Reinforcement Learning

Lecture 1: Introduction to Reinforcement Learning

Chong Li

Outline

- Admin
- Introduction to reinforcement learning
- Elements of reinforcement learning
- Reinforcement learning problem and example
- History

Admin

- Instructor: Chong Li, Lei Zhang
- Email: cl3607@columbia.edu & lz2671@columbia.edu
- Office hour: TBD
- TA/CA: TBD

Admin

- Textbook: “Reinforcement Learning: An Introduction”, R. Sutton and A. Barto, (2nd edition available online)
- References:
  - “Reinforcement Learning for Cyber Physical Systems with Cybersecurity Case Study ”, 2019, C. Li and M-K Qiu
  - “Algorithms for Reinforcement Learning”, Szepesvari, (available online)

Prerequisites

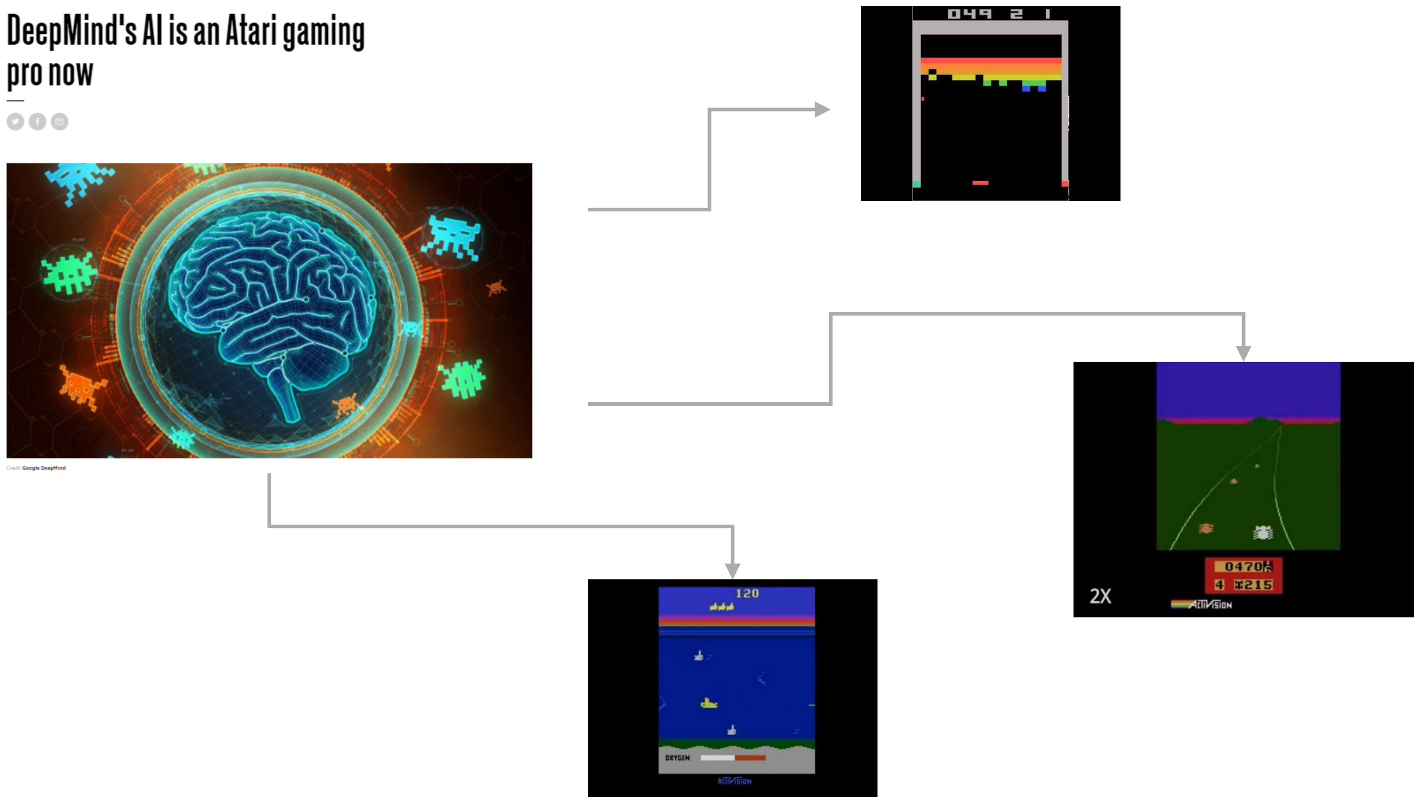
- Elementary statistics & Probability theory
  - Expectation, variance, distribution, …
- Basic linear algebra
  - Vectors, matrix operations, gradients, eigenvalue, …
- Basic programming skills
  - Proficiency in Python,
  - Knowledge of tensorflow and openAI gym
- Background on machine learning is a plus
- Your passion and interest

Grading

- Bi-weekly Assignments: 50%
- Midterm: 20%
  - In class
- Final Exam: 30%
  - In class

Significant RL Success

- Achieved human-level performance on Atari games from pixel-level visual input, in conjunction with deep learning (Google DeepMind 2015)



Significant RL Success

- AlphaGo was developed by Google DeepMind in London in October 2015
- It became the first Computer Go program to beat a human professional Go player on a full-sized 19×19 board. In March 2016, it beat Lee Sedol in a five game match
- AlphaGo Zero (2017) a new version created without using human input data and stronger than any previous version

What is RL?

- Agent-oriented learning—learning by interacting with an environment to achieve a goal
  - more realistic and ambitious than other kinds of machine learning
- Learning by **trial and error**, with only delayed evaluative feedback (reward)
  - the kind of machine learning most like natural learning
  - learning that can tell for itself when it is right or wrong

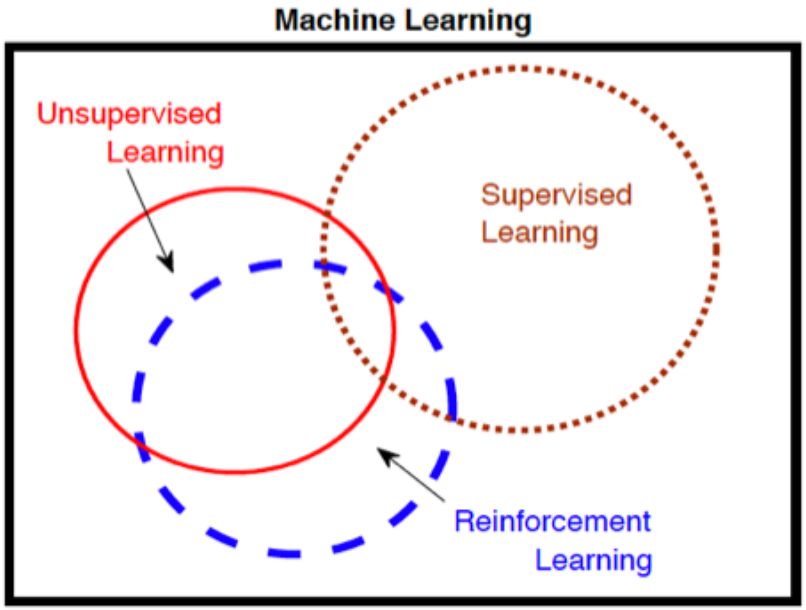
Characteristics of RL

- What makes RL different from other machine learning paradigms?
  - No supervisor, only a reward signal
  - Feedback is delayed, not instantaneous
  - Time matters, i.e., sequential decision making
  - Agent’s actions affect the subsequent data/feedback from the environment

Applications of RL

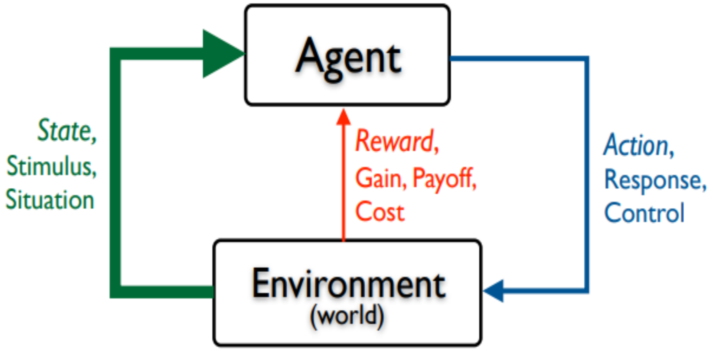
- Manufacturing:
  - Sort products in eCommerce and supermarkets
  - Assembling line: Tesla's factory
- Inventory Management
  - Reduce transit time for stocking/retrieving products
- Delivery Management
  - Delivery vehicle routing
- Power systems
  - Assess the security and enhance microgrid performance
- Finance
  - Evaluate trading strategies

Branches of Machine Learning



Basic RL Interface

- History and State
  - history is the sequence of observations, actions and rewards
  - state is the information used to determine what happens next. It is a function of the history
- At each time step, an agent
  - executes action
  - receives observation of the environment
  - receives reward from the environment



- At each time step, the environment
  - receives action from the agent
  - emits observation/changes its own states
  - emits reward to the agent

Elements of RL

- Policy
  - A policy, π, is a mapping from perceived states of the environment to (the probability of) actions $a \in \mathcal{A}(s)$ to be taken when in those states.

$$s \in \mathcal{S} \longrightarrow \pi(a|s)$$

  - the core of RL to determine behavior
  - Policy can be stochastic or deterministic

- Reward and Return
  - Reward is a mapping from each perceived state of the environment to a single number, indicating the intrinsic desirability of that state
  - Reward is immediate
  - Return is a cumulative sequence of received rewards after a given time step
  - Finite step return:

$$G_t = R_{t+1} + R_{t+2} + R_{t+3} + \cdots + R_T$$

  - Discounted return: $0 \leq \gamma \leq 1$

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$$

Elements of RL

- Value function
  - Functions of states (or of state-action pairs) that estimate *how good* it is for the agent to be in a given state
  - "how good" refers to the expected return
  - For Markov Decision Process (MDP), the value of a state is defined formally as

$$v_\pi(s) = \mathbb{E}_\pi[G_t \mid S_t = s] = \mathbb{E}_\pi\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \,\middle|\, S_t = s\right]$$

  - For MDP, the value of an action-state pair is defined formally as

$$q_\pi(s, a) = \mathbb{E}_\pi[G_t \mid S_t = s, A_t = a] = \mathbb{E}_\pi\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \,\middle|\, S_t = s, A_t = a\right]$$

- Model (optional)
  - Mimic the behavior of the environment
  - Used for planning (decide on a course of actions by considering future situations before experienced)
  - MDP model:

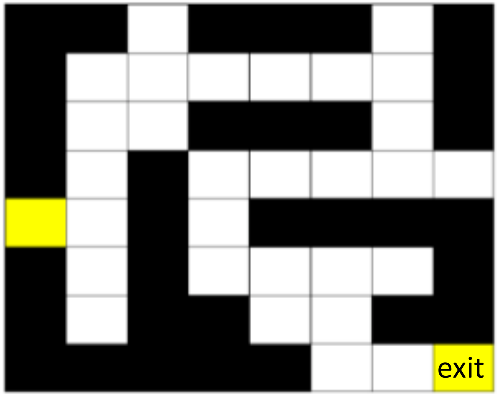
$$\mathcal{P}^a_{ss'} = \mathbb{P}[S_{t+1} = s' \mid S_t = s, A_t = a]$$
$$\mathcal{R}^a_s = \mathbb{E}[R_{t+1} \mid S_t = s, A_t = a]$$

What is RL problem?

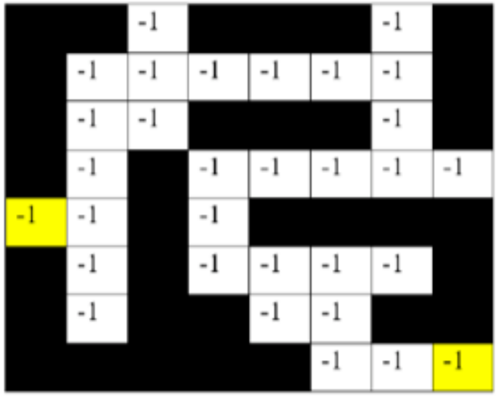
- RL problem is a considerable abstraction of the problem of goal-directed learning from interaction with the environment
- RL methods/solutions specify how the agent changes its policy as a result of its experience.
- The agent’s goal is to ***maximize*** the total amount of reward it receives over the long run

Maze Example: Model & Reward

- The internal model of the environment may or may not be given to the agent
- Actions: N, E, S, W
- States: Agent's location
- Reward: -1 per step (why?)

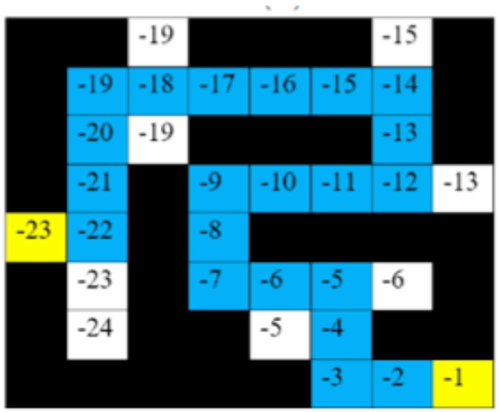


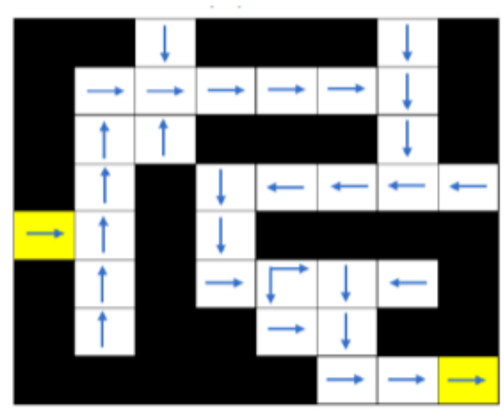
Model: Maze Map



Reward

Maze Example: Value Function & Policy

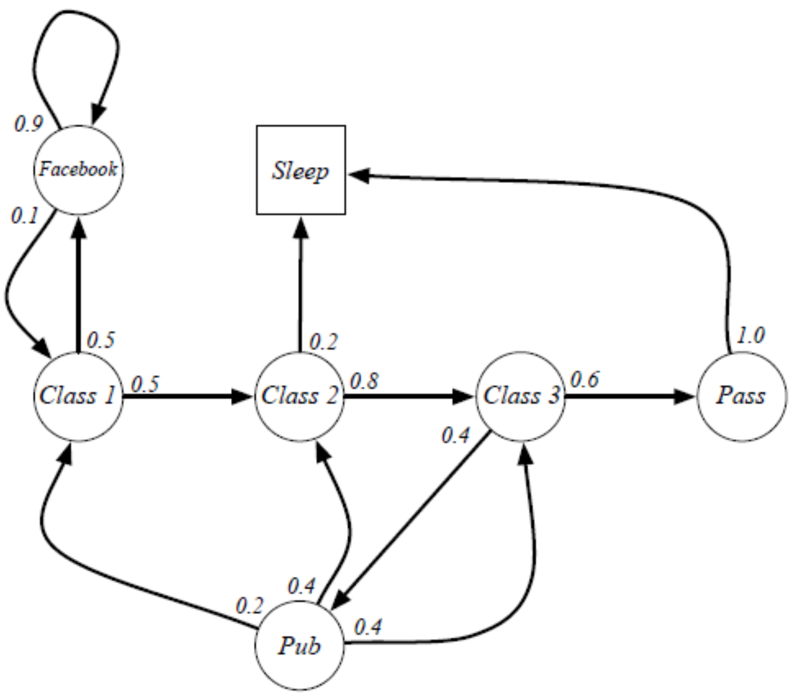




- Numbers represent value of each state
- Arrows represent policy (action) for each state

Example: Student Markov Chain*

- Stochastic policy:



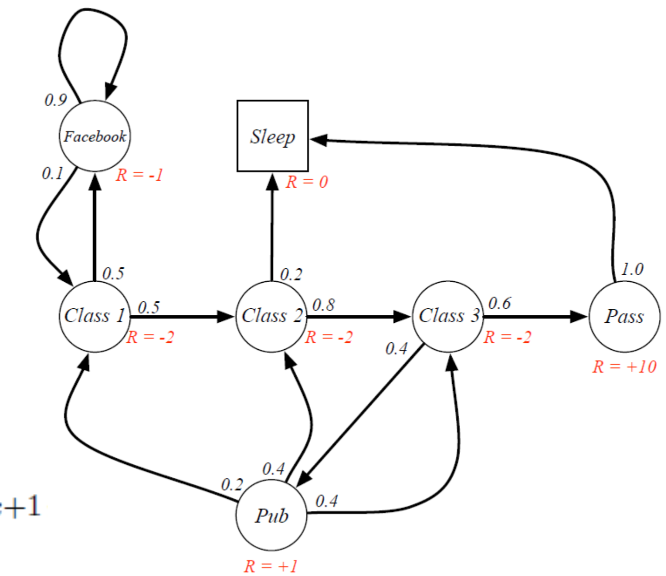
Sample episodes for Student Markov Chain starting from $S_1 = \text{C1}$

$$S_1, S_2, \ldots, S_T$$

- C1 C2 C3 Pass Sleep
- C1 FB FB C1 C2 Sleep
- C1 C2 C3 Pub C2 C3 Pass Sleep
- C1 FB FB C1 C2 C3 Pub C1 FB FB FB C1 C2 C3 Pub C2 Sleep

* This example is taken from David Silver's lecture notes

State-Value Function Evaluation



Sample returns for Student MRP:
Starting from $S_1 = \text{C1}$ with $\gamma = \frac{1}{2}$

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$$

C1 C2 C3 Pass Sleep	$v_1 = -2 - 2 * \frac{1}{2} - 2 * \frac{1}{4} + 10 * \frac{1}{8}$	$=$	-2.25
C1 FB FB C1 C2 Sleep	$v_1 = -2 - 1 * \frac{1}{2} - 1 * \frac{1}{4} - 2 * \frac{1}{8} - 2 * \frac{1}{16}$	$=$	-3.125
C1 C2 C3 Pub C2 C3 Pass Sleep	$v_1 = -2 - 2 * \frac{1}{2} - 2 * \frac{1}{4} + 1 * \frac{1}{8} - 2 * \frac{1}{16} \dots$	$=$	-3.41
C1 FB FB C1 C2 C3 Pub C1 ...	$v_1 = -2 - 1 * \frac{1}{2} - 1 * \frac{1}{4} - 2 * \frac{1}{8} - 2 * \frac{1}{16} \dots$	$=$	-3.20
FB FB FB C1 C2 C3 Pub C2 Sleep			

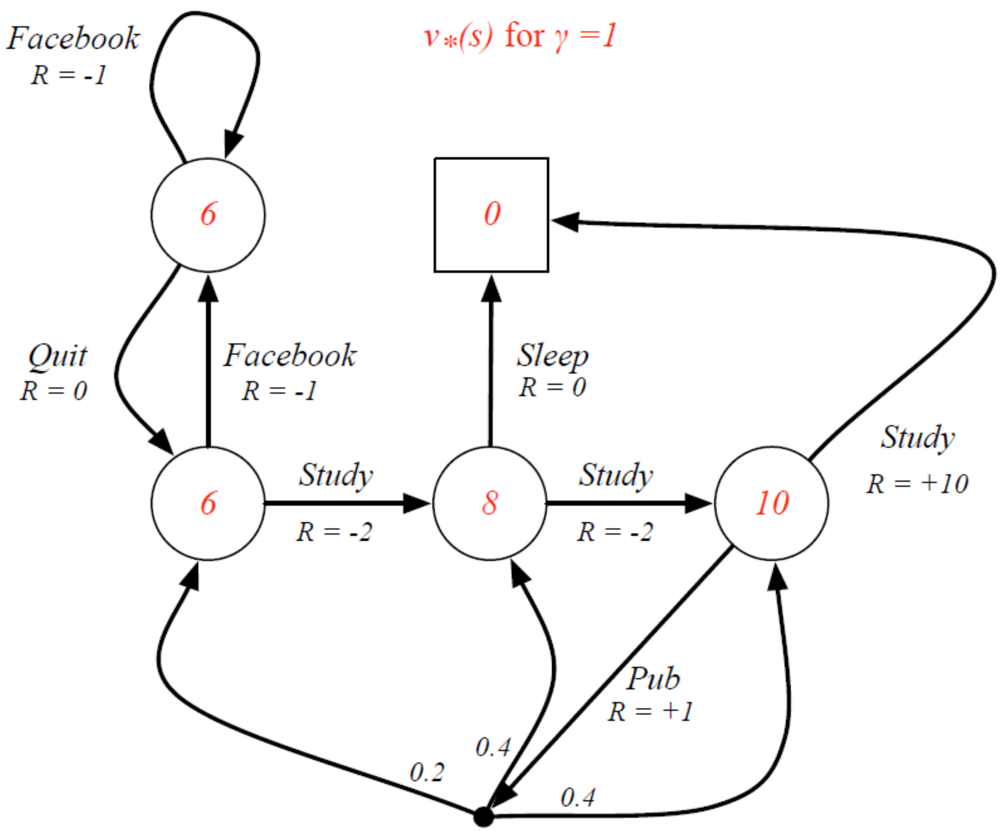
The *state value function* $v(s)$ of an MRP is the expected return starting from state s

$$v(s) = \mathbb{E}\left[G_t \mid S_t = s\right]$$

What is the optimal policy?

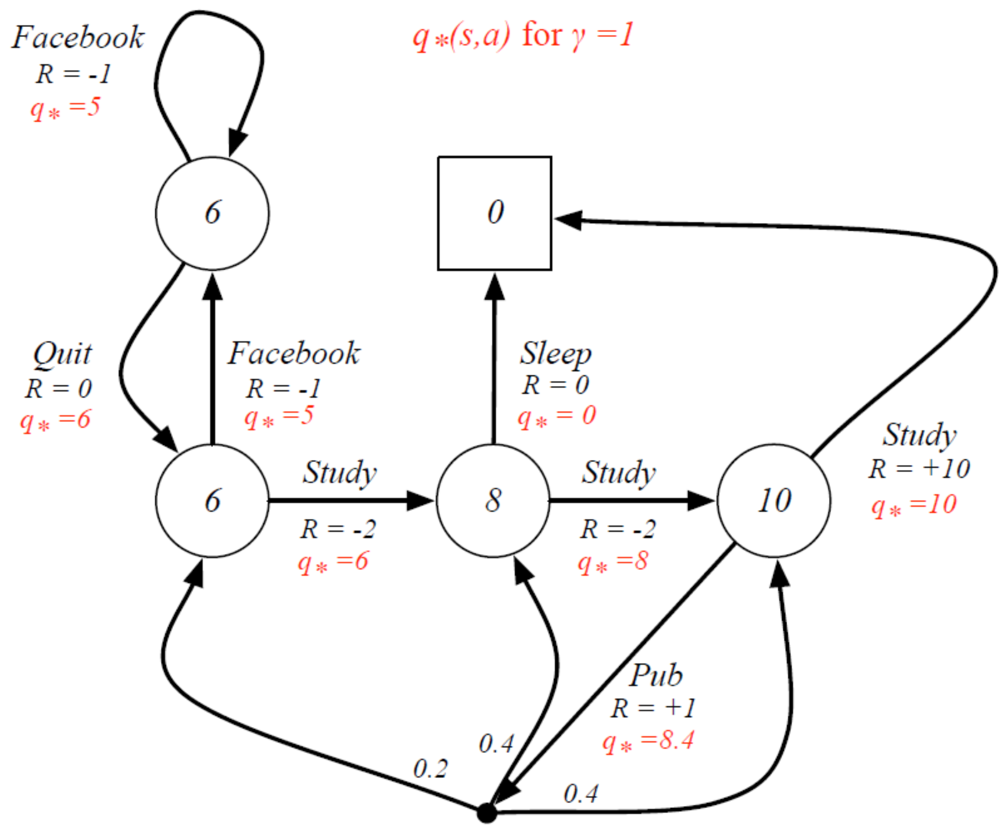
- We have evaluated the given stochastic policy
- The stochastic policy may not be optimal
- Can we do better …

Optimal Value Function

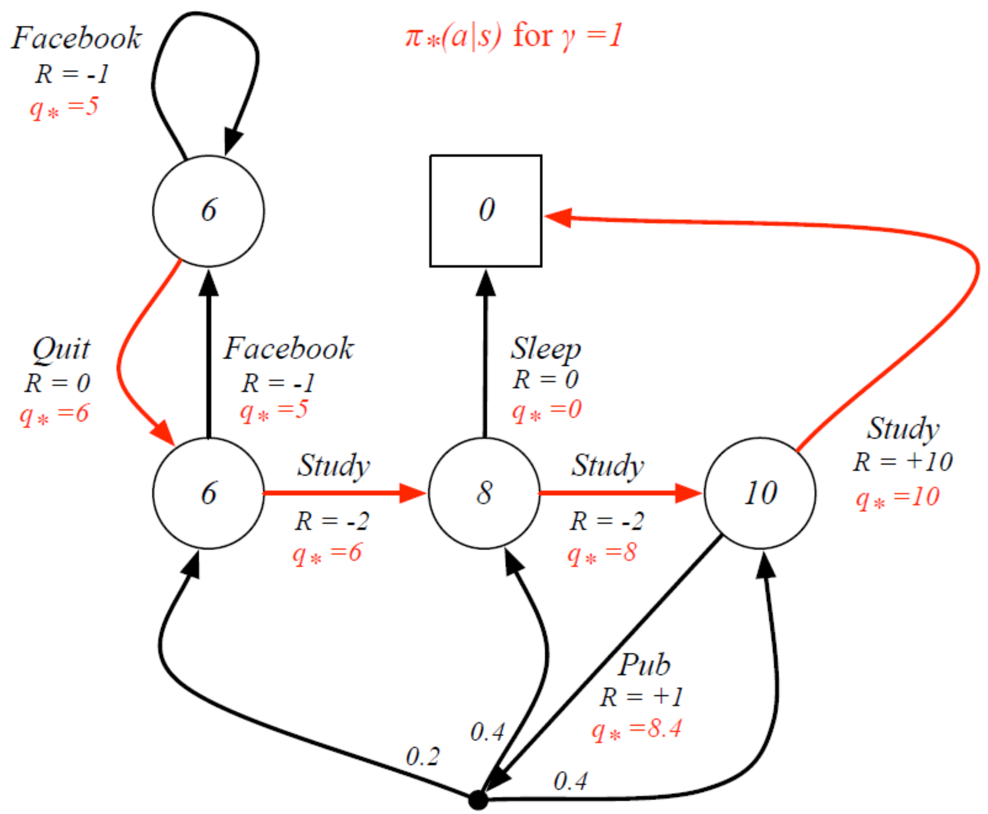


Assume Pub is NOT a state

Optimal Action-State Value Function

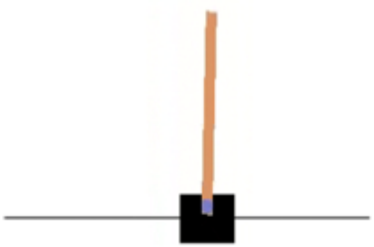


Optimal Policy

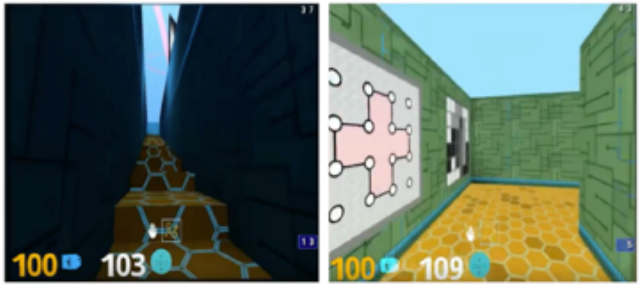


RL Simulation Toolkits

- To evaluate RL algorithms in simulations, need to first create an environment and the agent-environment interface
- Environment can be very complicated
- Widely used toolkits as a collection of environments designed for testing
  - OpenAI Gym: simple games/environment from walking to playing “pong”
  - OpenAI Universe: platform across the world’s supply of games and websites.
  - DeepMind Lab: 3D navigation and puzzle-solving environment



OpenAI Gym: CartPole



DeepMind Lab: 3D Maze

History of RL

- Two main threads to the modern RL theory. Developed independently and then merged in late 1980s

- Thread of learning by trial and error
  - started in the psychology of animal learning
  - earliest work in AI
  - lead to the revival of RL in early 1980s
- Thread of optimal control
  - the solutions use value function and dynamic programming
  - contribute to the basic framework of modern RL

Course Outline

Elementary RL

- Model-based learning: Markov Decision Process(MDP) and dynamic programming
- Model-free learning: prediction and control

Advanced RL

- Eligibility traces
- Solutions to the curse of dimensionality: function approximation
- Planning and learning

State of the art topics:

- Deep Reinforcement Learning