Sequential Decision Making II
— Week #12
Brief recap

- Markov Decision Processes (MDP)
  - Offer a framework for sequential decision making
    \[ \langle A, S, P, R, \gamma \rangle \]
  - Goal: find the optimal policy
- Dynamic programming several algorithms (e.g., VI, PI)
From MDPs to RL

• In MDPs we assume that we know

1. Transition probabilities: $P(s' \mid s, a)$
2. Reward function: $R(s)$

• RL is more general

• In RL both are typically unknown

• RL agents navigate the world to gather this information
Experience (I)

A. Supervised Learning:
   - Given fixed dataset
   - Goal: maximize objective on test set (population)

B. Reinforcement Learning
   - Collect data as agent interacts with the world
   - Goal: maximize sum of rewards
Experience (II)

• Any supervised learning problem can be mapped to a reinforcement learning problem
  • Loss function can be used as a reward function
  • Dependent variables (Y) become the actions
  • States encode information from the independent variables (x)
  • Such mapping isn’t very useful in practice
    • SL is easier than RL
Example

Supervised Learning

Don't touch your tongue will get stuck.

Reinforcement Learning

Slide adapted from Pascal Poupart

RL applications

• Key: decision making over time, uncertain environments.

• Robot navigation: Self-driving cars, helicopter control

• Interactive systems: recommender systems, chatbots

• Game playing: Backgammon, go.

• Healthcare: monitoring systems.
Reinforcement learning and recommender systems

• Most users have multiple interactions with the system over time.

• Making recommendations over time can be advantageous (e.g., you could better explore one's preference).

• States: Some representation of user preferences (e.g., previous items they consumed).

• Actions: what to recommend.

• Reward:
  • + user consumes the recommendation.
  • - user does not consume the recommendation.
Challenges of reinforcement learning
Challenges of reinforcement learning

- Credit assignment problem: which action(s) should be credited for obtaining a reward

- A series of actions (getting coffee from cafeteria)

- A small number of actions several time steps ago may be important (test taking: study before, getting grade long after)

- Exploration/Exploitation tradeoff: As agent interacts should it exploit its current knowledge (exploitation) or seek out additional information (exploration)
Algorithms for RL

- Two main classes of approach
Algorithms for RL

• Two main classes of approach

1. Model-based

• Learns a model of the transition and uses it to optimize a policy given the model
Algorithms for RL

• Two main classes of approach

  1. Model-based

      • Learns a model of the transition and uses it to optimize a policy given the model

  2. Model-free

      • Learns an optimal policy without explicitly learning transitions
Monte Carlo Methods

- Model-free
- Assume the environment is episodic
  - Think of a poker hand
  - Updates the policy after each episode
- Intuition
  - Experience many episodes
    - Play many hands of poker
  - Average the rewards received at each state
    - What is the proportion of wins of each hand
Prediction vs. control

1. Prediction: evaluate a given policy

2. Control: Learn a policy
   - Sometimes also called
     - passive (prediction)
     - active (control)
First-visit Monte Carlo

- Given a fixed policy (prediction)
- Calculate the value function $v(s)$ for each state
- Converges to $v_{\pi}(s)$ as the number of visits to each state goes to infinity

[Sutton & Barto, RL Book, Ch 5]
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy $\pi$ is given (gray arrows)

Episode:

First-visit MC prediction, for estimating $V \approx v_\pi$

Initialize:
- $\pi \leftarrow$ policy to be evaluated
- $V \leftarrow$ an arbitrary state-value function
- $\text{Returns}(s) \leftarrow$ an empty list, for all $s \in S$

Repeat forever:
- Generate an episode using $\pi$
- For each state $s$ appearing in the episode:
  - $G \leftarrow$ the return that follows the first occurrence of $s$
  - Append $G$ to $\text{Returns}(s)$
  - $V(s) \leftarrow$ average($\text{Returns}(s)$)
Example: grid world

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Example: grid world

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Episode: (1, $\rightarrow$)
Example: grid world

- Start state is top-left (start of episode)
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Episode: $(1, \rightarrow )$
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy $\pi$ is given (gray arrows)

Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow)$
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy $\pi$ is given (gray arrows)

Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow)$
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy $\pi$ is given (gray arrows)

Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow) \rightarrow (3, \downarrow)$
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy $\pi$ is given (gray arrows)

Episode: (1, $\rightarrow$) $\rightarrow$ (2, $\rightarrow$) $\rightarrow$ (3, $\downarrow$)
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy $\pi$ is given (gray arrows)

Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow) \rightarrow (3, \downarrow) \rightarrow (7, \downarrow)$
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy $\pi$ is given (gray arrows)

Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow) \rightarrow (3, \downarrow) \rightarrow (7, \downarrow)$
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy $\pi$ is given (gray arrows)

Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow) \rightarrow (3, \downarrow) \rightarrow (7, \downarrow) \rightarrow (6, \rightarrow)$
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy $\pi$ is given (gray arrows)

Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow) \rightarrow (3, \downarrow) \rightarrow (7, \downarrow) \rightarrow (6, \rightarrow)$
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy $\Pi$ is given (gray arrows)

Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow) \rightarrow (3, \downarrow) \rightarrow (7, \downarrow) \rightarrow (6, \rightarrow) \rightarrow (7, \downarrow)$
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy \( \pi \) is given (gray arrows)

Episode: (1, \( \rightarrow \)) \( \rightarrow \) (2, \( \rightarrow \)) \( \rightarrow \) (3, \( \downarrow \)) \( \rightarrow \) (7, \( \downarrow \)) \( \rightarrow \) (6, \( \rightarrow \)) \( \rightarrow \) (7, \( \downarrow \))
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy $\pi$ is given (gray arrows)

Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow) \rightarrow (3, \downarrow) \rightarrow (7, \downarrow) \rightarrow (6, \rightarrow) \rightarrow (7, \downarrow) \rightarrow (10, \downarrow)$
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy \( \pi \) is given (gray arrows)

Episode: 🩺 ← (1, →) → (2, →) → (3, ↓) → (7, ↓) → (6, →) → (7, ↓) → (10, ↓)
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy $\pi$ is given (gray arrows)

Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow) \rightarrow (3, \downarrow) \rightarrow (7, \downarrow) \rightarrow (6, \rightarrow) \rightarrow (7, \downarrow) \rightarrow (10, \downarrow) \rightarrow (13, \downarrow)$
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy $\pi$ is given (gray arrows)

Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow) \rightarrow (3, \downarrow) \rightarrow (7, \downarrow) \rightarrow (6, \rightarrow) \rightarrow (7, \downarrow) \rightarrow (10, \downarrow) \rightarrow (13, \downarrow)$
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Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow) \rightarrow (3, \downarrow) \rightarrow (7, \downarrow) \rightarrow (6, \rightarrow) \rightarrow (7, \downarrow) \rightarrow (10, \downarrow) \rightarrow (13, \downarrow) \rightarrow (17, \rightarrow)$
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For state 7:
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy $\pi$ is given (gray arrows)

Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow) \rightarrow (3, \downarrow) \rightarrow (7, \downarrow) \rightarrow (6, \rightarrow) \rightarrow (7, \downarrow) \rightarrow (10, \downarrow) \rightarrow (13, \downarrow) \rightarrow (17, \rightarrow)$

For state 7: $\text{return}(7) = \gamma R(6) + \gamma^2 R(7) + \gamma^3 R(10) + \gamma^4 R(13) + \gamma^5 R(17) + \gamma^6 R(18) = \gamma^6 10$
Example: grid world

- Start state is top-left (start of episode)
- Bottom right is absorbing (end of episode)
- Policy $\pi$ is given (gray arrows)

Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow) \rightarrow (3, \downarrow) \rightarrow (7, \downarrow) \rightarrow (6, \rightarrow) \rightarrow (7, \downarrow) \rightarrow (10, \downarrow) \rightarrow (13, \downarrow) \rightarrow (17, \rightarrow)$

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Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow) \rightarrow (3, \downarrow) \rightarrow (7, \downarrow) \rightarrow (6, \rightarrow) \rightarrow (7, \downarrow) \rightarrow (10, \downarrow) \rightarrow (13, \downarrow) \rightarrow (17, \rightarrow)$

For state 7:

\[
\text{return}(7) = \gamma R(6) + \gamma^2 R(7) + \gamma^3 R(10) + \gamma^4 R(13) + \gamma^5 R(17) + \gamma^6 R(18) \\
= \gamma^6 10
\]

\[
V(7) = \gamma^6 \times 10
\]
Example: Black Jack

- Episode: one hand
- States: Sum of player’s cards, dealer’s card, usable ace
- Actions: {Stay, Hit}
- Rewards: {Win +1, Tie 0, Loose -1}
- A few other assumptions: infinite deck
• Evaluates the policy that hits except when the sum of the cards is 20 or 21

[Figure 5.1, Sutton & Barto]
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[Figure 5.1, Sutton & Barto]
Q-value for control

- We know about state-value functions $V(s)$
Q-value for control

- We know about state-value functions $V(s)$

- If state transitions are known then they can be used to derive an optimal policy:

$$\pi^*(s) = \arg \max_a \left\{ R(s) + \gamma \sum_{s'} P(s' | s, a) V_i(s') \right\} \quad \forall s$$
Q-value for control

• We know about state-value functions $V(s)$

• If state transitions are known then they can be used to derive an optimal policy:

$$\pi^*(s) = \arg\max_a \left\{ R(s) + \gamma \sum_{s'} P(s' | s, a)V_i(s') \right\} \ \forall s$$

• When state transitions are unknown what can we do?

• $Q(s,a)$ the value function of a (state,action) pair

$$\pi^*(s) = \arg\max_a \{ Q(s, a) \}$$
Monte Carlo ES (control)

First-visit MC prediction, for estimating $V \approx V^*$

Initialize:
- $\pi \leftarrow$ policy to be evaluated
- $V \leftarrow$ an arbitrary state-value function
- $Returns(s) \leftarrow$ an empty list, for all $s \in \mathcal{S}$

Repeat forever:
- Generate an episode using $\pi$
- For each state $s$ appearing in the episode:
  - $G \leftarrow$ the return that follows the first occurrence of $s$
  - Append $G$ to $Returns(s)$
- $V(s) \leftarrow$ average($Returns(s)$)

Monte Carlo ES (Exploring Starts), for estimating $\pi \approx \pi^*$

Initialize, for all $s \in \mathcal{S}, a \in A(s)$:
- $Q(s, a) \leftarrow$ arbitrary
- $\pi(s) \leftarrow$ arbitrary
- $Returns(s, a) \leftarrow$ empty list

Repeat forever:
- Choose $S_0 \in \mathcal{S}$ and $A_0 \in A(S_0)$ s.t. all pairs have probability $> 0$
- Generate an episode starting from $S_0, A_0$, following $\pi$
- For each pair $s, a$ appearing in the episode:
  - $G \leftarrow$ the return that follows the first occurrence of $s, a$
  - Append $G$ to $Returns(s, a)$
- $Q(s, a) \leftarrow$ average($Returns(s, a)$)

For each $s$ in the episode:
- $\pi(s) \leftarrow \arg \max_a Q(s, a)$

[Sutton & Barto, RL Book, Ch.5]
Monte Carlo ES (control)

- Strong reasons to believe that it converges to the optimal policy
- “Exploring starts” requirement may be unrealistic
Learning without “exploring states”

- Exploring states ensure that all states can be visited regardless of the policy
- Specific policy may not visit all states
Learning without “exploring states”

• Exploring states ensure that all states can be visited regardless of the policy

• Specific policy may not visit all states

• Solution: inject some uncertainty in the policy
Monte Carlo without exploring states (on policy)

[Sutton & Barto, RL Book, Ch.5]
Monte Carlo without exploring states (on policy)

- Policy value cannot decrease
  \[ v_{\pi'}(s) \geq v_{\pi}(s), \forall s \in S \]

\[ \pi \]: policy at previous step
\[ \pi' \]: policy at previous step

[Sutton & Barto, RL Book, Ch.5]
Monte-Carlo methods summary

- Allow a policy to be learned through interactions
- States are effectively treated as being independent
- Focus on a subset of states (e.g., states for which playing optimally is of particular importance)
- Episodic (with or without exploring stats)
Temporal Difference (TD) Learning
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- One of the “central ideas of RL” [Sutton & Barto, RL book]
Temporal Difference (TD) Learning

- One of the “central ideas of RL” [Sutton & Barto, RL book]

- Monte Carlo methods

\[ V(s_t) = V(s_t) + \alpha [G_t - V(s_t)] \]

Observed return:

\[ G_t = \sum_{t}^{T} \gamma^t R(s_t) \]

Step size
Temporal Difference (TD) Learning

- One of the “central ideas of RL” [Sutton & Barto, RL book]

- Monte Carlo methods

\[ V(s_t) = V(s_t) + \alpha [G_t - V(s_t)] \]

Observed returned: \( G_t = \sum_t \gamma^t R(s_t) \)

First-visit MC prediction, for estimating \( V(s) \):

Initialize:
- \( \pi \) → policy to be evaluated
- \( V \) → an arbitrary state-value function
- \( Returns(s) \) → an empty list, for all \( s \in \mathcal{S} \)

Repeat forever:
- Generate an episode using \( \pi \)
- For each state \( s \) appearing in the episode:
  - \( G \) → the return that follows the first \( s \)
  - Append \( G \) to \( Returns(s) \)
- \( V(s) \) ← average(\( Returns(s) \))
Temporal Difference (TD) Learning

- One of the “central ideas of RL” [Sutton & Barto, RL book]

- Monte Carlo methods

- TD(0)

- updates “instantly”

\[ V(s_t) = V(s_t) + \alpha [G_t - V(s_t)] \]

\[ V(s_t) = V(s_t) + \alpha [R_{t+1} + \gamma V(s_{t+1}) - V(s_t)] \]
TD(0) for prediction

[Sutton & Barto, RL Book, Ch.6]
• Demo: http://www.cs.toronto.edu/~lcharlin/courses/80-629/reinforcejs/gridworld_td.html

(from Andrej Karpathy)
Comparing TD and MC

- MC requires going through full episodes before updating the value function. Episodic.
- Converges to the optimal solution

- TD updates each V(s) after each transition. Online.
- Converges to the optimal solution (some conditions on $\alpha$)
- Empirically TD methods tend to converge faster
Q-learning for control

Q-learning (off-policy TD control) for estimating $\pi \approx \pi_*$

1. Initialize $Q(s,a)$, for all $s \in S, a \in A(s)$, arbitrarily, and $Q(\text{terminal-state}, \cdot) = 0$
2. Repeat (for each episode):
   1. Initialize $S$
   2. Repeat (for each step of episode):
      1. Choose $A$ from $S$ using policy derived from $Q$ (e.g., $\epsilon$-greedy)
      2. Take action $A$, observe $R, S'$
      3. $Q(S, A) \leftarrow Q(S, A) + \alpha [R + \gamma \max_a Q(S', a) - Q(S, A)]$
      4. $S \leftarrow S'$
   3. until $S$ is terminal

[Sutton & Barto, RL Book, Ch.6]
Q-learning for control

$\epsilon$-greedy policy $a = \begin{cases} \arg \max_a Q(a,s) & \text{with probability } 1 - \epsilon, \\ \text{random } a & \text{with probability } \epsilon. \end{cases}$

[Sutton & Barto, RL Book, Ch.6]
Q-learning for control

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Repeat (for each step of episode):
  Choose $A$ from $S$ using policy derived from $Q$ (e.g., $\epsilon$-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

$\epsilon$-greedy policy $a = \begin{cases} \arg \max_a Q(a, s) & \text{with probability } 1 - \epsilon, \\ \text{random } a & \text{with probability } \epsilon. \end{cases}$

[Sutton & Barto, RL Book, Ch.6]
Q-learning for control

$. \epsilon$-greedy policy

\[
\begin{aligned}
\alpha &= \begin{cases} 
\text{arg max}_a Q(a, s) & \text{with probability } 1 - \epsilon, \\
\text{random } a & \text{with probability } \epsilon. 
\end{cases}
\end{aligned}
\]
Q-learning for control

Q-learning (off-policy TD control) for estimating $\pi \approx \pi_*$

Initialize $Q(s, a)$, for all $s \in S, a \in A(s)$, arbitrarily, and $Q(terminal-state, \cdot) = 0$
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  Initialize $S$
  Repeat (for each step of episode):
    Choose $A$ from $S$ using policy derived from $Q$ (e.g., $\epsilon$-greedy)
    Take action $A$, observe $R, S'$
    $Q(S, A) \leftarrow Q(S, A) + \alpha [R + \gamma \max_a Q(S', a) - Q(S, A)]$
    $S \leftarrow S'$
  until $S$ is terminal

$\epsilon$-greedy policy $a = \begin{cases} 
\arg \max_a Q(a, s) & \text{with probability } 1 - \epsilon, \\
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[Sutton & Barto, RL Book, Ch.6]
Q-learning for control

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Repeat (for each episode):
  Initialize $S$
  Repeat (for each step of episode):
    Choose $A$ from $S$ using policy derived from $Q$ (e.g., $\epsilon$-greedy)
    Take action $A$, observe $R, S'$
    $Q(S, A) \leftarrow Q(S, A) + \alpha [R + \gamma \max_{a} Q(S', a) - Q(S, A)]$
    $S \leftarrow S'$
  until $S$ is terminal

[Sutton & Barto, RL Book, Ch.6]

- Converges to $Q^*$ as long as all (s,a) pairs continue to be updated and with minor constraints on learning rate
Approximation techniques

- Methods we studied are “tabular”

- State value functions (and Q) can be approximated
  
  - Linear approximation: \( V(s) = w^T x(s) \)
    
    - Coupling between states through \( x(s) \)

- Adapt the algorithms for this case.

  - Updates to the value function now imply updating the weights \( w \) based using a gradient
Approximation techniques (prediction)

- Linear approximation: \( V(s) = w^T x(s) \)
Approximation techniques (prediction)

- Linear approximation: \( V(s) = w^T x(s) \)

- Objective: \( \sum_{s \in S} [v_\pi(s) - w^T x(s)]^2 \)
Approximation techniques (prediction)

- Linear approximation: \( V(s) = w^T x(s) \)

- Objective: \( \sum_{s \in S} [v_\pi(s) - w^T x(s)]^2 \)

- Gradient update: \( w_{t+1} = w_t - 2\alpha \sum_{s \in S} [v_\pi(s) - w^T x(s)] x(s) \)
Approximation techniques (prediction)

- Linear approximation: \( V(s) = w^\top x(s) \)

- Objective: \( \sum_{s \in S} [v_\pi(s) - w^\top x(s)]^2 \)

- Gradient update: \( w_{t+1} = w_t - 2\alpha \sum_{s \in S} [v_\pi(s) - w^\top x(s)] x(s) \)

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**Gradient Monte Carlo Algorithm for Estimating \( \hat{v} \approx v_\pi \)**

Input: the policy \( \pi \) to be evaluated
Input: a differentiable function \( \hat{v} : S \times \mathbb{R}^d \rightarrow \mathbb{R} \)

Initialize value-function weights \( w \) as appropriate (e.g., \( w = 0 \))
Repeat forever:
  - Generate an episode \( S_0, A_0, R_1, S_1, A_1, \ldots, R_T, S_T \) using \( \pi \)
  - For \( t = 0, 1, \ldots, T - 1 \):
    - \( w \leftarrow w + \alpha [G_t - \hat{v}(S_t, w)] \nabla \hat{v}(S_t, w) \)

[Sutton & Barto, RL Book, Ch.9]
Approximation techniques (prediction)

- **Linear approximation:** \( V(s) = w^T x(s) \)

- **Objective:** \( \sum_{s \in S} \left[ v_\pi(s) - w^T x(s) \right]^2 \)

- **Gradient update:** \( w_{t+1} = w_t - 2\alpha \sum_{s \in S} \left[ v_\pi(s) - w^T x(s) \right] x(s) \)

\[
V(s) = w^T x(s)
\]

\[
G_t \text{ is an unbiased estimator of } v_\pi(s_t)
\]

[Sutton & Barto, RL Book, Ch.9]
Approximation techniques

- Works both for prediction and control
Approximation techniques

- Works both for prediction and control
- Any model can be used to approximate
Approximation techniques

- Works both for prediction and control

- Any model can be used to approximate

- Recent work using deep neural networks yield impressive performance on computer (Atari) games
Summary

• Today we have defined RL studied several algorithms for solving RL problems (mostly for for tabular case)

• Main challenges
  • Credit assignment
  • Exploration/Exploitation tradeoff

• Algorithms
  • Prediction
    • Monte Carlo and TD(0)
  • Control
    • Q-learning

• Approximation algorithms can help scale reinforcement learning
Practical difficulties

- Compared to supervised learning setting up an RL problem is often harder
  - Need an environment (or at least a simulator)
- Rewards
  - In some domains it’s clear (e.g., in games)
  - In others it’s much more subtle (e.g., you want to please a human)
• The algorithms are from “Reinforcement Learning: An Introduction” by Richard Sutton and Andrew Barto

• The definitive RL reference

• Some of these slides were adapted from Pascal Poupart’s slides (CS686 U.Waterloo)

• The TD demo is from Andrej Karpathy
Administration

- Project
  - Poster presentation (November 29, room: CSC Groupe Cholette)
    - Get there by 8:30am be ready to present by 8:45am
    - Adhesive putty will be provided
  - Project report (December 5)
  - Exam (December 8, 9am-12pm, room: CSC Deloitte.)
    - Material: all slides, all required readings.
      - Except probabilistic clustering (after slide 15)
    - Documentation: 1 double-sided standard sheet of notes (format 8.5x11 inches)