

# Learning Summary

- Given a task, use
  - ▶ data/experience
  - ▶ bias/background knowledge
  - ▶ measure of improvement or errorto improve performance on the task.
- Representations for:
  - ▶ Data (e.g., discrete values, indicator functions)
  - ▶ Models (e.g., decision trees, linear functions, linear separators)
- A way to handle overfitting (e.g., trade-off model complexity and fit-to-data, cross validation).
- Search algorithm (usually local, myopic search) to find the best model that fits the data given the bias.

# Learning Objectives - Reinforcement Learning

At the end of the class you should be able to:

- Explain the relationship between decision-theoretic planning (MDPs) and reinforcement learning
- Implement basic state-based reinforcement learning algorithms: Q-learning and SARSA
- Explain the explore-exploit dilemma and solutions
- Explain the difference between on-policy and off-policy reinforcement learning

# Reinforcement Learning

What should an agent do given:

- **Prior knowledge** possible states of the world  
possible actions
- **Observations** current state of world  
immediate reward / punishment
- **Goal** act to maximize accumulated (discounted) reward

Like decision-theoretic planning, except model of dynamics and model of reward not given.

# Reinforcement Learning Examples

- Game - reward winning, punish losing
- Dog - reward obedience, punish destructive behavior
- Robot - reward task completion, punish dangerous behavior

- We assume there is a sequence of experiences:

*state, action, reward, state, action, reward, ....*

- At any time it must decide whether to
  - ▶ **explore** to gain more knowledge
  - ▶ **exploit** knowledge it has already discovered

# Why is reinforcement learning hard?

- What actions are responsible for a reward may have occurred a long time before the reward was received.
- The long-term effect of an action depend on what the agent will do in the future.
- The explore-exploit dilemma: at each time should the agent be greedy or inquisitive?

# Reinforcement learning: main approaches

- search through a space of policies (controllers)
- learn a model consisting of state transition function  $P(s'|a, s)$  and reward function  $R(s, a, s')$ ; solve this as an MDP.
- learn  $Q^*(s, a)$ , use this to guide action.

# Recall: Asynchronous VI for MDPs, storing $Q[s, a]$

(If we knew the model:)

Initialize  $Q[S, A]$  arbitrarily

Repeat forever:

- Select state  $s$ , action  $a$
- $Q[s, a] \leftarrow \sum_{s'} P(s'|s, a) \left( R(s, a, s') + \gamma \max_{a'} Q[s', a'] \right)$



# Reinforcement Learning (Deterministic case)

- flat or modular or hierarchical
- explicit states or features or individuals and relations
- static or finite stage or indefinite stage or infinite stage
- fully observable or partially observable
- deterministic or stochastic dynamics
- goals or complex preferences
- single agent or multiple agents
- knowledge is given or knowledge is learned
- perfect rationality or bounded rationality

# Experiential Asynchronous Value Iteration for Deterministic RL

initialize  $Q[S, A]$  arbitrarily

observe current state  $s$

**repeat forever:**

    select and carry out an action  $a$

    observe reward  $r$  and state  $s'$

*What do we know now?*

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# Temporal Differences

- Suppose we have a sequence of values:

$$v_1, v_2, v_3, \dots$$

and want a running estimate of the average of the first  $k$  values:

$$A_k = \frac{v_1 + \dots + v_k}{k}$$

# Temporal Differences (cont)

- Suppose we know  $A_{k-1}$  and a new value  $v_k$  arrives:

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Let  $\alpha_k = \frac{1}{k}$ , then

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Let  $\alpha_k = \frac{1}{k}$ , then

$$\begin{aligned}A_k &= (1 - \alpha_k) A_{k-1} + \alpha_k v_k \\ &= A_{k-1} + \alpha_k (v_k - A_{k-1})\end{aligned}$$

“TD formula”

- Often we use this update with  $\alpha$  fixed.
- We can guarantee convergence to average if

$$\sum_{k=1}^{\infty} \alpha_k = \infty \text{ and } \sum_{k=1}^{\infty} \alpha_k^2 < \infty.$$



- **Idea:** store  $Q[\text{State}, \text{Action}]$ ; update this as in asynchronous value iteration, but using experience (empirical probabilities and rewards).
- Suppose the agent has an experience  $\langle s, a, r, s' \rangle$
- This provides one piece of data to update  $Q[s, a]$ .
- An experience  $\langle s, a, r, s' \rangle$  provides a new estimate for the value of  $Q^*(s, a)$ :

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# Q-learning

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which can be used in the TD formula giving:

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

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# Properties of Q-learning

- Q-learning converges to an optimal policy, no matter what the agent does, as long as it tries each action in each state enough.
- But what should the agent do?
  - ▶ exploit: when in state  $s$ ,
  - ▶ explore:

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- But what should the agent do?
  - ▶ exploit: when in state  $s$ , select an action that maximizes  $Q[s, a]$
  - ▶ explore: select another action

# Exploration Strategies

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$$\frac{e^{Q[s,a]/\tau}}{\sum_a e^{Q[s,a]/\tau}}$$

where  $\tau > 0$  is the *temperature*.



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- “optimism in the face of uncertainty”: initialize  $Q$  to values that encourage exploration.
- “upper confidence bounds” - take into account average + variance

# Problems with Q-learning

- It does one backup between each experience.
  - ▶ Is this appropriate for a robot interacting with the real world?

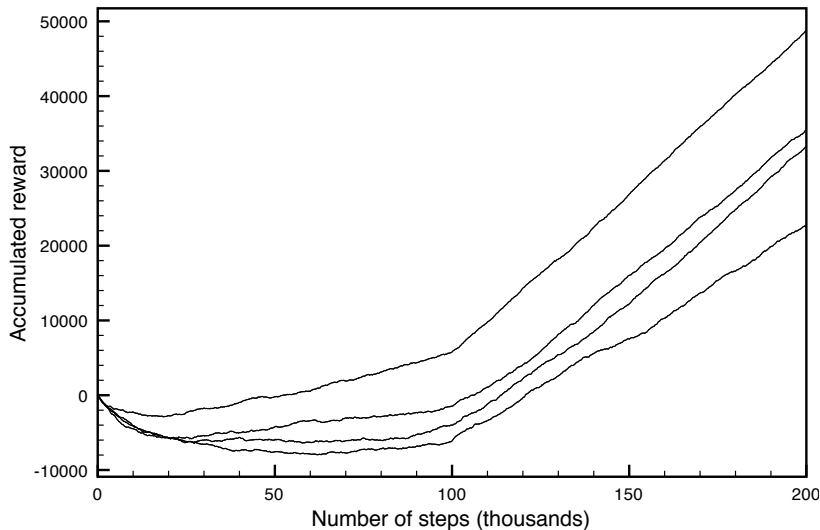
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- It does one backup between each experience.
  - ▶ Is this appropriate for a robot interacting with the real world?
  - ▶ An agent can make better use of the data by
    - doing multi-step backups
    - building a model, and using MDP methods to determine optimal policy.
- It learns separately for each state.

# Evaluating Reinforcement Learning Algorithms



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e.g., act greedily 80% of the time and act randomly 20% of the time
- Why?



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- **On-policy learning** learns the value of the policy being followed.  
e.g., act greedily 80% of the time and act randomly 20% of the time
- Why? If the agent is actually going to explore, it may be better to optimize the actual policy it is going to do.
- SARSA uses the experience  $\langle s, a, r, s', a' \rangle$  to update  $Q[s, a]$ .

initialize  $Q[S, A]$  arbitrarily

observe current state  $s$

select action  $a$  using a policy based on  $Q$

**repeat forever:**

    carry out action  $a$

    observe reward  $r$  and state  $s'$

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# Reinforcement Learning with Features

- Usually we don't want to reason in terms of states, but in terms of features.
- In state-based methods, information about one state cannot be used by similar states.
- If there are too many parameters to learn, it takes too long.
- **Idea:** Express the value function as a function of the features. Most typical is a linear function of the features.

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# Gradient descent

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  - for each  $x_i$

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# Linear Regression

- A linear function of variables  $x_1, \dots, x_n$  is of the form

$$f^{\bar{w}}(x_1, \dots, x_n) = w_0 + w_1x_1 + \dots + w_nx_n$$

$\bar{w} = \langle w_0, w_1, \dots, w_n \rangle$  are weights. (Let  $x_0 = 1$ ).

- Given a set  $E$  of examples.

Example  $e$  has input  $x_i = e_i$  for each  $i$  and observed value,  $o_e$ :

$$Error_E(\bar{w}) = \sum_{e \in E} (o_e - f^{\bar{w}}(e_1, \dots, e_n))^2$$

- Minimizing the error using gradient descent, each example should update  $w_i$  using:

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$$w_i \leftarrow w_i - \eta \frac{\partial Error_E(\bar{w})}{\partial w_i}$$

# Gradient Descent for Linear Regression

Given  $E$ : set of examples over  $n$  features

each example  $e$  has inputs  $(e_1, \dots, e_n)$  and output  $o_e$ :

Assign weights  $\bar{w} = \langle w_0, \dots, w_n \rangle$  arbitrarily

**repeat:**

**For each** example  $e$  in  $E$ :

let  $\delta = o_e - f^{\bar{w}}(e_1, \dots, e_n)$

**For each** weight  $w_j$ :

$$w_j \leftarrow w_j + \eta \delta e_j$$

# SARSA with linear function approximation

- One step backup provides the examples that can be used in a linear regression.
- Suppose  $F_1, \dots, F_n$  are the features of the state and the action.
- So  $Q_w(s, a) = w_0 + w_1 F_1(s, a) + \dots + w_n F_n(s, a)$
- An experience  $\langle s, a, r, s', a' \rangle$  provides the “example”:
  - ▶ old predicted value:
  - ▶ new “observed” value:

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  - ▶ old predicted value:  $Q_{\bar{w}}(s, a)$
  - ▶ new “observed” value:  $r + \gamma Q_{\bar{w}}(s', a')$

# SARSA with linear function approximation

Given  $\gamma$ :discount factor;  $\eta$ :step size

Assign weights  $\bar{w} = \langle w_0, \dots, w_n \rangle$  arbitrarily

observe current state  $s$

select action  $a$

**repeat forever:**

    carry out action  $a$

    observe reward  $r$  and state  $s'$

    select action  $a'$  (using a policy based on  $Q_{\bar{w}}$ )

    let  $\delta = r + \gamma Q_{\bar{w}}(s', a') - Q_{\bar{w}}(s, a)$

    For  $i = 0$  to  $n$

$$w_i \leftarrow w_i + \eta \delta F_i(s, a)$$

$s \leftarrow s'$

$a \leftarrow a'$



# Example Features

- $F_1(s, a) = 1$  if  $a$  goes from state  $s$  into a monster location and is 0 otherwise.
- $F_2(s, a) = 1$  if  $a$  goes into a wall, is 0 otherwise.
- $F_3(s, a) = 1$  if  $a$  goes toward a prize.
- $F_4(s, a) = 1$  if the agent is damaged in state  $s$  and action  $a$  takes it toward the repair station.
- $F_5(s, a) = 1$  if the agent is damaged and action  $a$  goes into a monster location.
- $F_6(s, a) = 1$  if the agent is damaged.
- $F_7(s, a) = 1$  if the agent is not damaged.
- $F_8(s, a) = 1$  if the agent is damaged and there is a prize in direction  $a$ .
- $F_9(s, a) = 1$  if the agent is not damaged and there is a prize in direction  $a$ .

# Example Features

- $F_{10}(s, a)$  is the distance from the left wall if there is a prize at location  $P_0$ , and is 0 otherwise.
- $F_{11}(s, a)$  has the value  $4 - x$ , where  $x$  is the horizontal position of state  $s$  if there is a prize at location  $P_0$ ; otherwise is 0.
- $F_{12}(s, a)$  to  $F_{29}(s, a)$  are like  $F_{10}$  and  $F_{11}$  for different combinations of the prize location and the distance from each of the four walls.

For the case where the prize is at location  $P_0$ , the  $y$ -distance could take into account the wall.

# Model-based Reinforcement Learning

- Model-based reinforcement learning uses the experiences in a more effective manner.
- It is used when collecting experiences is expensive (e.g., in a robot or an online game); an agent can do lots of computation between each experience.
- Idea: learn the MDP and interleave acting and planning.
- After each experience, update probabilities and the reward, then do some steps of asynchronous value iteration.

# Model-based learner

Data Structures:  $Q[S, A]$ ,  $T[S, A, S]$ ,  $C[S, A]$ ,  $R[S, A]$

Assign  $Q$ ,  $R$  arbitrarily,  $C = 0$ ,  $T = 0$

observe current state  $s$

**repeat forever:**

select and carry out action  $a$

observe reward  $r$  and state  $s'$

$$T[s, a, s'] \leftarrow T[s, a, s'] + 1$$

$$C[s, a] \leftarrow C[s, a] + 1$$

$$R[s, a] \leftarrow R[s, a] + (r - R[s, a]) / C[s, a]$$

**repeat for a while:**

select state  $s_1$ , action  $a_1$

$$Q[s_1, a_1] \leftarrow R[s_1, a_1] + \sum_{s_2} \frac{T[s_1, a_1, s_2]}{C[s_1, a_1]} \left( \gamma \max_{a_2} Q[s_2, a_2] \right)$$

$$s \leftarrow s'$$

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What goes wrong with this?

# Evolutionary Algorithms

- Idea:
  - ▶ maintain a population of controllers
  - ▶ evaluate each controller by running it in the environment
  - ▶ at each generation, the best controllers are combined to form a new population of controllers

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  - ▶ maintain a population of controllers
  - ▶ evaluate each controller by running it in the environment
  - ▶ at each generation, the best controllers are combined to form a new population of controllers
- If there are  $n$  states and  $m$  actions, there are  $m^n$  policies.
- Experiences are used wastefully: only used to judge the whole controller. They don't learn after every step.
- Performance is very sensitive to representation of controller.