CS 440/ECE448 Lecture 22: Reinforcement Learning

Slides by Svetlana Lazebnik, 11/2016

Modified by Mark Hasegawa-Johnson, 4/2019

By Nicolas P. Rougier - Own work, CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=29327040

Reinforcement learning

- **Regular MDP**
  - Given:
    - Transition model $P(s' \mid s, a)$
    - Reward function $R(s)$
  - Find:
    - Policy $\pi(s)$

- **Reinforcement learning**
  - Transition model and reward function initially unknown
  - Still need to find the right policy
  - “Learn by doing”

Reinforcement learning: Basic scheme

- In each time step:
  - Take some action
  - Observe the outcome of the action: successor state and reward
  - Update some internal representation of the environment and policy
  - If you reach a terminal state, just start over (each pass through the environment is called a *trial*)

- Why is this called reinforcement learning?

Outline

- Applications of Reinforcement Learning
- Model-Based Reinforcement Learning
  - Estimate P(s'|s,a) and R(s)
  - Exploration vs. Exploitation
- Model-Free Reinforcement Learning
  - Q-learning
  - Temporal Difference Learning
  - SARSA
- Function approximation; policy learning

Applications of reinforcement learning

Spoken Dialog Systems (Litman et al., 2000)

Action	
GreetS	Welcome to NJFun. Please say an activity name or say 'list activities' for a list of activities I know about.
GreetU	Welcome to NJFun. How may I help you?
ReAsk 1 S	I know about amusement parks, aquariums, cruises, historic sites, museums, parks, theaters, wineries, and zoos. Please say an activity name from this list.
ReAsk 1M	Please tell me the activity type. You can also tell me the location and time.

Applications of reinforcement learning

- Learning a fast gait for Aibos

Initial gait

Learned gait

Policy Gradient Reinforcement Learning for Fast Quadrupedal Locomotion
Nate Kohl and Peter Stone.
IEEE International Conference on Robotics and Automation, 2004.

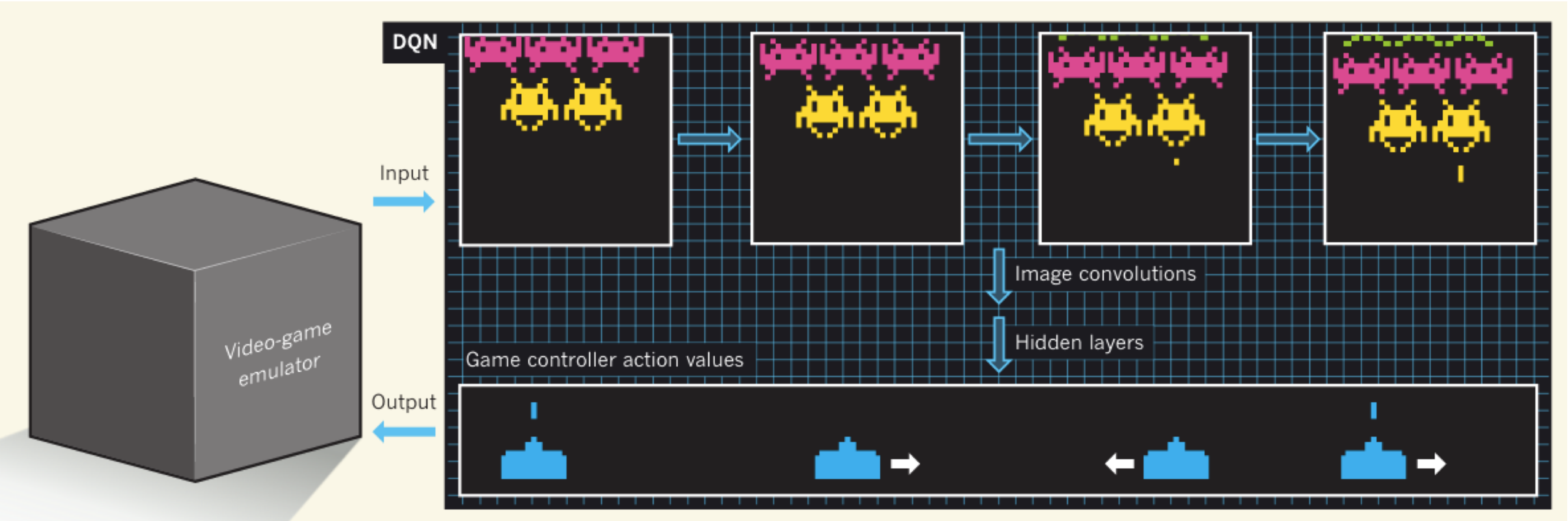
Applications of reinforcement learning

- [Stanford autonomous helicopter]

Pieter Abbeel et al.

Applications of reinforcement learning

- [Playing Atari with deep reinforcement learning]()



[Video]()

V. Mnih et al., *Nature*, February 2015

Applications of reinforcement learning

- [End-to-end training of deep visuomotor policies]()

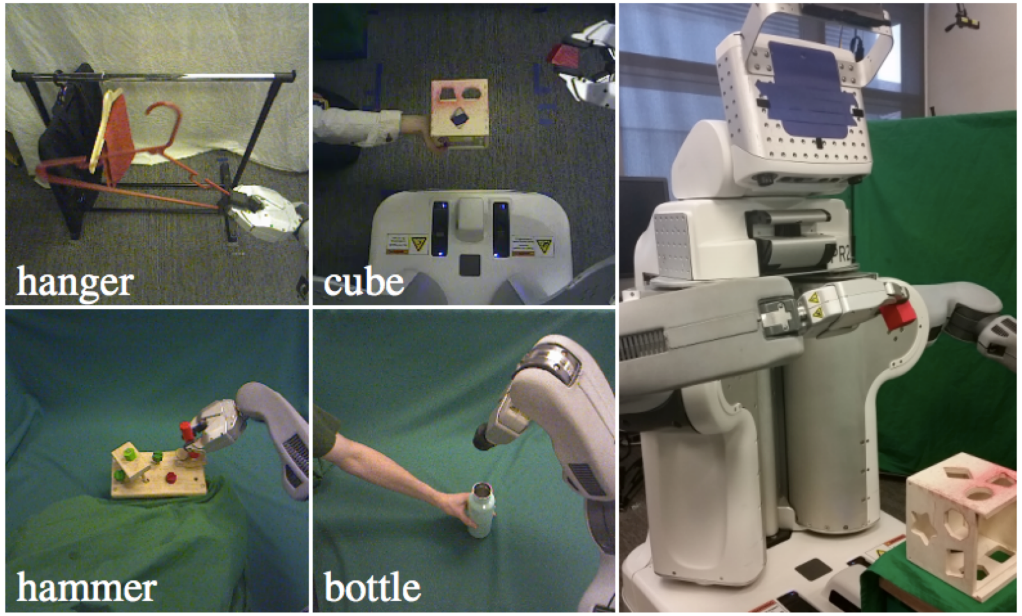


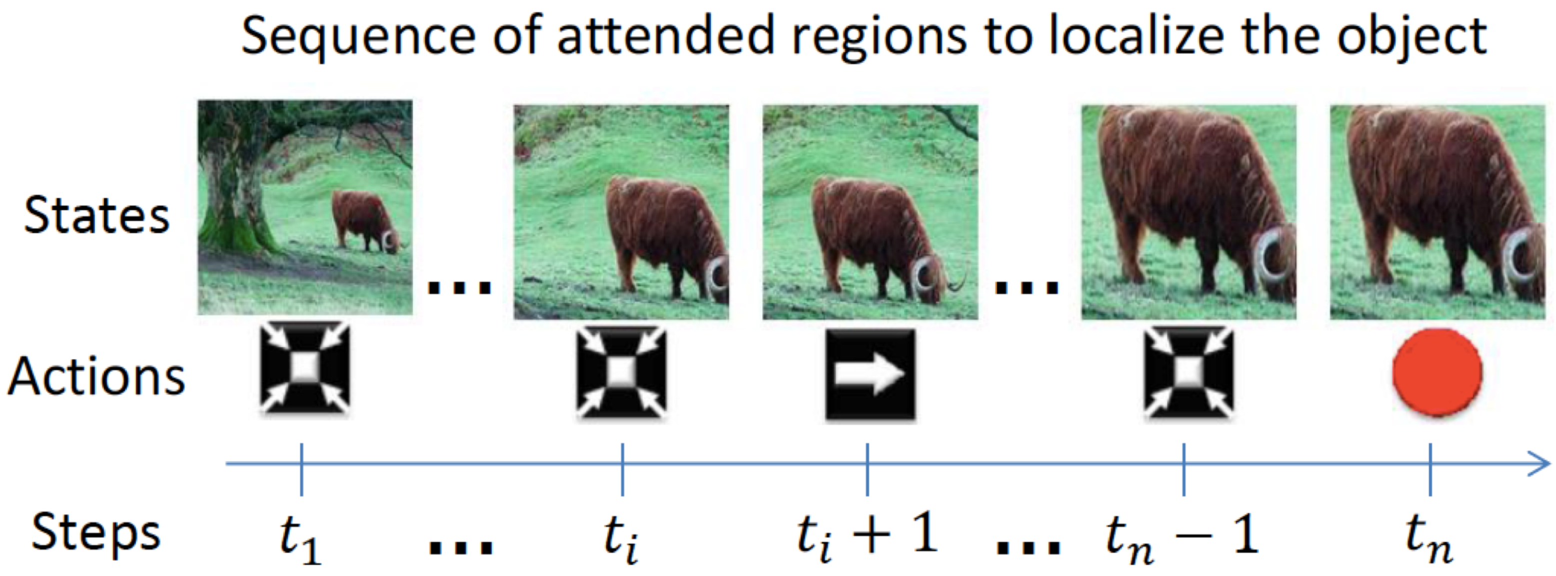
Fig. 1: Our method learns visuomotor policies that directly use camera image observations (left) to set motor torques on a PR2 robot (right).

Video

Sergey Levine et al., Berkeley

Applications of reinforcement learning

- [Active object localization with deep reinforcement learning]



J. Caicedo and S. Lazebnik, ICCV 2015

Learning to Translate in Real Time with Neural Machine Translation

Graham Neubig, Kyunghyun Cho, Jiatao Gu, Victor O. K. Li

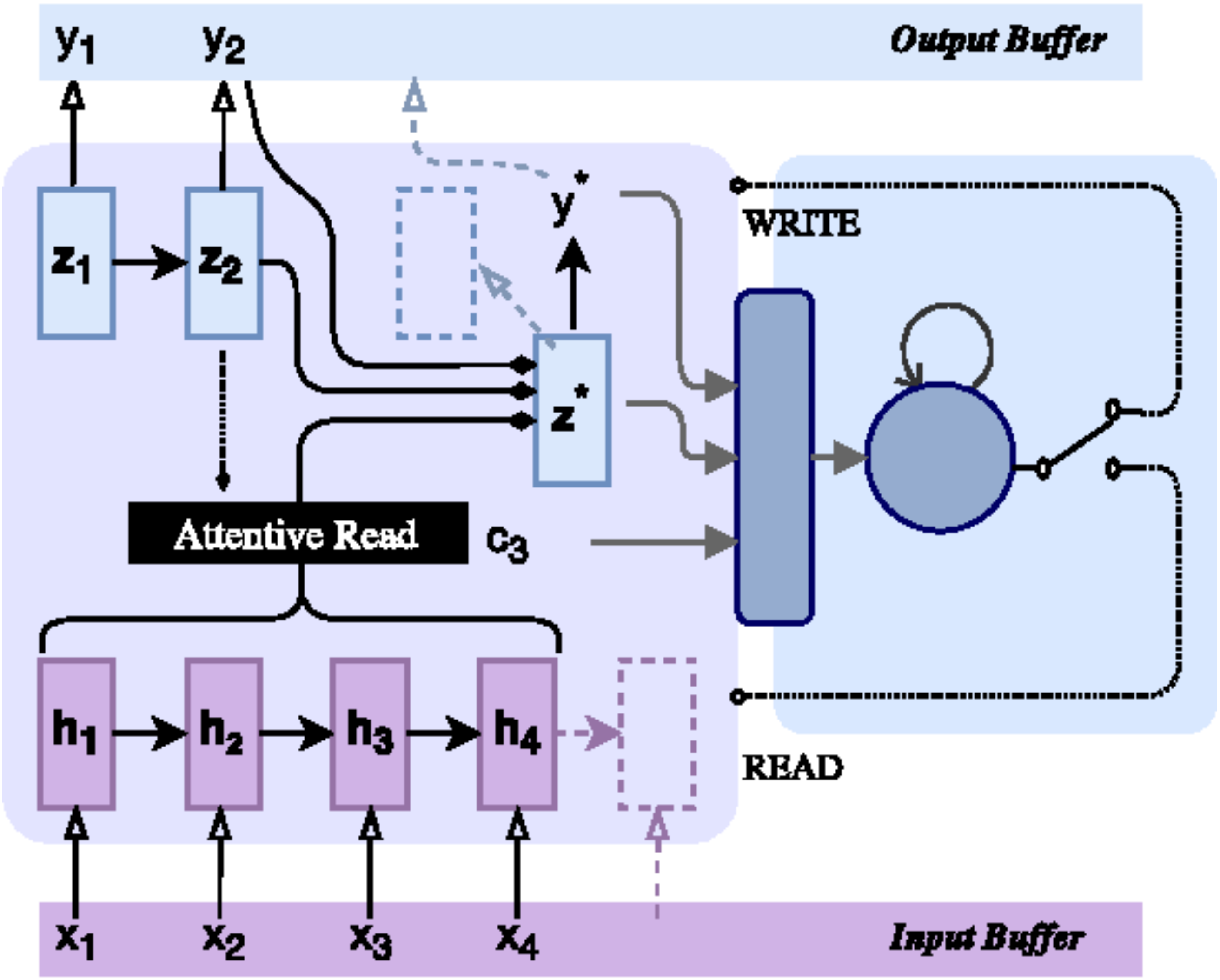


Figure 2: Illustration of the proposed framework: at each step, the NMT environment (left) computes a candidate translation. The recurrent agent (right) will the observation including the candidates and send back decisions–READ or WRITE.

Reinforcement learning strategies

- **Model-based**
  - Learn the **model** of the MDP (**transition probabilities and rewards**) and try to **solve the MDP** concurrently
- **Model-free**
  - **Learn how to act** *without* explicitly learning the transition probabilities $P(s' \mid s, a)$
  - **Q-learning:** learn an **action-utility function** $Q(s,a)$ that tells us the value of doing action a in state s

Outline

- Applications of Reinforcement Learning
- Model-Based Reinforcement Learning
  - Estimate P(s'|s, a) and R(s)
  - Exploration vs. Exploitation
- Model-Free Reinforcement Learning
  - Q-learning
  - Temporal Difference Learning
  - SARSA
- Function approximation; policy learning

Model-based reinforcement learning

- **Basic idea:**
  Try to **learn the model** of the MDP (transition probabilities and rewards) and **learn how to act** (solve the MDP) simultaneously
- **Learning the model:**
  - Keep track of how many times **state s' follows state s when you take action a**
  - **Update the transition probability** P(s' | s, a) according to these relative frequencies
  - **Keep track of the rewards** R(s)
- **Learning how to act:**
  - **Estimate the utilities** U(s) using Bellman's equations
  - Choose the **action that maximizes expected future utility**:

$$\pi^*(s) = \arg\max_{a \in A(s)} \sum_{s'} P(s' | s, a) U(s')$$

Model-based reinforcement learning

- **Learning how to act:**
  - **Estimate the utilities** U(s) using Bellman's equations
  - Choose the action that **maximizes expected future utility** given the model of the environment we've experienced through our actions so far:

$$\pi^*(s) = \arg\max_{a \in A(s)} \sum_{s'} P(s' \mid s, a) U(s')$$

- Is there any problem with this "greedy" approach?

Exploration vs. exploitation

- **Exploration:** take a **new action** with **unknown consequences**
  - Pros:
    - Get a more accurate model of the environment
    - Discover higher-reward states than the ones found so far
  - Cons:
    - When you’re exploring, you’re not maximizing your utility
    - Something bad might happen
- **Exploitation:** go with the **best strategy found so far**
  - Pros:
    - Maximize reward as reflected in the current utility estimates
    - Avoid bad stuff
  - Cons:
    - Might also prevent you from discovering the true optimal strategy

Incorporating exploration

- **Idea:** explore more in the beginning, become more and more greedy over time
- **Standard ("greedy") selection of optimal action**:

$$a = \arg\max_{a' \in A(s)} \sum_{s'} P(s' | s, a') U(s')$$

- **Modified strategy** with exploration function *f*(*u*,*n*)

  f(*u*,*n*) trades off **greed** [preference for high utility *u*] against **curiosity** [preference for low observed frequencies *n*]

$$f(u,n) = \begin{cases} R^+ & \text{if } n < N_e \\ u & \text{otherwise} \end{cases}$$

Set utility of a' to R^+ [= optimistic reward estimate] if a' in state s explored less than N_e [a constant] times

Set utility to actual observed utility

$$a = \arg\max_{a' \in A(s)} f\left(\sum_{s'} P(s' | s, a') U(s'), N(s, a') \right)$$

exploration function

Number of times we've taken action a' in state s

Outline

- Applications of Reinforcement Learning
- Model-Based Reinforcement Learning
  - Estimate P(s'|s,a) and R(s)
  - Exploration vs. Exploitation
- Model-Free Reinforcement Learning
  - Q-learning
  - Temporal Difference Learning
  - SARSA
- Function approximation; policy learning

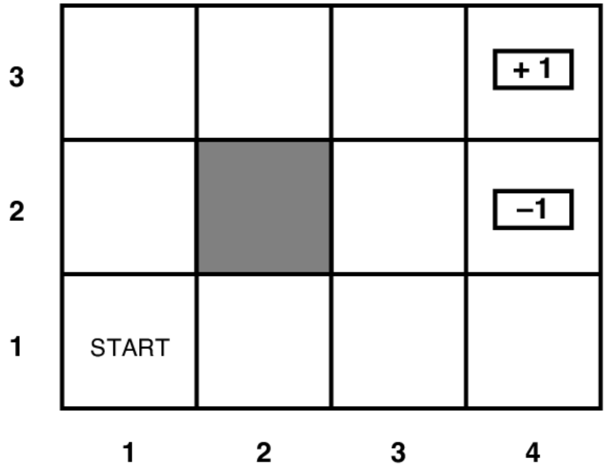
Model-free reinforcement learning

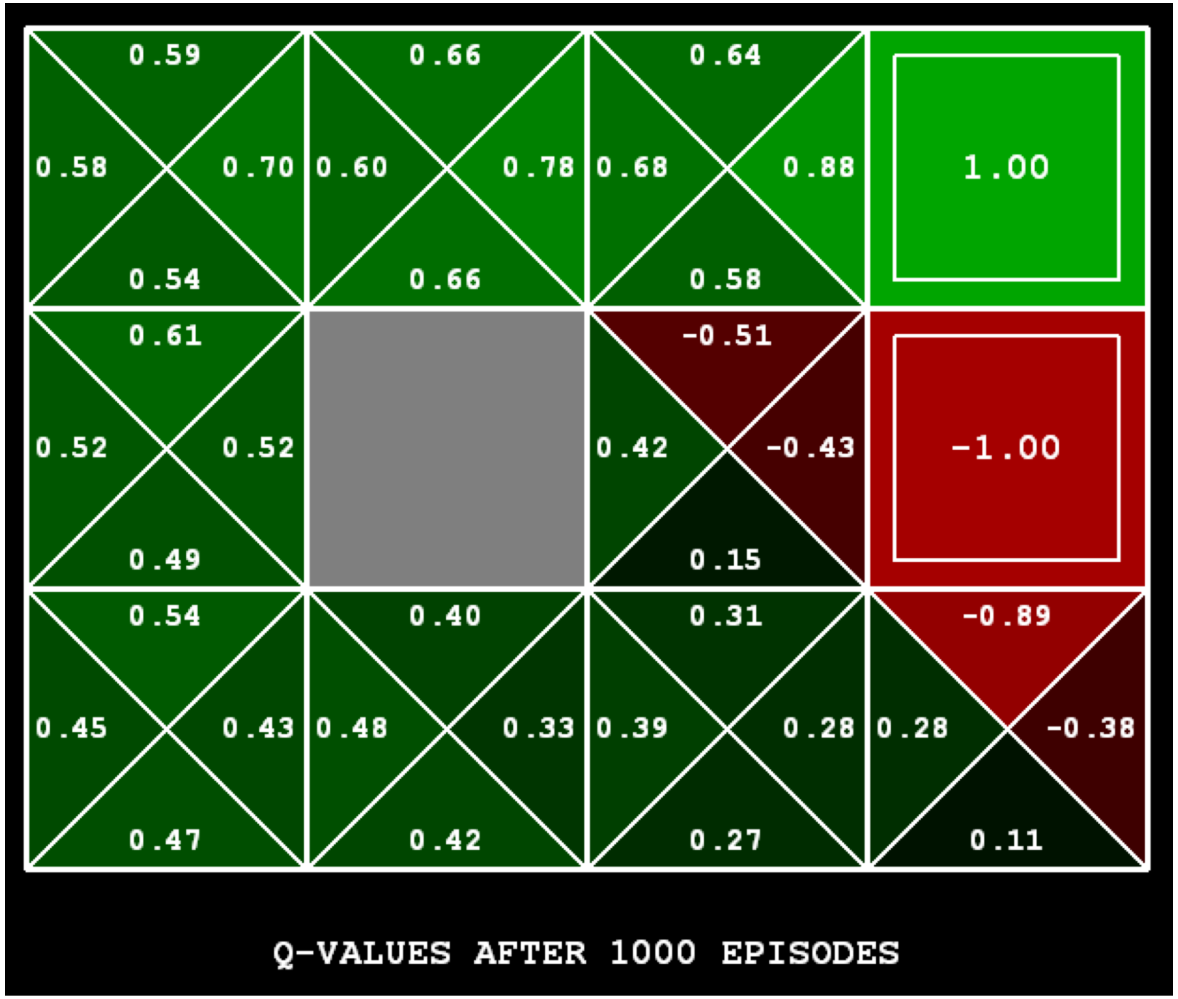
- **Idea:** learn how to act *without* explicitly learning the transition probabilities P(s' | s, a)
- **Q-learning:** learn an *action-utility function* Q(s,a) that tells us the value of doing action a in state s
- Relationship between Q-values and utilities:

$$U(s) = \max_a Q(s,a)$$

- Selecting an action: $\pi^*(s) = \arg\max_a Q(s,a)$
- Compare with: $\pi^*(s) = \arg\max_a \sum_{s'} P(s'|s,a)U(s')$
  - With Q-values, don't need to know the transition model to select the next action

TD Q-learning result





Source: Berkeley CS188

Model-free reinforcement learning

- **Q-learning: learn an action-utility function Q(s,a)** that tells us the value of doing action a in state s

$$U(s) = \max_a Q(s,a)$$

- **Equilibrium constraint** on Q values:

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

- What is the relationship between this constraint and the Bellman equation?

$$U(s) = R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s,a) U(s')$$

Model-free reinforcement learning

- **Q-learning: learn an action-utility function Q(s,a)** that tells us the value of doing action a in state s

$$U(s) = \max_a Q(s,a)$$

- **Equilibrium constraint** on Q values:

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

- Problem: we don’t know (and don’t want to learn) P(s’ | s, a)

Temporal difference (TD) learning

- **Equilibrium constraint** on Q values:

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

- **Temporal difference (TD) update:**
  - Pretend that the currently observed transition (s,a,s’) is the *only* possible outcome.
    Call this “local quality” as $Q^{local}(s,a)$;
    it is computed using $Q(s,a)$.

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

  - Then interpolate between $Q(s,a)$ and $Q^{local}(s,a)$ to compute $Q^{new}(s,a)$.

$$Q^{new}(s,a) = (1-\alpha)Q(s,a) + \alpha Q^{local}(s,a)$$

Temporal difference (TD) learning

- The **interpolated** form:

$$Q^{local}(s,a) = R(s) + \gamma \max_{a'} Q(s',a')$$
$$Q^{new}(s,a) = (1-\alpha)Q(s,a) + \alpha Q^{local}(s,a)$$

- The **temporal-difference** form:

$$Q^{local}(s,a) = R(s) + \gamma \max_{a'} Q(s',a')$$
$$Q^{new}(s,a) = Q(s,a) + \alpha\left(Q^{local}(s,a) - Q(s,a)\right)$$

- The **computationally efficient** form (all calculations rolled into one):

$$Q^{new}(s,a) = Q(s,a) + \alpha\left(R(s) + \gamma \max_{a'} Q(s',a') - Q(s,a)\right)$$

Temporal difference (TD) learning

- At each time step t
  - From current state s, select an action a:

$$a = \arg\max_{a'} \underbrace{f}_{\text{Exploration function}}\big(Q(s,a'), \underbrace{N(s,a')}_{\text{Number of times we've taken action a' from state s}}\big)$$

  - Observe the reward r, next state s'
  - Perform the TD update:

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

$$s \leftarrow s'$$

Temporal difference (TD) learning

- At each time step t
  - From current state s, select an action a:

$$a = \arg\max_{a'} f\left(Q(s,a'), N(s,a')\right)$$

Exploration function

Number of times we've taken action a' from state s

  - Observe the reward r, next state s'
  - Perform the TD update:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left(R(s) + \gamma \boxed{\max_{a'} Q(s',a')} - Q(s,a)\right)$$

$$s \leftarrow s'$$

???

Temporal difference (TD) learning

- At each time step t
  - From current state s, select an action a:

$$a = \arg\max_{a'} f\big(Q(s,a'), N(s,a')\big)$$

Exploration function

Number of times we've taken action a' from state s

  - Observe the reward r, next state s'
  - Perform the TD update:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\big(R(s) + \gamma \boxed{\max_{a'} Q(s',a')} - Q(s,a)\big)$$

$$s \leftarrow s'$$

That's not necessarily the action we will take next time…

SARSA: State-Action-Reward-State-Action

- Initialize: choose an initial state **s**, initial action **a**
- At each time step t
  - Observe the reward **r**, next state s'
  - From **next** state s', select **next** action a':

$$a' = \arg\max_{a'} f(Q(s', a'), N(s', a'))$$

Exploration function

Number of times we've taken action a' from state s'

  - Perform the TD update:

$$Q(s,a) \leftarrow Q(s,a) + \alpha(R(s) + \boxed{\gamma Q(s', a')} - Q(s,a))$$

$$s \leftarrow s'$$

That **is** the action we will take next time…

Outline

- Applications of Reinforcement Learning
- Model-Based Reinforcement Learning
  - Estimate $P(s'|s,a)$ and $R(s)$
  - Exploration vs. Exploitation
- Model-Free Reinforcement Learning
  - Q-learning
  - Temporal Difference Learning
- Function approximation; policy learning

Function approximation

- So far, we've assumed a lookup table representation for utility function U(s) or action-utility function Q(s,a)
- But what if the state space is really large or continuous?
- Alternative idea: approximate the utility function, e.g., as a weighted linear combination of *features*:

$$U(s) = w_1 f_1(s) + w_2 f_2(s) + \ldots w_n f_n(s)$$

  - RL algorithms can be modified to estimate these weights
  - More generally, functions can be nonlinear (e.g., neural networks)
- Recall: features for designing evaluation functions in games
- Benefits:
  - Can handle very large state spaces (games), continuous state spaces (robot control)
  - Can *generalize* to previously unseen states

Other techniques

- **Policy search**: instead of getting the Q-values right, you simply need to get their ordering right
  - Write down the policy as a function of some parameters and adjust the parameters to improve the expected reward
- **Learning from imitation**: instead of an explicit reward function, you have expert demonstrations of the task to learn from