Lecture 1: Introduction to RL

Professor Emma Brunskill

CS234 RL

Winter 2022

- Today the 3rd part of the lecture includes slides from David Silver's introduction to RL slides or modifications of those slides

Today's Plan

- Overview of reinforcement learning
- Course logistics
- Introduction to sequential decision making under uncertainty

Make good sequences of decisions

Learn to make good sequences of decisions

Reinforcement Learning

Fundamental challenge in artificial intelligence and machine learning is learning to make good decisions under uncertainty

2010s: New Era of RL. Atari

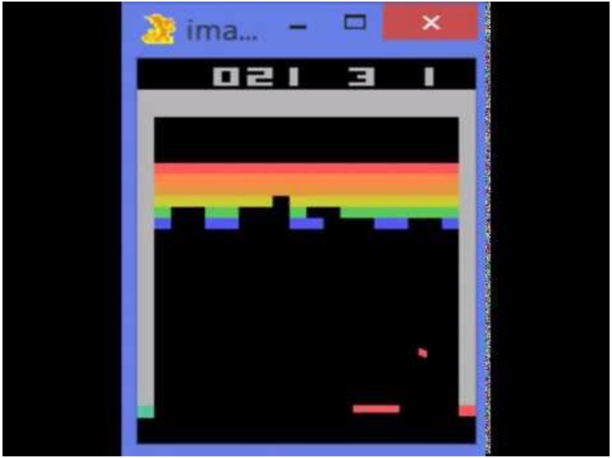


Figure: DeepMind Nature, 2015

2010s: New Era of RL. Robotics

Figure: Chelsea Finn, Sergey Levine, Pieter Abbeel

Expanding Reach. Educational Games

Figure: RL used to optimize Refraction 1, Madel, Liu, Brunskill, Popvic AAMAS 2014.

Expanding Reach. Health

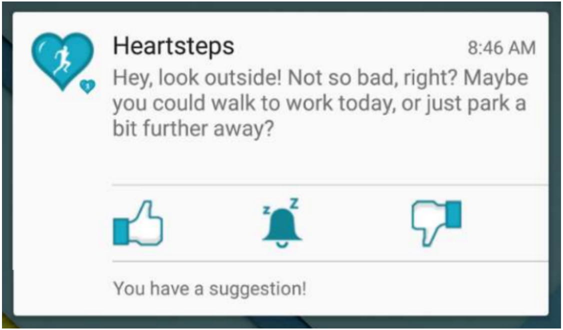


Figure: Personalized HeartSteps: A Reinforcement Learning Algorithm for Optimizing Physical Activity. Liao, Greenewald, Klasnja, Murphy 2019 arxiv

With great power there must also come – great responsibility
–Spiderman comics (though related comments appear in the French National Convention 1793, by Lamb 1817 & Churchill 1906)

Reinforcement Learning Involves

- Optimization
- Delayed consequences
- Exploration
- Generalization

Optimization

- Goal is to find an optimal way to make decisions
  - Yielding best outcomes or at least very good outcomes
- Explicit notion of utility of decisions
- Example: finding minimum distance route between two cities given network of roads

Delayed Consequences

- Decisions now can impact things much later...
  - Saving for retirement
  - Finding a key in video game Montezuma's revenge
- Introduces two challenges
  - When planning: decisions involve reasoning about not just immediate benefit of a decision but also its longer term ramifications
  - When learning: temporal credit assignment is hard (what caused later high or low rewards?)

Exploration

- Learning about the world by making decisions
  - Agent as scientist
  - Learn to ride a bike by trying (and failing)
  - Finding a key in Montezuma's revenge
- Censored data
  - Only get a reward (label) for decision made
  - Don't know what would have happened if we had taken red pill instead of blue pill (Matrix movie reference)
- Decisions impact what we learn about
  - If we choose to go to Stanford instead of MIT, we will have different later experiences...

- Policy is mapping from past experience to action
- Why not just pre-program a policy?

Generalization

- Policy is mapping from past experience to action
- Why not just pre-program a policy?

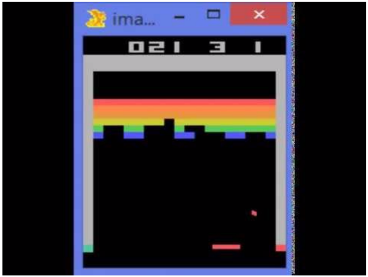


Figure: DeepMind Nature, 2015

- How many possible images are there?
    - $\left(256^{100\times 200}\right)^3$

Reinforcement Learning Involves

- Optimization
- Exploration
- Generalization
- Delayed consequences

RL vs Other AI and Machine Learning

	AI Planning	SL	UL	RL	IL
Optimization					
Learns from experience					
Generalization					
Delayed Consequences					
Exploration					

- SL = Supervised learning; UL = Unsupervised learning; RL = Reinforcement Learning; IL = Imitation Learning

RL vs Other AI and Machine Learning

	AI Planning	SL	UL	RL	IL
Optimization	X				
Learns from experience					
Generalization	X				
Delayed Consequences	X				
Exploration					

- SL = Supervised learning; UL = Unsupervised learning; RL = Reinforcement Learning; IL = Imitation Learning
- AI planning assumes have a model of how decisions impact environment

RL vs Other AI and Machine Learning

	AI Planning	SL	UL	RL	IL
Optimization	X				
Learns from experience		X			
Generalization	X	X			
Delayed Consequences	X				
Exploration					

- SL = Supervised learning; UL = Unsupervised learning; RL = Reinforcement Learning; IL = Imitation Learning
- Supervised learning has access to the correct labels

RL vs Other AI and Machine Learning

	AI Planning	SL	UL	RL	IL
Optimization	X				
Learns from experience		X	X		
Generalization	X	X	X		
Delayed Consequences	X				
Exploration					

- SL = Supervised learning; UL = Unsupervised learning; RL = Reinforcement Learning; IL = Imitation Learning
- Unsupervised learning has access to no labels

RL vs Other AI and Machine Learning

	AI Planning	SL	UL	RL	IL
Optimization	X			X	
Learns from experience		X	X	X	
Generalization	X	X	X	X	
Delayed Consequences	X			X	
Exploration				X	

- SL = Supervised learning; UL = Unsupervised learning; RL = Reinforcement Learning; IL = Imitation Learning
- Reinforcement learning is given censored labels

Sidenote: Imitation Learning

	AI Planning	SL	UL	RL	IL
Optimization	X			X	X
Learns from experience		X	X	X	X
Generalization	X	X	X	X	X
Delayed Consequences	X			X	X
Exploration				X	

- SL = Supervised learning; UL = Unsupervised learning; RL = Reinforcement Learning; IL = Imitation Learning
- Imitation learning assumes input demonstrations of good policies
- IL reduces RL to SL. IL + RL is promising area

How Do We Proceed?

- Explore the world
- Use experience to guide future decisions

Other Issues

- Where do rewards come from?
  - And what happens if we get it wrong?
- Robustness / Risk sensitivity
- We are not alone...
  - Multi-agent RL

Break

Today's Plan

- Overview of reinforcement learning
- **Course structure overview**
- Introduction to sequential decision making under uncertainty

High Level Learning Goals*

- Define the key features of RL
- Given an application probem how (and whether) to use RL for it
- Compare and contrast RL algorithms on multiple criteria
- *For more detailed descriptions, see website

Course Staff

- Instructor: Emma Brunskill
- CAs: Dilip Arumugam, Jean-Raymond Betterton, Evan Liu, Allen Nie, Jupinder Parmar, Nikhil Sardana, Skanda Vaidyanath and Cassie Zhang
- Additional information
  - Course webpage: http://cs234.stanford.edu
  - Schedule, Ed (fastest way to get help), lecture slides
  - Prerequisites, grading details, late policy, see webpage

Standing on the shoulders of giants...

- A key part of human progress is our ability to learn beyond our own experience
- Enormous variability in the effectiveness of education
- Practice, coupled with prompt feedback, is key
- Use some of our class time to provide opportunities for practice and feedback
- Huge body of evidence which supports that retrieval practice helps increase retention more than many other methods, and can support deep learning: "Refresh your understanding" exercises in many lectures

Basic Class Format

- Live lectures
- Five homeworks
- Two exams
- Check/Refresh your understanding exercises
- 1 short multiple choice quiz

Effective Practice Strategies for Learning Class Content

- Keep up with Refresh/Check your understanding exercises
- Do homework
- Attend office hours for help
- Go through problem session material for additional practice
- Do past quiz or exam problems for practice without referring to solutions

Criteria for Doing Well in Class

- **All of you can succeed if you put in the effort**
- We, the class staff, and your fellow classmates, are here to help

Class Structure

- Synchronous class lectures every Tuesday and Thursday. Via zoom for first two weeks
- Recorded material covering lecture material will also be released by the end of lecture day
- Friday 6pm Pacific: This is generally when homeworks will be due. All homeworks will be submitted on gradescope.

Learning in a Time of Covid

- I know the pandemic is hard for everyone, and for some of you, an extraordinarily hard time
- We expect much of the class to be live, but the first two weeks are remote.

Break

Today's Plan

- Overview of reinforcement learning
- Course logistics
- **Introduction to sequential decision making under uncertainty**

Refresher Exercise: AI Tutor as a Decision Process

- Student initially does not know addition (easier) nor subtraction (harder)
- AI tutor agent can provide practice problems about addition or subtraction
- AI agent gets rewarded $+1$ if student gets problem right, -1 if get problem wrong
- Model this as a Decision Process. Define state space, action space, and reward model. What does the dynamics model represent? What would a policy to optimize the expected discounted sum of rewards yield?
- Write down your own answers (5 min) and then (if watching live) discuss in small breakout groups..

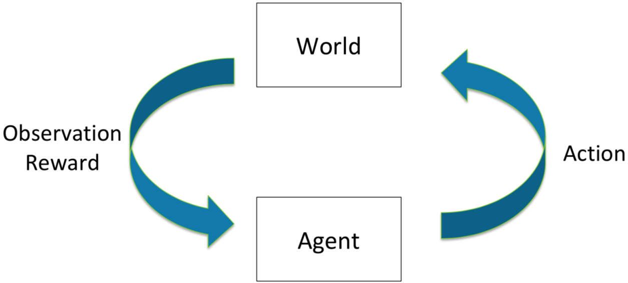
Refresher Exercise: AI Tutor as a Decision Process

- State:
- Actions:
- Reward model:
- Meaning of dynamics model:

Refresher Exercise: AI Tutor as a Decision Process

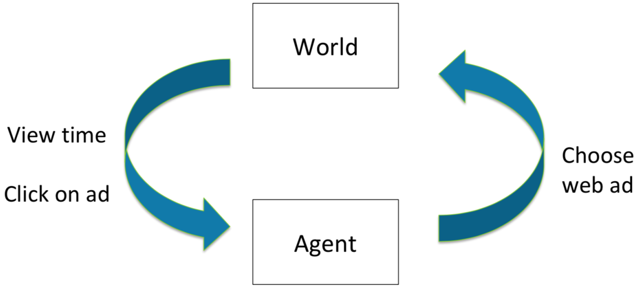
- Student initially does not know addition (easier) nor subtraction (harder)
- Teaching agent can provide activities about addition or subtraction
- Agent gets rewarded for student performance: $+1$ if student gets problem right, -1 if get problem wrong
- Which items will agent learn to give to max expected reward? Is this the best way to optimize for learning? If not, what other reward might one give to encourage learning?

Sequential Decision Making



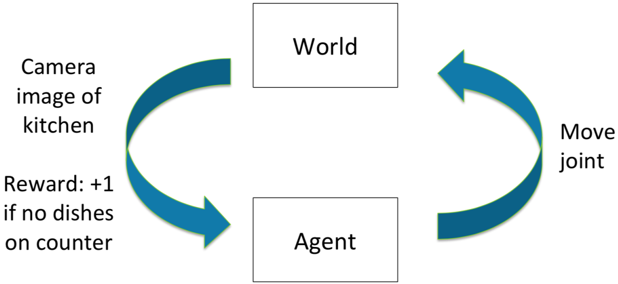
- Goal: Select actions to maximize total expected future reward
- May require balancing immediate & long term rewards

Example: Web Advertising



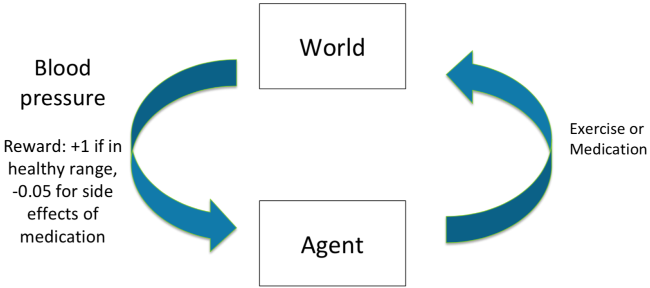
- Goal: Select actions to maximize total expected future reward
- May require balancing immediate & long term rewards

Example: Robot Unloading Dishwasher



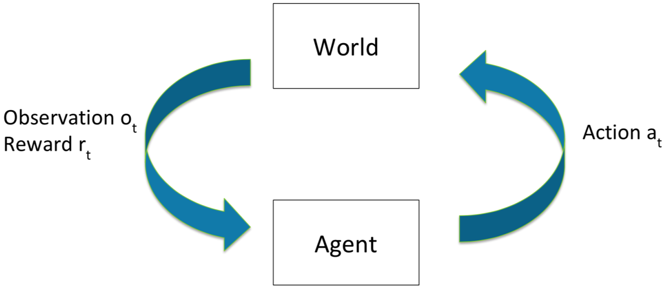
- Goal: Select actions to maximize total expected future reward
- May require balancing immediate & long term rewards

Example: Blood Pressure Control



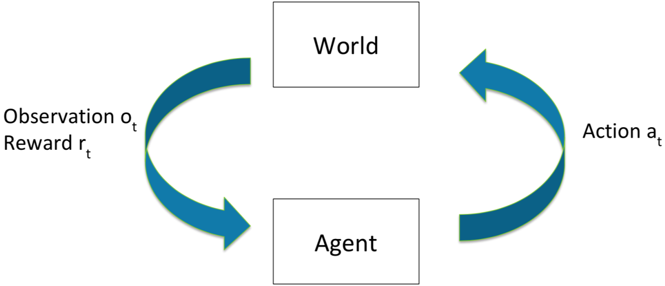
- Goal: Select actions to maximize total expected future reward
- May require balancing immediate & long term rewards

Sequential Decision Process: Agent & the World (Discrete Time)



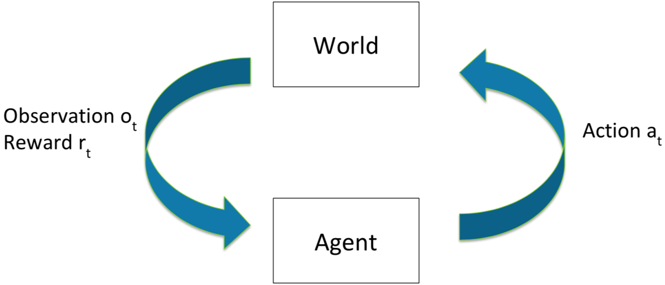
- Each time step t:
  - Agent takes an action a_t
  - World updates given action a_t, emits observation o_t and reward r_t
  - Agent receives observation o_t and reward r_t

History: Sequence of Past Observations, Actions & Rewards



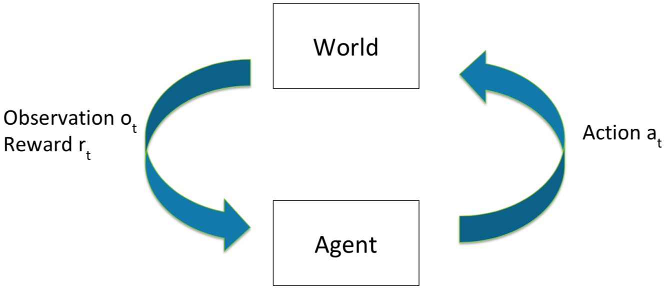
- History $h_t = (a_1, o_1, r_1, \ldots, a_t, o_t, r_t)$
- Agent chooses action based on history
- State is information assumed to determine what happens next
    - Function of history: $s_t = (h_t)$

World State



- This is true state of the world used to determine how world generates next observation and reward
- Often hidden or unknown to agent
- Even if known may contain information not needed by agent

Agent State: Agent's Internal Representation



- What the agent / algorithm uses to make decisions about how to act
- Generally a function of the history: $s_t = f(h_t)$
- Could include meta information like state of algorithm (how many computations executed, etc) or decision process (how many decisions left until an episode ends)

Markov Assumption

- Information state: sufficient statistic of history
- State s_t is Markov if and only if:

$$p(s_{t+1}|s_t, a_t) = p(s_{t+1}|h_t, a_t)$$

- Future is independent of past given present

Markov Assumption for Prior Examples

- Information state: sufficient statistic of history
- State s_t is Markov if and only if:

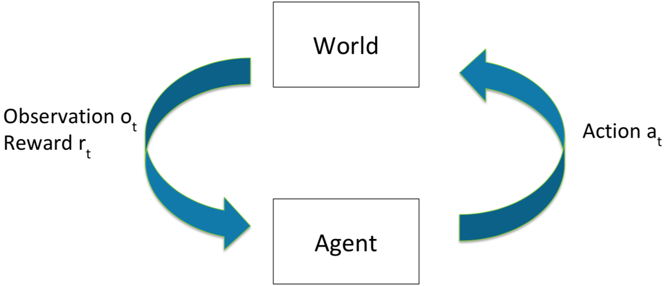
$$p(s_{t+1}|s_t, a_t) = p(s_{t+1}|h_t, a_t)$$

- Future is independent of past given present
- Hypertension control: let state be current blood pressure, and action be whether to take medication or not. Is this system Markov?
- Website shopping: state is current product viewed by customer, and action is what other product to recommend. Is this system Markov?

Why is Markov Assumption Popular?

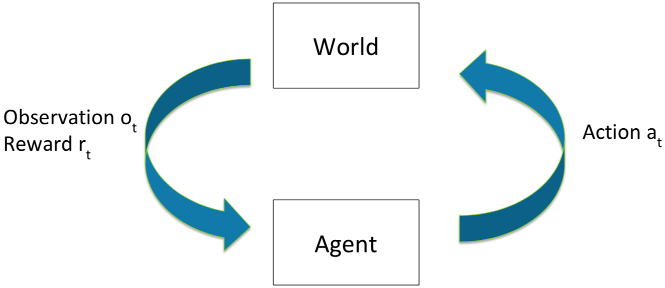
- Can always be satisfied
  - Setting state as history is always Markov: $s_t = h_t$
- In practice often assume most recent observation is sufficient statistic of history: $s_t = o_t$
- State representation has big implications for:
  - Computational complexity
  - Data required
  - Resulting performance

Full Observability / Markov Decision Process (MDP)



- Environment and world state $s_t = o_t$

Types of Sequential Decision Processes



- Is state Markov? Is world partially observable? (POMDP)
- Are dynamics deterministic or stochastic?
- Do actions influence only immediate reward or reward and next state?

Example: Mars Rover as a Markov Decision Process

s_1	s_2	s_3	s_4	s_5	s_6	s_7
						

Figure: Mars rover image: NASA/JPL-Caltech

- States: Location of rover $(s_1, \ldots, s_7)$
- Actions: TryLeft or TryRight
- Rewards:
  - $+1$ in state s_1
  - $+10$ in state s_7
  - 0 in all other states

RL Algorithm Components

- Often includes one or more of: Model, Policy, Value Function

MDP Model

- Agent's representation of how world changes given agent's action
- Transition / dynamics model predicts next agent state

$$p(s_{t+1} = s' | s_t = s, a_t = a)$$

- Reward model predicts immediate reward

$$r(s_t = s, a_t = a) = \mathbb{E}[r_t | s_t = s, a_t = a]$$

Example: Mars Rover Stochastic Markov Model

s_1	s_2	s_3	s_4	s_5	s_6	s_7
$\hat{r} = 0$	$\hat{r} = 0$	$\hat{r} = 0$	$\hat{r} = 0$	$\hat{r} = 0$	$\hat{r} = 0$	$\hat{r} = 0$

- Numbers above show RL agent's reward model
- Part of agent's transition model:
  - $0.5 = P(s_1|s_1, \text{TryRight}) = P(s_2|s_1, \text{TryRight})$
  - $0.5 = P(s_2|s_2, \text{TryRight}) = P(s_3|s_2, \text{TryRight}) \cdots$
- Model may be wrong

Policy

- Policy π determines how the agent chooses actions
- $\pi : S \to A$, mapping from states to actions
- Deterministic policy:
$$\pi(s) = a$$
- Stochastic policy:
$$\pi(a|s) = Pr(a_t = a|s_t = s)$$

Example: Mars Rover Policy

s_1	s_2	s_3	s_4	s_5	s_6	s_7
						

- $\pi(s_1) = \pi(s_2) = \cdots = \pi(s_7) = \text{TryRight}$
- Quick check: is this a deterministic policy or a stochastic policy?

Value Function

- Value function V^π: expected discounted sum of future rewards under a particular policy π

$$V^\pi(s_t = s) = \mathbb{E}_\pi[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \gamma^3 r_{t+3} + \cdots | s_t = s]$$

- Discount factor γ weighs immediate vs future rewards
- Can be used to quantify goodness/badness of states and actions
- And decide how to act by comparing policies

Example: Mars Rover Value Function

s_1	s_2	s_3	s_4	s_5	s_6	s_7
$V^\pi(s_1) = +1$	$V^\pi(s_2) = 0$	$V^\pi(s_3) = 0$	$V^\pi(s_4) = 0$	$V^\pi(s_5) = 0$	$V^\pi(s_6) = 0$	$V^\pi(s_7) = +10$

- Discount factor, $\gamma = 0$
- $\pi(s_1) = \pi(s_2) = \cdots = \pi(s_7) = \text{TryRight}$
- Numbers show value $V^\pi(s)$ for this policy and this discount factor

Types of RL Agents

- Model-based
  - Explicit: Model
  - May or may not have policy and/or value function
- Model-free
  - Explicit: Value function and/or policy function
  - No model

RL Agents

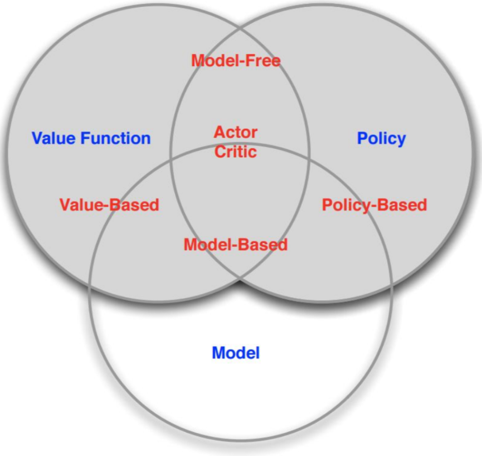


Figure: Figure from David Silver's RL course

Evaluation and Control

- Evaluation
  - Estimate/predict the expected rewards from following a given policy
- Control
  - Optimization: find the best policy

Example: Mars Rover Policy Evaluation

s_1	s_2	s_3	s_4	s_5	s_6	s_7
$\rightarrow$	$\rightarrow$	$\rightarrow$	$\rightarrow$	$\rightarrow$	$\rightarrow$	$\rightarrow$

- $\pi(s_1) = \pi(s_2) = \cdots = \pi(s_7) =$ TryRight
- Discount factor, $\gamma = 0$
- What is the value of this policy?

$$V^\pi(s_t = s) = \mathbb{E}_\pi[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \cdots | s_t = s]$$

Example: Mars Rover Policy Evaluation

s_1	s_2	s_3	s_4	s_5	s_6	s_7
→	→	→	→	→	→	→

- $\pi(s_1) = \pi(s_2) = \cdots = \pi(s_7) = \text{TryRight}$
- Discount factor, $\gamma = 0$
- What is the value of this policy?

$$V^\pi(s_t = s) = \mathbb{E}_\pi[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \cdots | s_t = s]$$

- Answer:

$$V^\pi(s_t = s) = r(s)$$

Course Outline

- Markov decision processes & planning (**Continued next time**)
- Model-free policy evaluation
- Model-free control
- Reinforcement learning with function approximation & Deep RL
- Policy Search
- Exploration
- Advanced Topics

See website for more details

Tasks

- Due Friday at 6pm: Quiz 0. Short multiple choice quiz (open book) to check your own understanding and background for the class. Credit will be given if you complete it (not for correctness). 1% of grade
- Homework 1 will be released this week.
- Check your understanding exercises will be announced in lectures and on Ed.
- See website for more details