CS 498 Reinforcement Learning

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Logistics

All information about this course: http://nanjiang.cs.illinois.edu/cs498/

- campuswire (please **self enroll**!)
  - main platform for course-related communications
  - you can post to instructors only; please post before requesting an individual meeting
- Slides & schedule (updated every week)
- textbook links
- TA & office hours (TBD)
- course policies

What's this course about?

- A 400-level special topics course on reinforcement learning
- Will have some (minimum) programming components, but **still lean heavily towards the mathematical side**
  - **Think of this mainly as a mathematical course;** the programming component is to ensure that you have some exposure to (some of) the actual algorithms
- "I want to do cool RL applications" — this course does **not** teach you that (but hopefully will give you a good foundation for it)
- "I want to add another cool ML course to my CV" — this course is probably **not** going to be useful
- Intellectual curiosity is the only reason you should take this course
- For a deeper course that prepares you for research in RL theory, check out my CS 598

Prerequisites

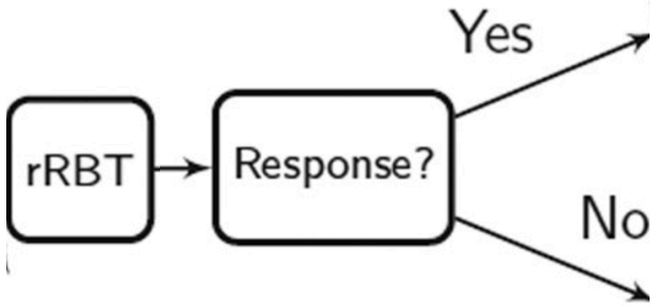
- Maths
  - Linear algebra, probability & statistics, basic calculus
  - Optional: Markov chains, stochastic processes, numerical analysis
- Exposure to ML
  - e.g., CS 446 Machine Learning
- We will soon have a homework 0 that helps you recall some of the math tools needed

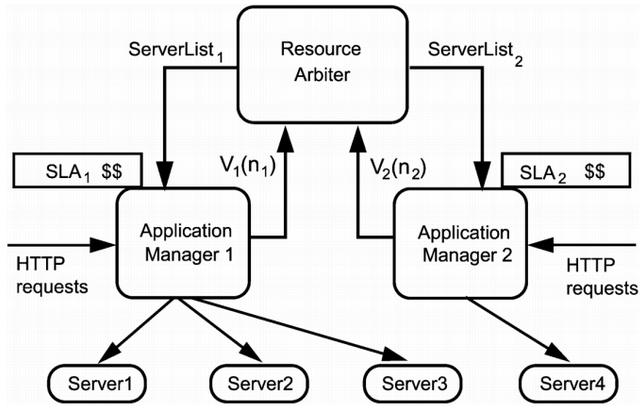
Coursework & Grading

- Some readings after/before class
- Homework (60%): ~5 assignments, with both programming & writing components
  - Will likely to be handled via compass—more on this later
- Exam (40%): Either final or a late mid exam
- For 4 credit students: an additional course project (reproducing part of an empirical or theory paper)

Introduction to MDPs and RL

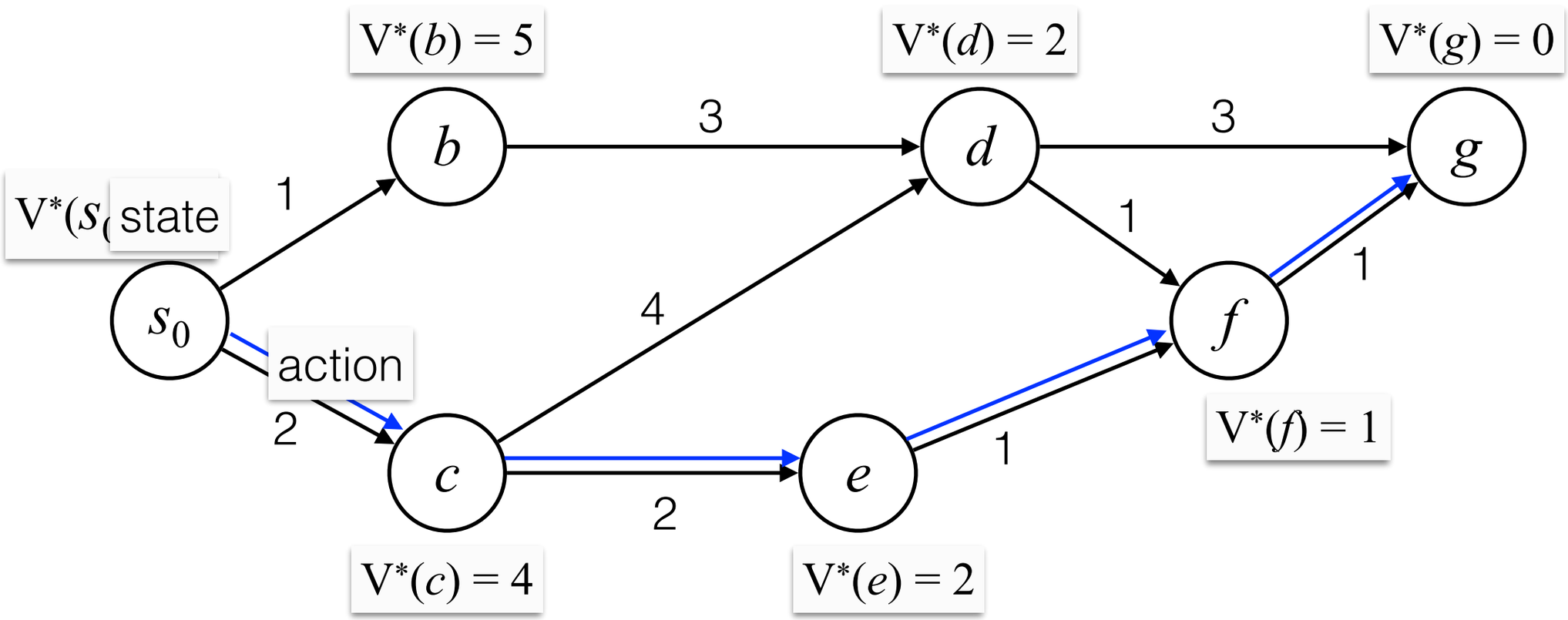
Reinforcement Learning (RL) Applications





[Levine et al'16] [Ng et al'03] [Singh et al'02] [Lei et al'12]
[Mandel et al'16] [Tesauro et al'07] [Mnih et al'15] [Silver et al'16]

Shortest Path

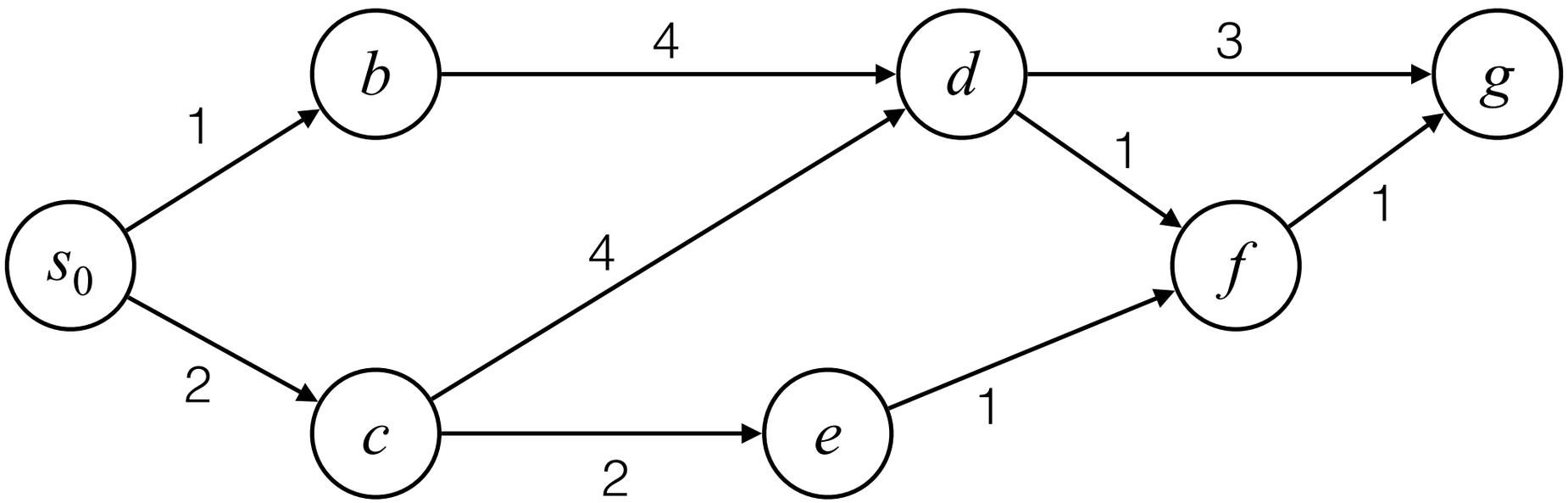


Bellman Equation $V^*(d) = \min\{3 + V^*(g)\ ,\ 2 + V^*(f)\}$

Greedy is suboptimal due to delayed effects

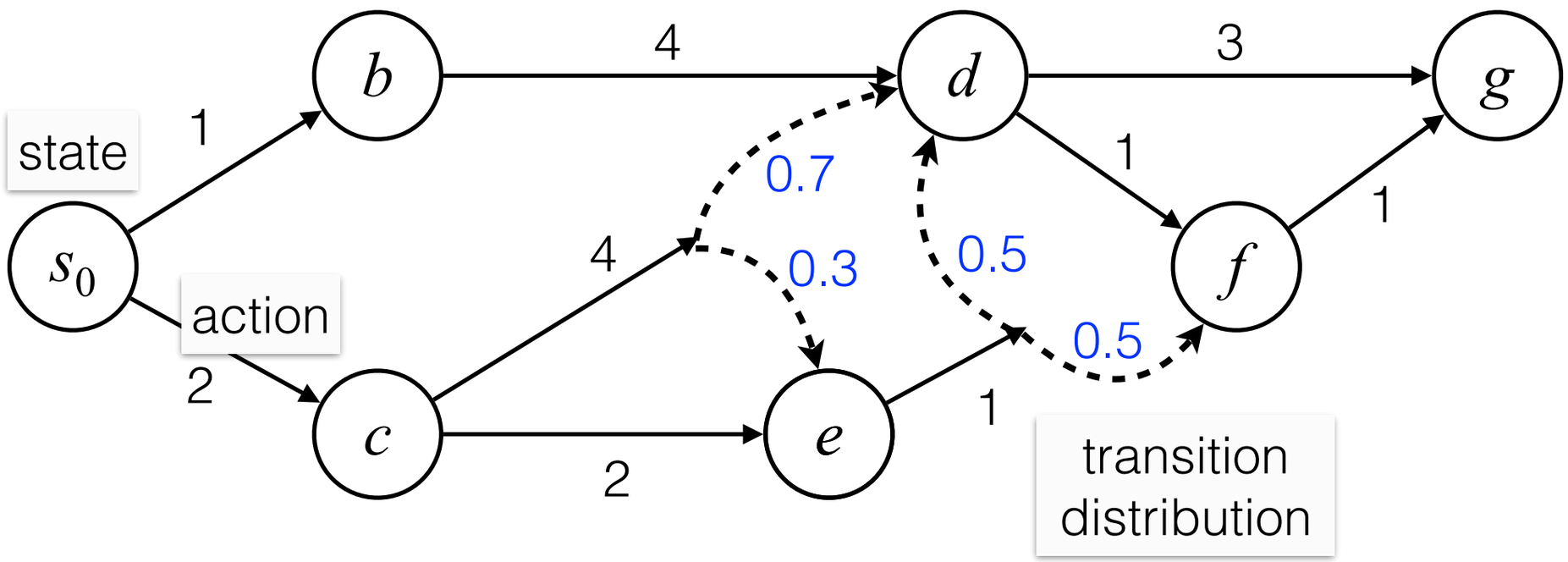
Need **long-term planning**

Shortest Path

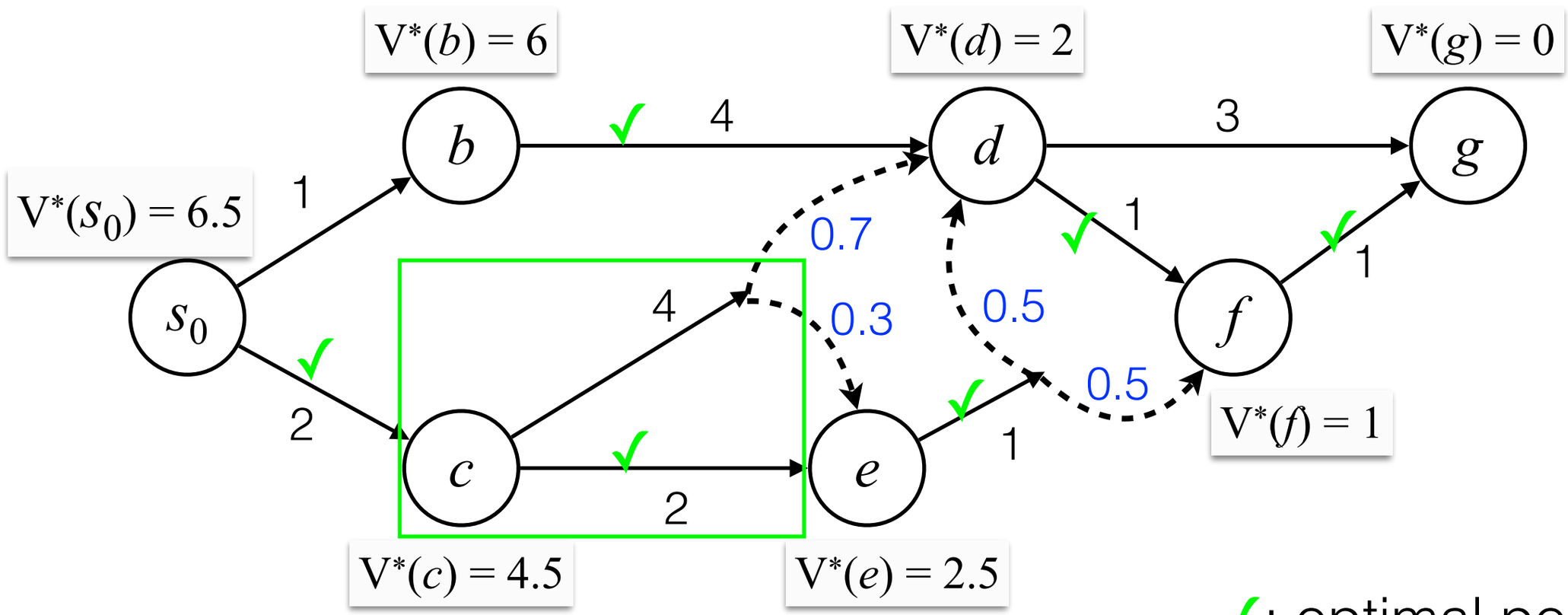


Stochastic Shortest Path

Markov Decision Process (MDP)



Stochastic Shortest Path



✓: optimal policy π^*

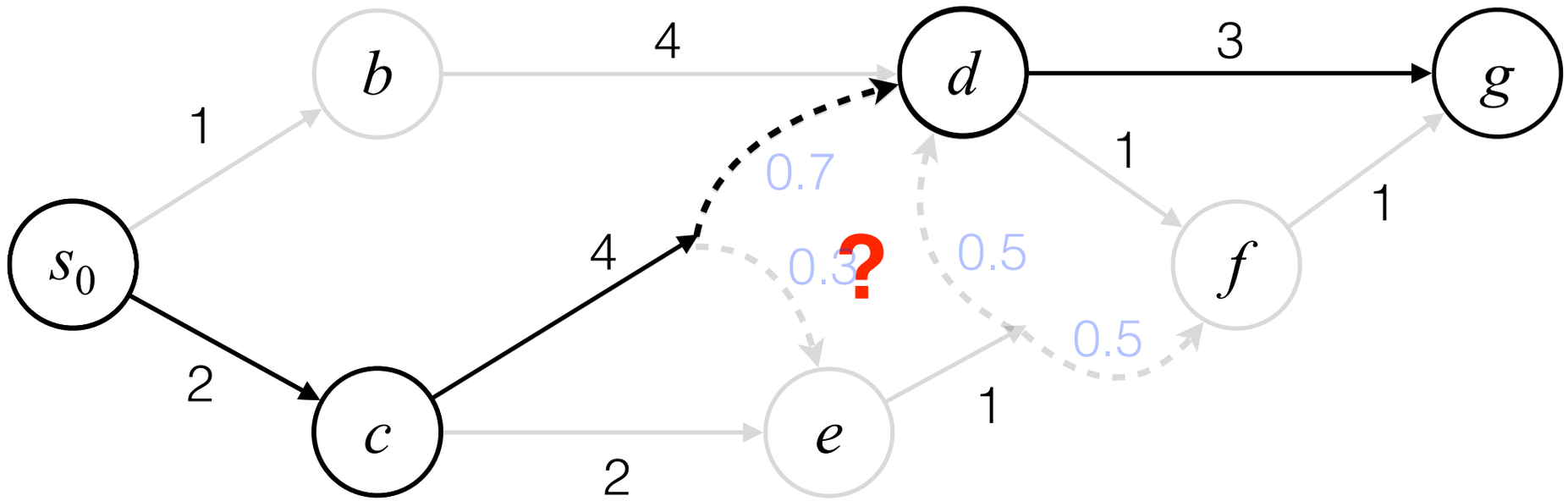
Bellman Equation

$$V^*(c) = \min\{4 + 0.7 \times V^*(d) + 0.3 \times V^*(e)\ ,\ 2 + V^*(e)\}$$

Greedy is suboptimal due to delayed effects

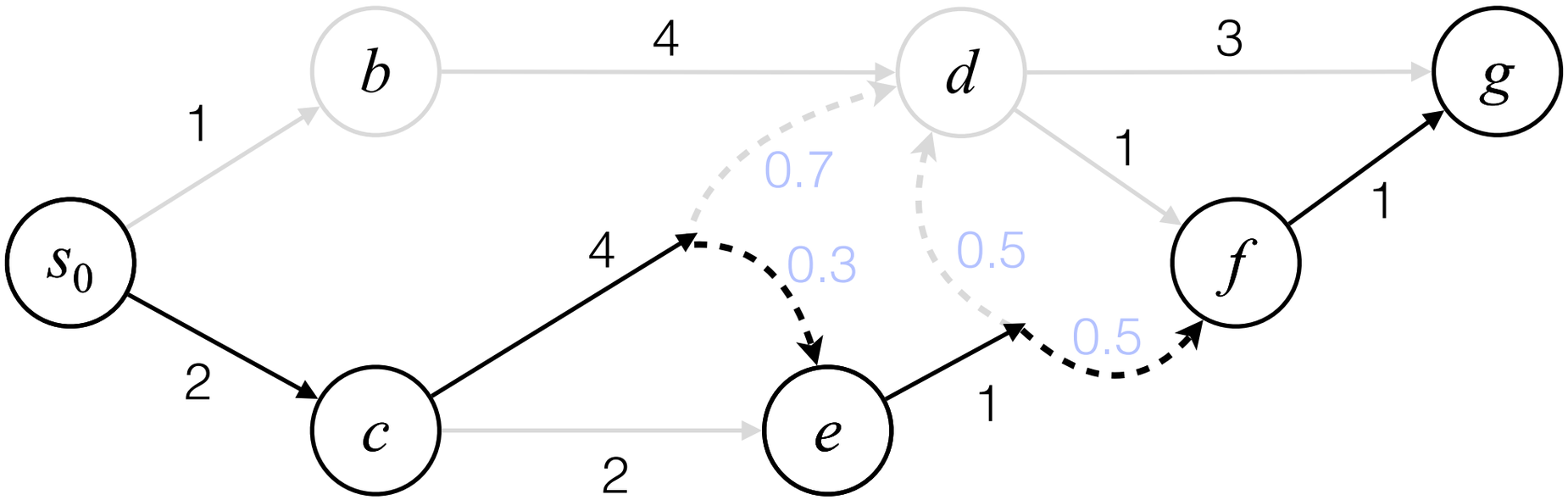
Need **long-term planning**
(also known as *temporal credit assignment* in RL)

Stochastic Shortest Path
via trial-and-error



s_0

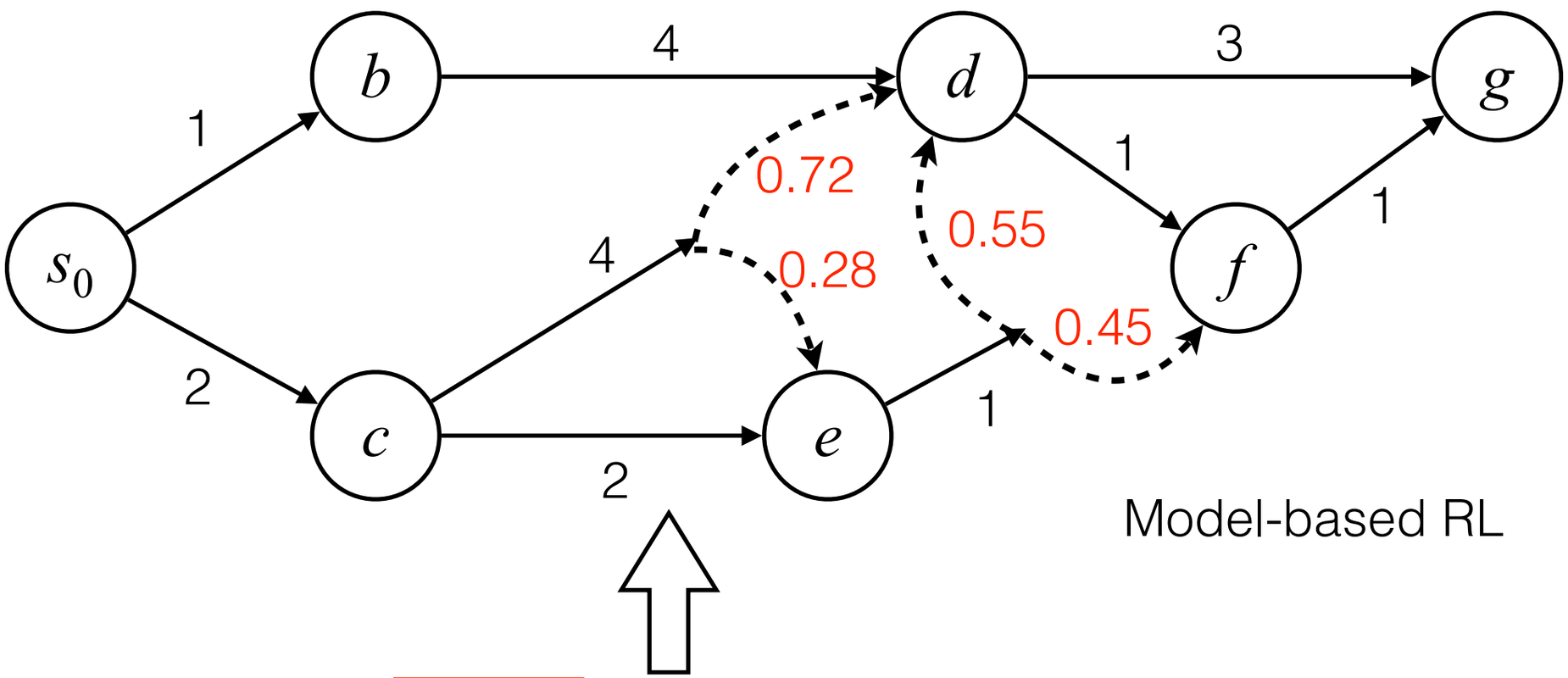
Stochastic Shortest Path
via trial-and-error



Trajectory 1: $s_0 \searrow c \nearrow d \rightarrow g$

Trajectory 2:

Stochastic Shortest Path
via trial-and-error



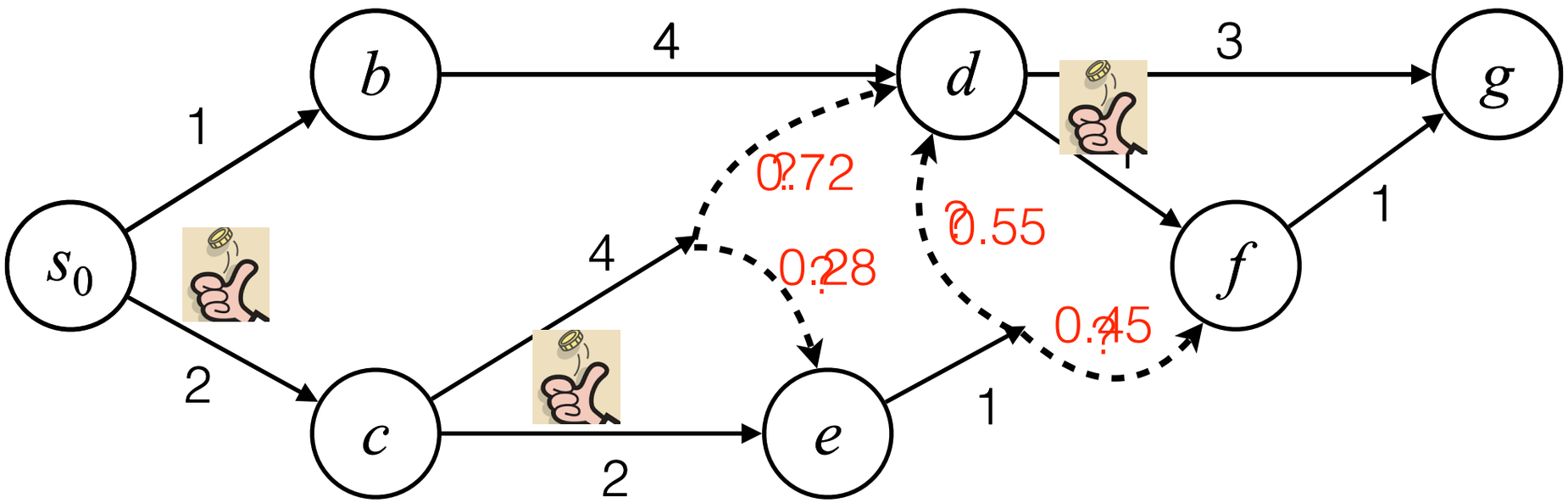
Model-based RL

Trajectory 1: $s_0 \searrow \boxed{c \nearrow d} \rightarrow g$

Trajectory 2: $s_0 \searrow \boxed{c \nearrow e} \rightarrow f \nearrow g$

...

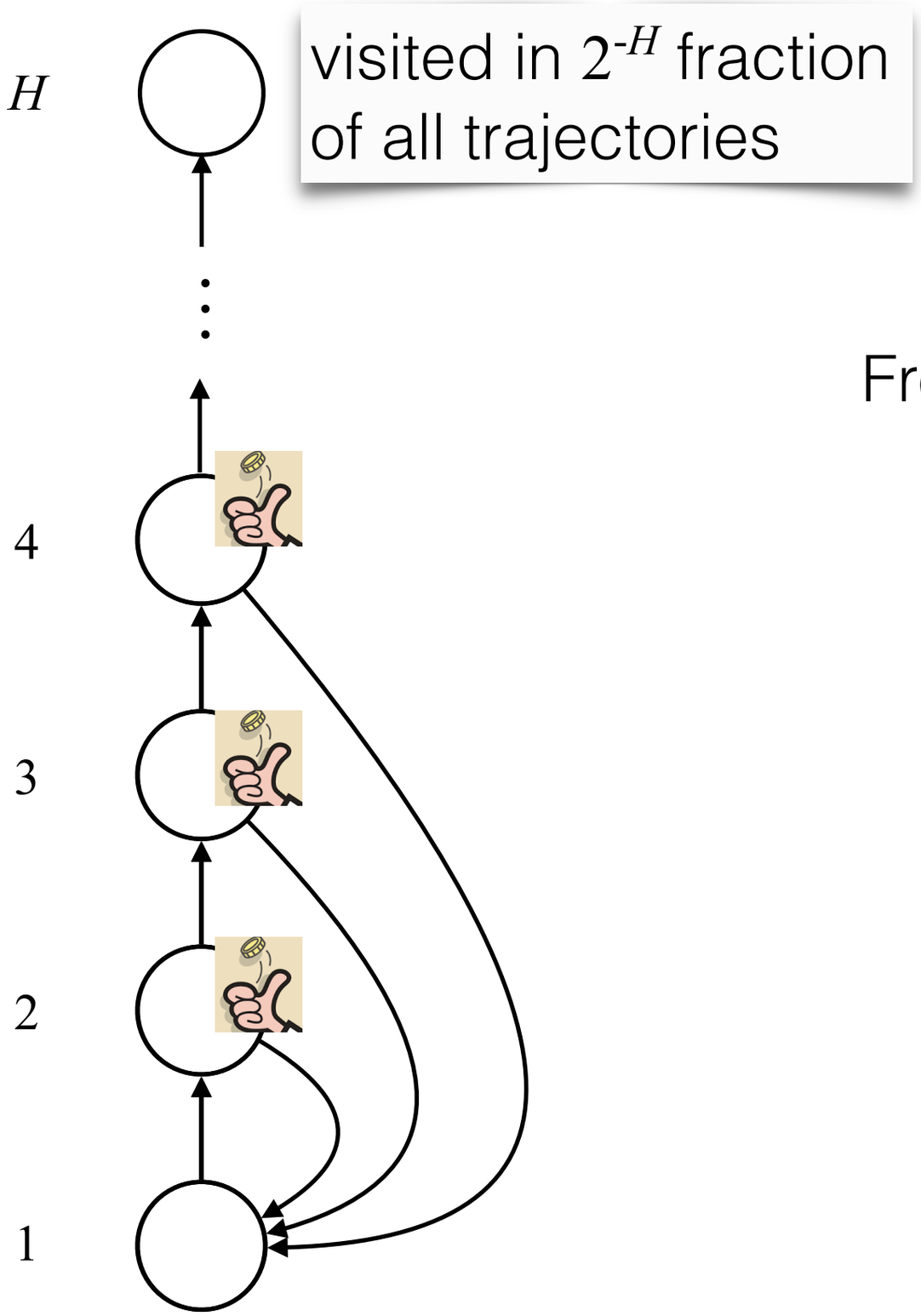
Stochastic Shortest Path
via trial-and-error



Nontrivial! Need **exploration**

- Assume states & actions are visited uniformly
- As we have more data, the estimated distributions will be closer to true distributions, and the learned policy will be closer to optimal
- Sample complexity: the amount of data needed to guarantee that a certain level of near-optimality is achieved

Random exploration can be inefficient



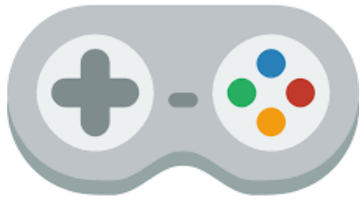
Freeway (one of the Atari games)

Video game playing

reward $r_t = R\,(s_t\,,\,a_t)$

state
$s_t \in S$

+20



e.g., random
spawn of enemies

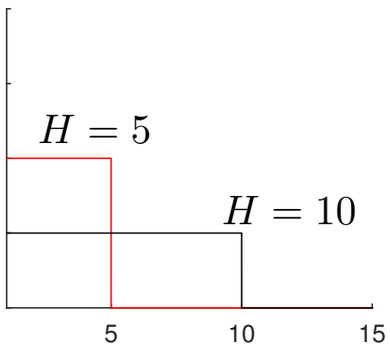
policy
$\pi\colon S \to A$

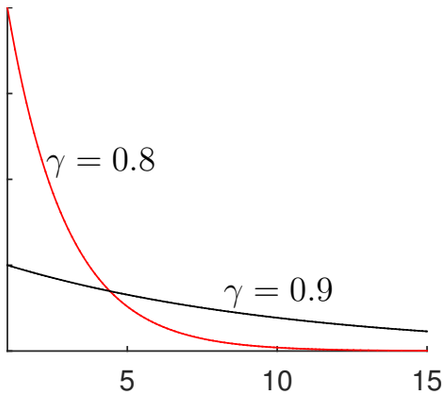
action $a_t \in A$

transition dynamics
$P\,(\,\cdot\,|\,s_t\,,\,a_t)$

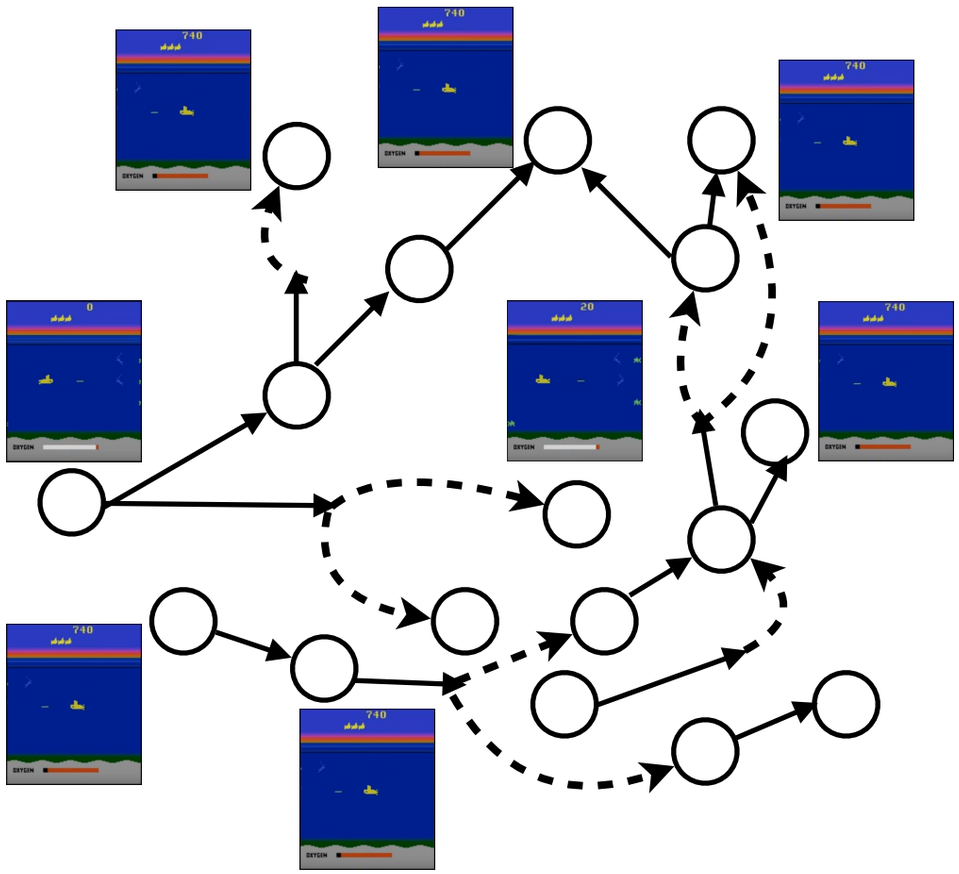
(unknown)

objective: maximize $\mathbb{E}\left[\sum_{t=1}^{H} r_t \,|\, \pi\right]$





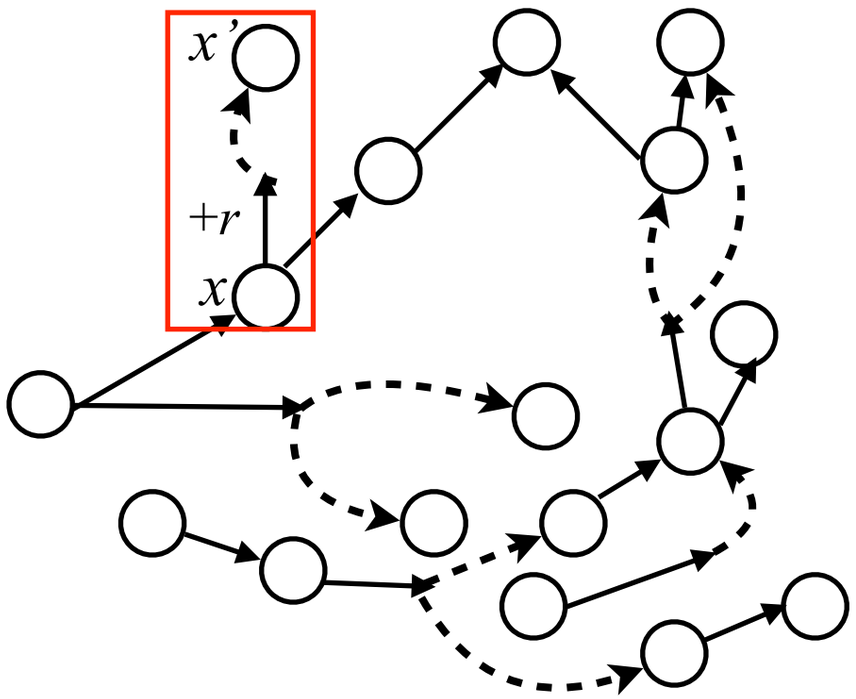
Video game playing

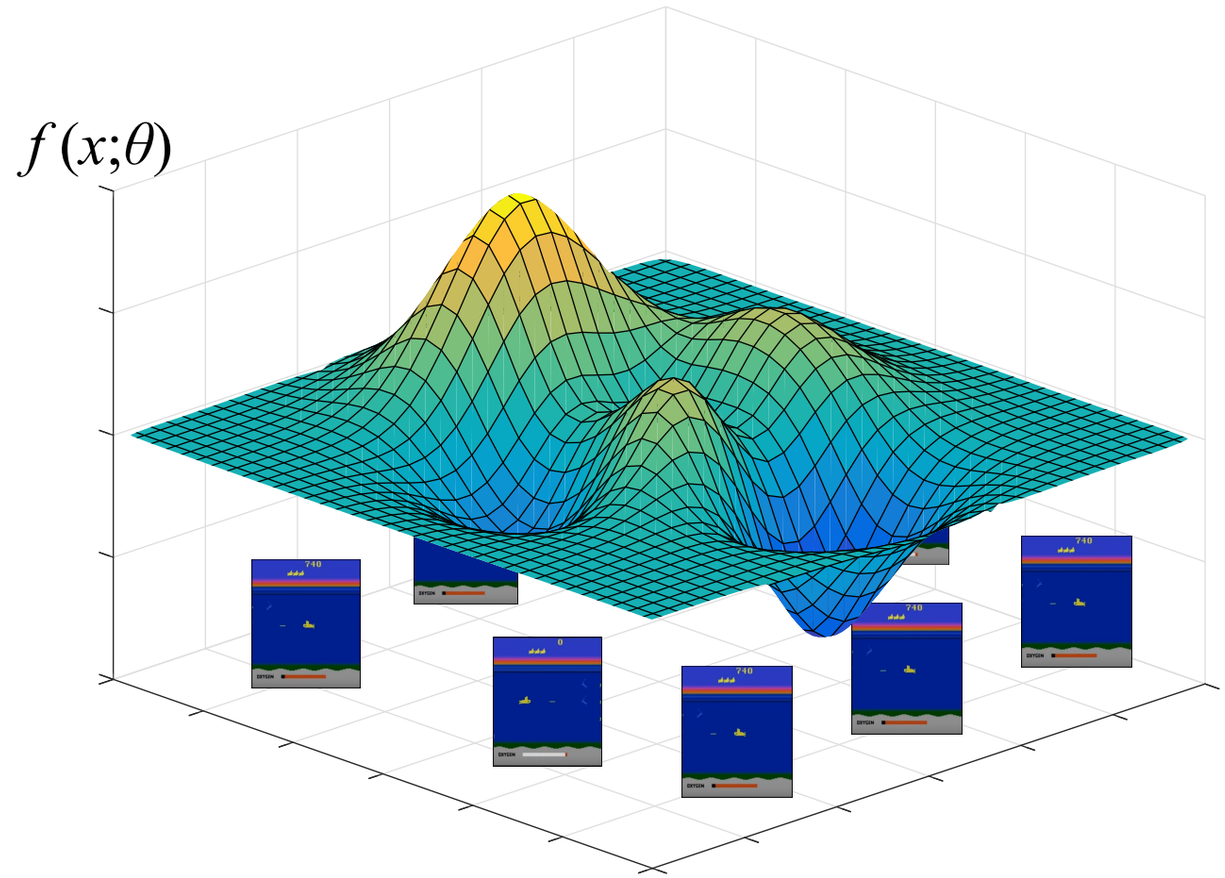


Need **generalization**

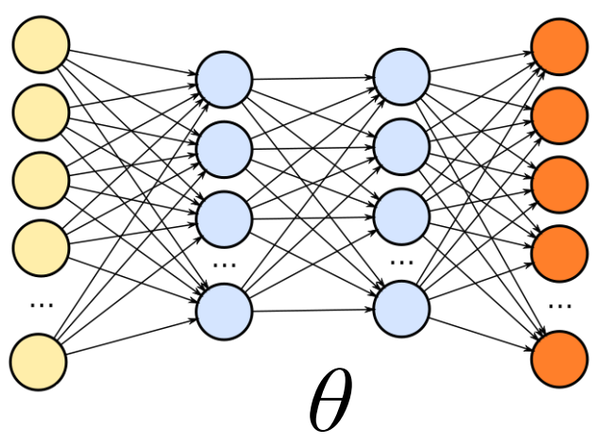
Value function approximation

Video game playing





state features x



$f(x;\theta)$

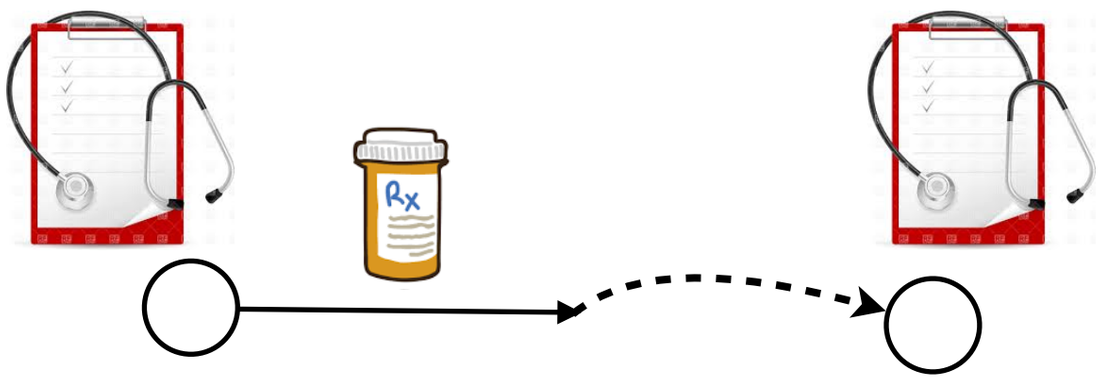
Need **generalization**

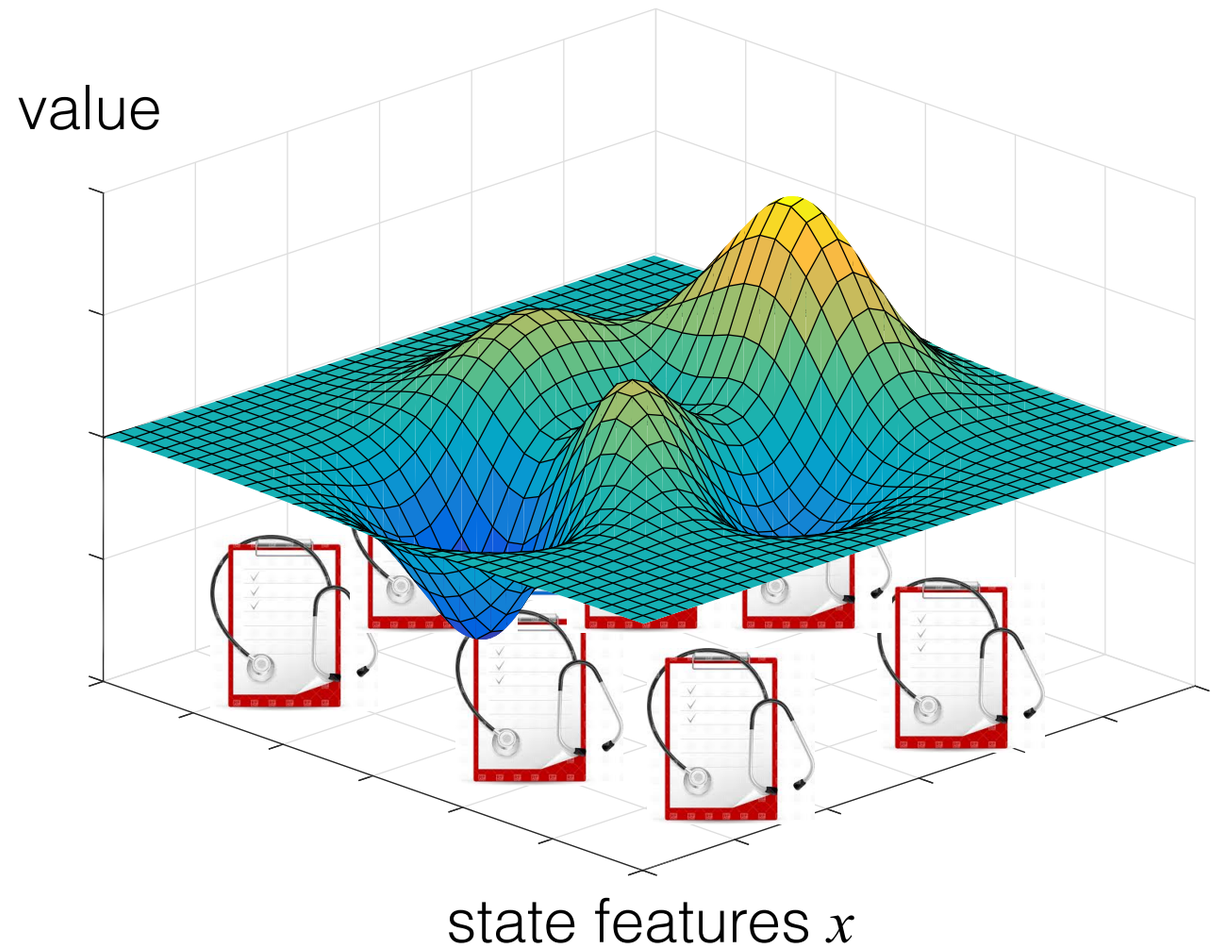
Value function approximation

$$f(\cdot\,;\theta) \approx \mathrm{V}^*$$

Find θ s.t.

Adaptive medical treatment





- State: diagnosis
- Action: treatment
- Reward: progress in recovery

Formulating a real problem in the RL framework is difficult, and defining your state, action, horizon, and reward can be tricky—will come back later in the course.

Summary of this Part: 3 core challenges of RL

Temporal credit assignment

- A sequence of actions led to success/failure: which action(s) to attribute the consequence to?

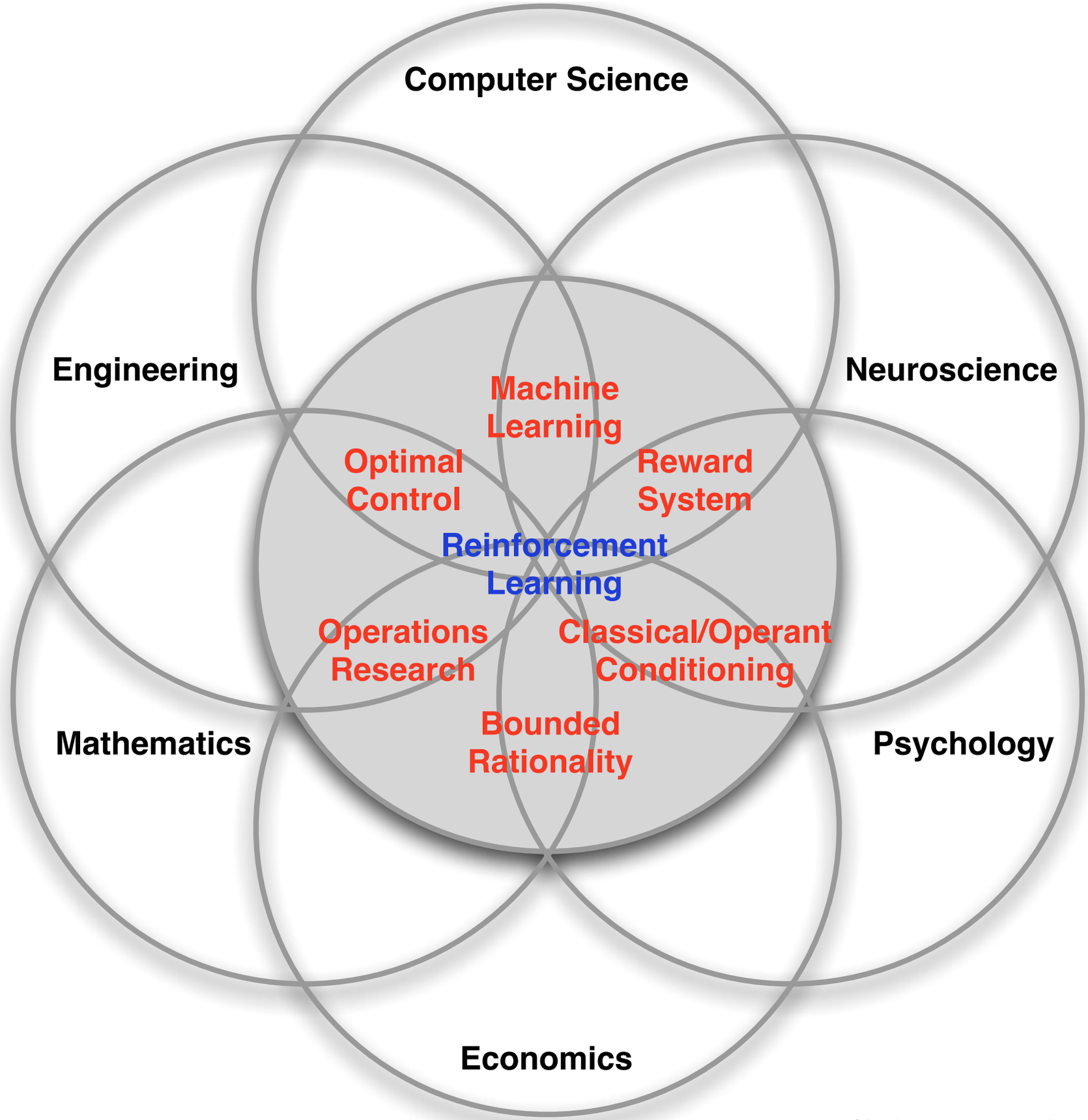
Exploration

- How to take actions to collect a dataset that provides a comprehensive description of the environment?

Generalization

- How do deal with (very) large state spaces?

A Machine Learning view of RL



slide credit: David Silver

Supervised Learning

Given $\{(x^{(i)}, y^{(i)})\}$, learn $f : x \mapsto y$

- Online version: for round $t = 1, 2, \ldots,$ **the learner**
  - observes $x^{(t)}$
  - predicts $\hat{y}^{(t)}$
  - receives $y^{(t)}$
- Want to maximize # of correct predictions
- e.g., classifies if an image is about a dog, a cat, a plane, etc. (multi-class classification)
- Dataset is fixed for everyone
- “Full information setting”
- Core challenge: generalization

Contextual bandits

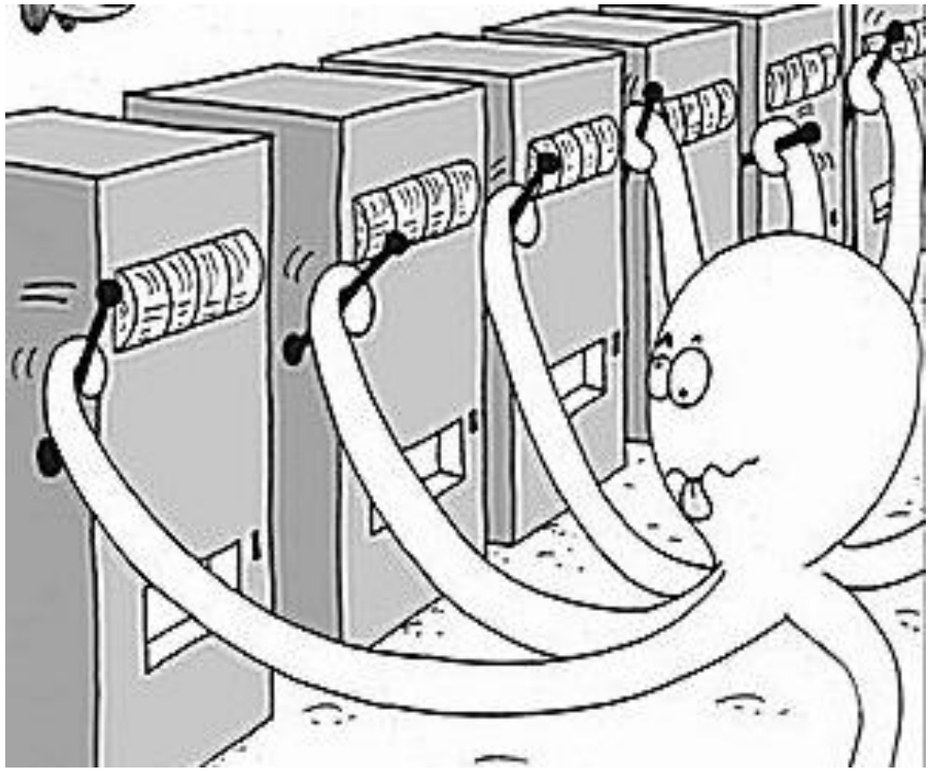
For round $t = 1, 2, \ldots,$ **the learner**

- Given $x^{(t)}$, chooses from a set of actions $a^{(t)} \in A$
- Receives reward $r^{(t)} \sim R(x^{(t)}, a^{(t)})$ (i.e., can be random)
- Want to maximize total reward
- You generate your own dataset $\{(x^{(t)}, a^{(t)}, r^{(t)})\}$!
  - e.g., for an image, the learner guesses a label, and is told whether correct or not (reward = 1 if correct and 0 otherwise). **Do not know the true label.**
  - e.g., for an user, the website recommends a movie, and observes whether the user likes it or not. **Do not know what movies the user really want to see.**
  - "Partial information setting"

Contextual bandits

Contextual Bandits (cont.)

- Simplification: no x, Multi-Armed Bandits (MAB)
- Bandit is a research area by itself. we will not do a lot of bandits but will introduce some concepts that are useful for general RL



RL

For round $t = 1, 2, \ldots,$

- For time step h=1, 2, …, H, the learner
  - Observes $x_h^{(t)}$
  - Chooses $a_h^{(t)}$
  - Receives $r_h^{(t)} \sim R(x_h^{(t)}, a_h^{(t)})$
  - Next $x_{h+1}^{(t)}$ is generated as a function of $x_h^{(t)}$ and $a_h^{(t)}$ (or sometimes, all previous x's and a's within round t)
- Bandits + "Delayed rewards/consequences"
- The protocol here is for episodic RL (each t is an *episode*).

A few misconceptions about RL

RL: Planning or Learning?

Two types of scenarios in RL research

1. Solving a large planning problem using a learning approach
   - e.g., AlphaGo, video game playing, simulated robotics
   - Transition dynamics (Go rules) known, but too many states
   - Run the simulator to collect data
   - RL proved to be successful
2. Solving a learning problem
   - e.g., adaptive medical treatment
   - Transition dynamics unknown (and too many states)
   - Interact with the environment to collect data
   - Great potential for RL, but not realized yet!

Is RL the magical blackbox in machine learning?

- More basic frameworks in machine learning: supervised/ unsupervised learning
- Contextual bandit is an intermediate framework between SL & RL
- **General rule: more flexibility/generality = less tractability!**
  - RL is (often much) more general/flexible than SL / bandits
  - So, RL should be your *last resort* when the problem cannot be handled by any simpler framework
  - Be cautious about reducing an SL problem to RL—some are legit but many fall into the trap of reducing a simple problem to a more difficult one