube.com/watch?v=ppALjH0kYPE`

The source code for this:

`https://github.com/alecKarfonta/Gridworld`

Worked example: a complete worked example of using Q-learning to calculate the optimal path:

`http://www.mnemstudio.org/path-finding-q-learning-tutorial.htm`

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Summary

If we know the MDP:

- **Offline**: Value Iteration, Policy Iteration,
- **Online**: Monte Carlo Search Tree and friends.

If we do *not* know MDP:

- **Offline**: Reinforcement Learning
- **Online**: Monte Carlo Tree Search and friends.

Once you've got your pacman Q-learning working in python (bonus exercise in next week's workshop), you can test it on all the environments on OpenAI, Toolkit for developing and testing reinforcement learning algorithms:

`https://gym.openai.com/`

Applications of Reinforcement Learning

- Checkers (Samuel, 1959)
  first use of RL in an interesting real game
- (Inverted) Helicopter Flight (Ng et al. 2004)
  better than any human
- Computer Go (AlphaGo 2016)
  AlphaGo beats Go world champion Lee Sedol 4:1
- Atari 2600 Games (DQN & Blob-PROST 2015)
  human-level performance on half of 50+ games
- Robocup Soccer Teams (Stone & Veloso, Reidmiller et al.)
  World's best player of simulated soccer, 1999; Runner-up 2000
- Inventory Management (Van Roy, Bertsekas, Lee & Tsitsiklis)
  10-15% improvement over industry standard methods
- Dynamic Channel Assignment (Singh & Bertsekas, Nie & Haykin)
  World's best assigner of radio channels to mobile telephone calls
- Elevator Control (Crites & Barto)
  (Probably) world's best down-peak elevator controller
- Many Robots
  navigation, bi-pedal walking, grasping, switching between skills, ...
- TD-Gammon and Jellyfish (Tesauro, Dahl)
  World's best backgammon player. Grandmaster level

Applications of Deep Reinforcement Learning

A great application of using off-policy updates in deep Q-learning for robotic arms to learn how to grasp unknown objects. The only input for the problem is the camera data:
`https://www.youtube.com/watch?v=cXaic_k80uM&feature=youtu.be`

Reading

- *Introduction to Reinforcement Learning* [*Sutton and Barto*]

  Available at:

  `https://webdocs.cs.ualberta.ca/~sutton/book/the-book.html`

  Content: Great entry level book to Reinforcement Level written by the founders of the field.

- *Slides about Approximate Q-learning for PacMan*

  Available at:

  `https://www.cs.swarthmore.edu/~bryce/cs63/s16/slides/3-25_approximate_Q-learning.pdf`

  Content: Great technique if you want to use reinforcement learning for the competition!

- *Deep Q-learning for Atari*

  Available at:

  `http://www.davidqiu.com:8888/research/nature14236.pdf`

  Content: Convolutional Neural Networks (NN) to estimate $\mathcal{Q}(s, a)$. The input for the NN is the state, and the output is the esimated reward for each action.