

# Lecture 1: Introduction to RL

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CS234 RL

Winter 2019

- Today the 3rd part of the lecture is based on David Silver's introduction to RL slides

# Today's Plan

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

# Reinforcement Learning

Learn to make good sequences of decisions

# Repeated Interactions with World

Learn to make good **sequences of decisions**

# Reward for Sequence of Decisions

Learn to make **good** sequences of decisions

# Don't Know in Advance How World Works

**Learn** to make good sequences of decisions

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



Figure: Example from Yael Niv

- Childhood: primitive brain & eye, swims around, attaches to a rock
- Adulthood: digests brain, sits
- Suggests brain is helping guide decisions (no more decisions, no need for brain?)

# Atari

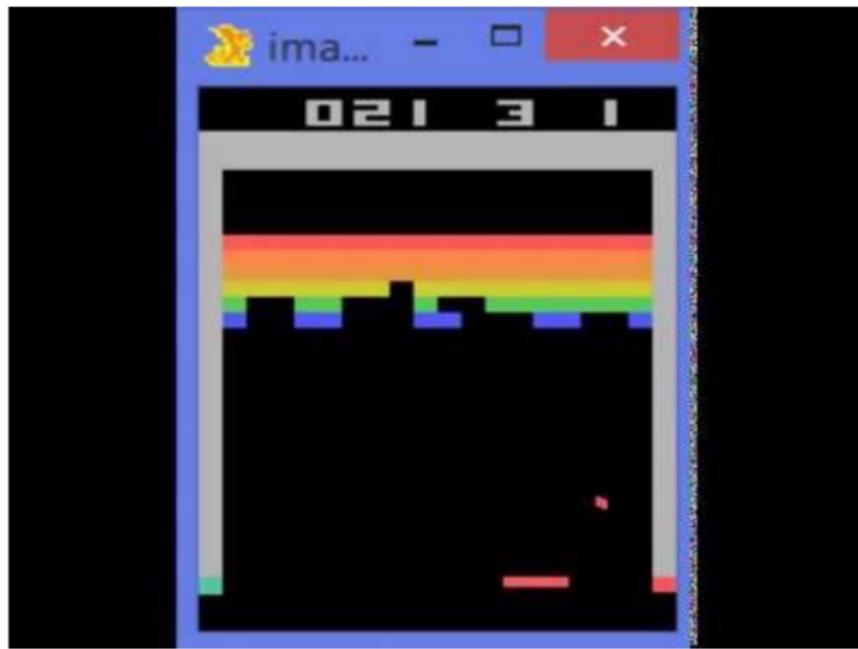


Figure: DeepMind Nature, 2015

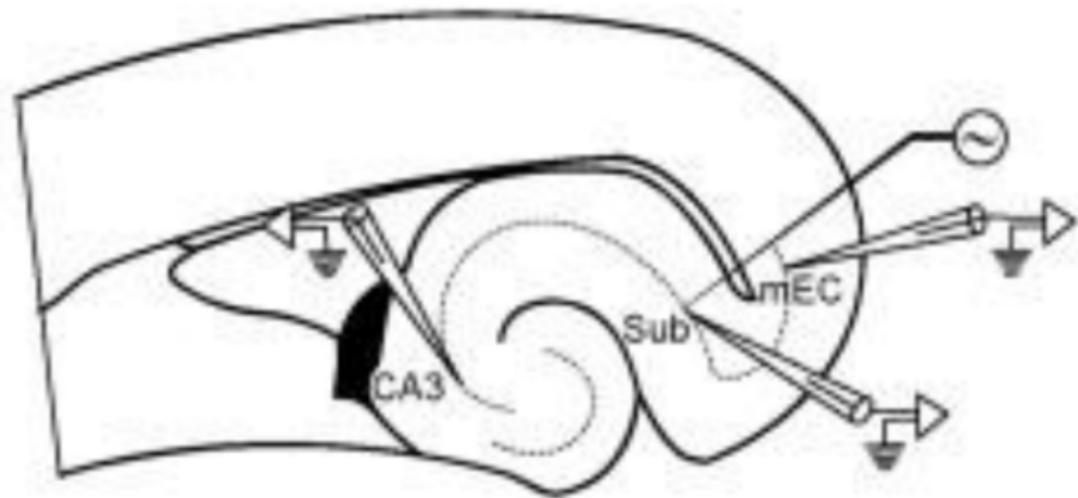
# Robotics



# Educational Games



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



**Figure:** Adaptive control of epileptiform excitability in an in vitro model of limbic seizures. Panuccio, Quez, Vincent, Avoli, Pineau



Figure: Yeung, Russakovsky, Mori, Li 2016.

# 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 a very good strategy

# Delayed Consequences

- Decisions now can impact things much later...
  - Saving for retirement
  - Finding a key in Montezuma's revenge
- Introduces two challenges
  - ① When planning: decisions involve reasoning about not just immediate benefit of a decision but also its longer term ramifications
  - ② 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?

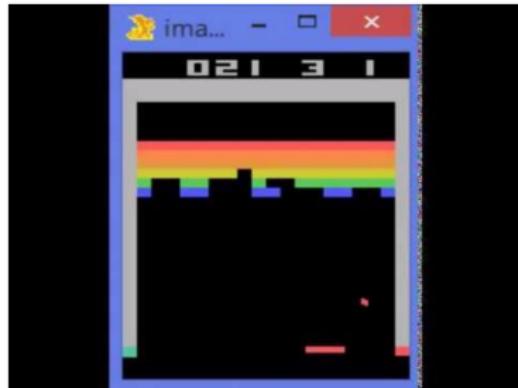


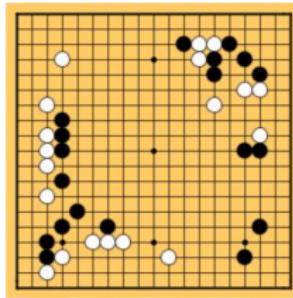
Figure: DeepMind Nature, 2015

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

# Reinforcement Learning Involves

- Optimization
- Exploration
- Generalization
- Delayed consequences

# AI Planning (vs RL)



- Optimization
- Generalization
- Exploration
- Delayed consequences
- Computes good sequence of decisions
- **But given model of how decisions impact world**

# Supervised Machine Learning (vs RL)

- **Optimization**
- **Generalization**
- Exploration
- Delayed consequences
- Learns from experience
- **But provided correct labels**

# Unsupervised Machine Learning (vs RL)

- **Optimization**
- **Generalization**
- Exploration
- Delayed consequences
- Learns from experience
- **But no labels from world**

# Imitation Learning (vs RL)

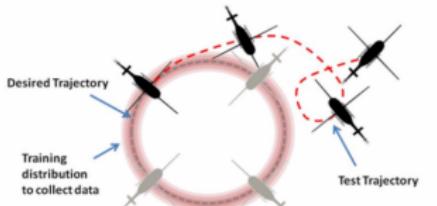
- **Optimization**
- **Generalization**
- Exploration
- **Delayed consequences**
- Learns from experience...**of others**
- **Assumes input demos of good policies**

# Imitation Learning



Figure: Abbeel, Coates and Ng helicopter team, Stanford

# Imitation Learning



Ross & Bagnell 2013

- Reduces RL to supervised learning
- Benefits
  - Great tools for supervised learning
  - Avoids exploration problem
  - With big data lots of data about outcomes of decisions
- Limitations
  - Can be expensive to capture
  - Limited by data collected
- Imitation learning + RL promising!

# 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

# Today's Plan

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

# Basic Logistics

- Instructor: Emma Brunskill
- CA's: Ramtin Keramati (Head CA), Patrick Cho, Anchit Gupta, Bo Liu, Sudarshan Seshadri, Jay Whang, Yongshang Wu, Andrea Zanette
- Time: Monday, Wednesday 11:30-12:50
- Location: Gates B1
- Additional information
  - Course webpage: <http://cs234.stanford.edu>
  - Schedule, Piazza, lecture slides

# Prerequisites

- Python proficiency
- Basic probability and statistics
- Multivariate calculus and linear algebra
- Machine learning or AI (e.g. CS229, CS221)
- Loss functions, derivatives, gradient descent should be familiar
- Have heard of Markov decision processes and RL before in an AI or ML class
  - We will cover the basics, but quickly

# End of Class Goals

- Define the key features of reinforcement learning that distinguish it from AI and non-interactive machine learning (as assessed by the exam)
- Given an application problem (e.g. from computer vision, robotics, etc) decide if it should be formulated as a RL problem, if yes be able to define it formally (in terms of the state space, action space, dynamics and reward model), state what algorithm (from class) is best suited to addressing it, and justify your answer. (as assessed by the project and the exam)
- Implement (in code) common RL algorithms including a deep RL algorithm (as assessed by the homeworks)
- Describe (list and define) multiple criteria for analyzing RL algorithms and evaluate algorithms on these metrics: e.g. regret, sample complexity, computational complexity, empirical performance, convergence, etc. (as assessed by homeworks and the exam)
- Describe the exploration vs exploitation challenge and compare and contrast at least two approaches for addressing this challenge (in terms of performance, scalability, complexity of implementation, and theoretical guarantees) (as assessed by an assignment and the exam)

# Grading

- Assignment 1 10%
- Assignment 2 20%
- Assignment 3 16%
- Midterm 25%
- Quiz 5%
- Final Project 24%
  - Proposal 1%
  - Milestone 2%
  - Poster presentation 5%
  - Final Report 16%

If you choose to do the default project/4th assignment, your breakdown will instead be

- Poster presentation 5%
- Paper/assignment write up 19%

# Communication

- We believe students often learn an enormous amount from each other as well as from us, the course staff.
- We will use Piazza to facilitate discussion and peer learning
- Please use Piazza for all questions related to lectures, homeworks, and projects

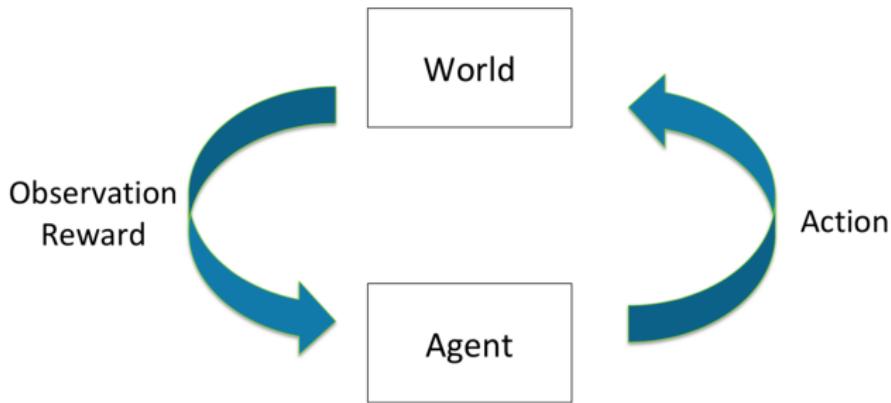
# Grading

- Late policy
  - 6 free late days
  - See webpage for details on how many per assignment/project and penalties for using more
- Collaboration: see webpage and reach out to us if you have any questions about what is considered permissible collaboration

# Today's Plan

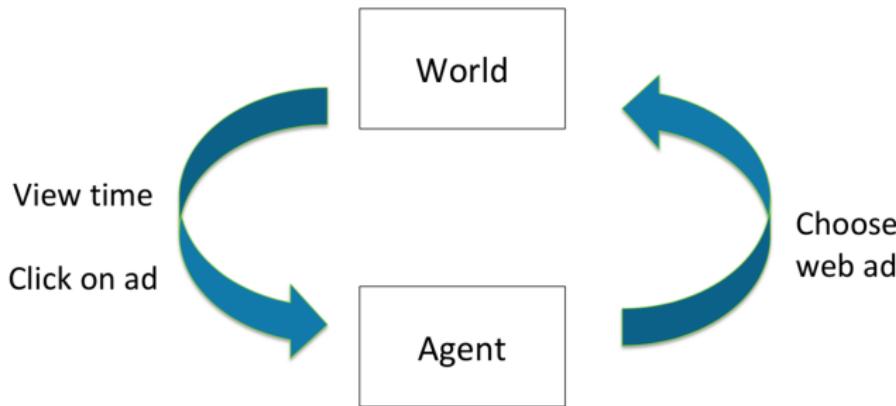
- Overview of reinforcement learning
- Course logistics
- **Introduction to sequential decision making under uncertainty**

# Sequential Decision Making



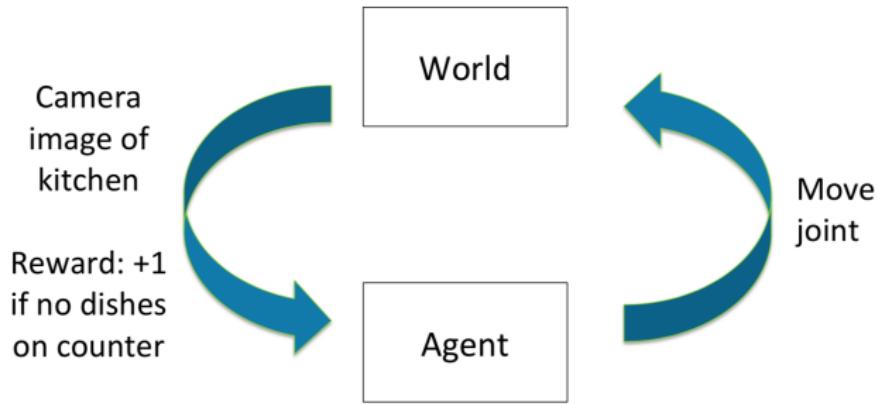
- Goal: Select actions to maximize total expected future reward
- May require balancing immediate & long term rewards
- May require strategic behavior to achieve high rewards

# Example: Web Advertising



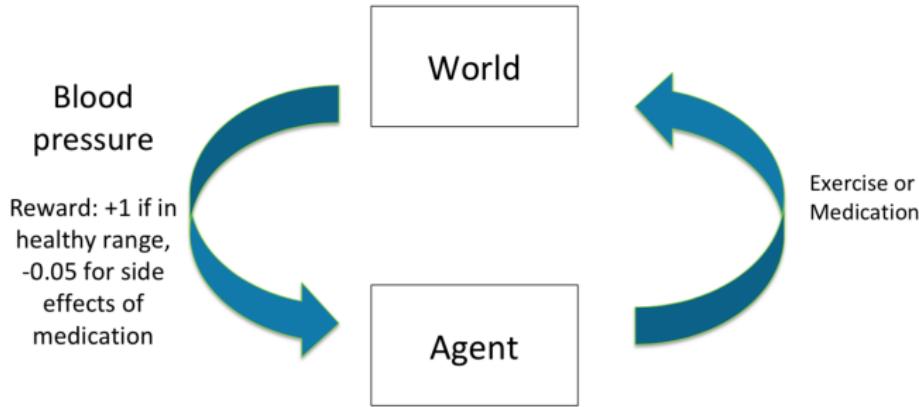
- Goal: Select actions to maximize total expected future reward
- May require balancing immediate & long term rewards
- May require strategic behavior to achieve high rewards

# Example: Robot Unloading Dishwasher



- Goal: Select actions to maximize total expected future reward
- May require balancing immediate & long term rewards
- **May require strategic behavior to achieve high rewards**

# Example: Blood Pressure Control



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

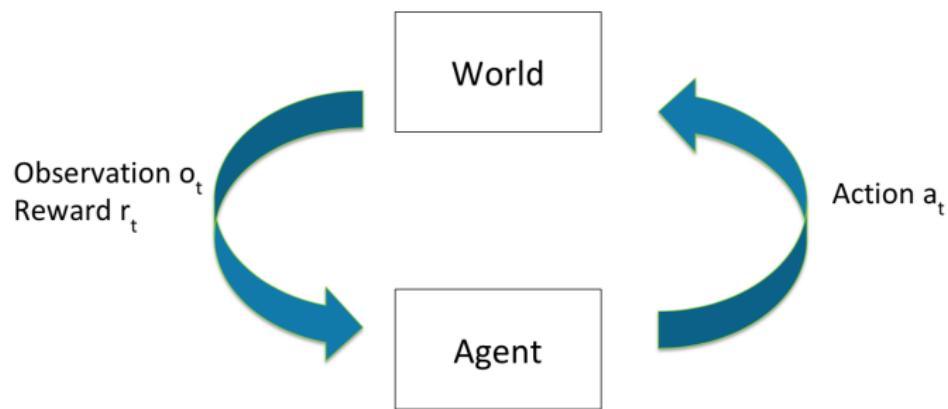
## Check Your Understanding: Artificial Tutor

- 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

## Check Your Understanding: Artificial Tutor

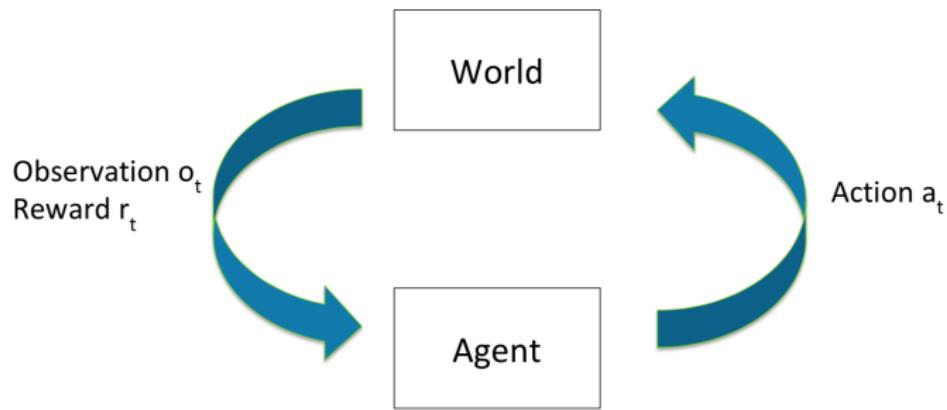
- Student initially does not know addition (easier) nor subtraction (harder)
- Teaching agent can provide activities about addition or subtraction
- Agent gets rewarded for student performance: +1 if student gets problem right, -1 if get problem wrong
- Which items will agent learn to give to max expected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

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



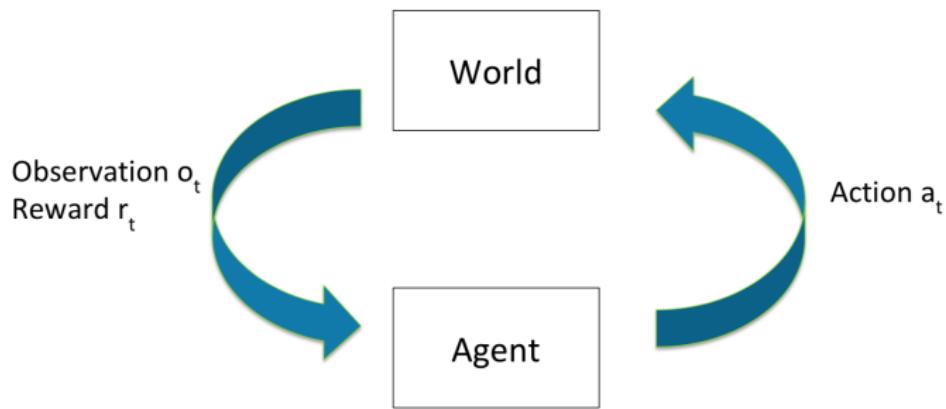
- Each time step  $t$ :
  - Agent takes an action  $a_t$
  - World updates given action  $a_t$ , emits observation  $o_t$  and reward  $r_t$
  - Agent receives observation  $o_t$  and reward  $r_t$

# History: Sequence of Past Observations, Actions & Rewards



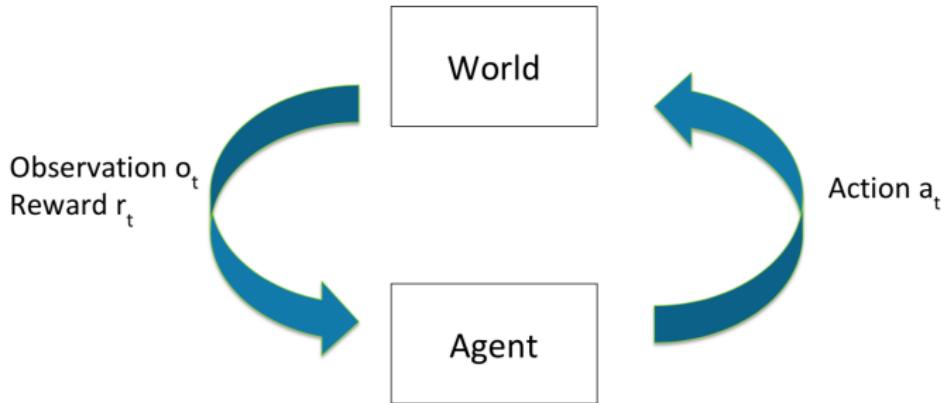
- History  $h_t = (a_1, o_1, r_1, \dots, a_t, o_t, r_t)$
- Agent chooses action based on history
- State is information assumed to determine what happens next
  - Function of history:  $s_t = (h_t)$

# 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?

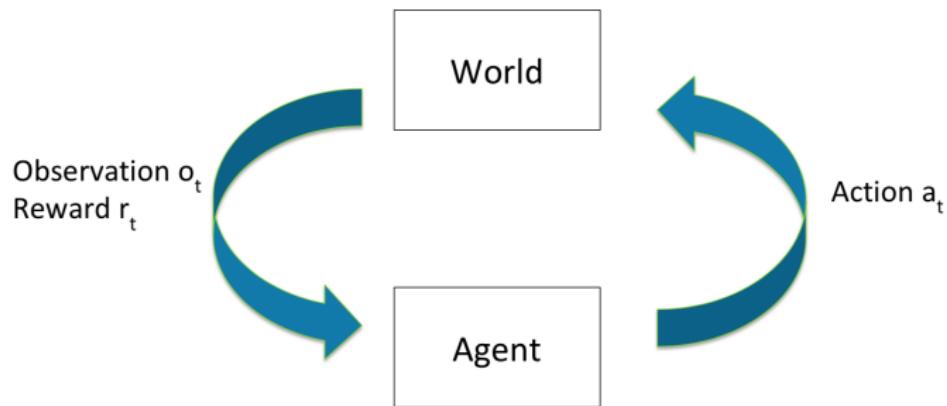
Almost Definitely Not

Yes

# Why is Markov Assumption Popular?

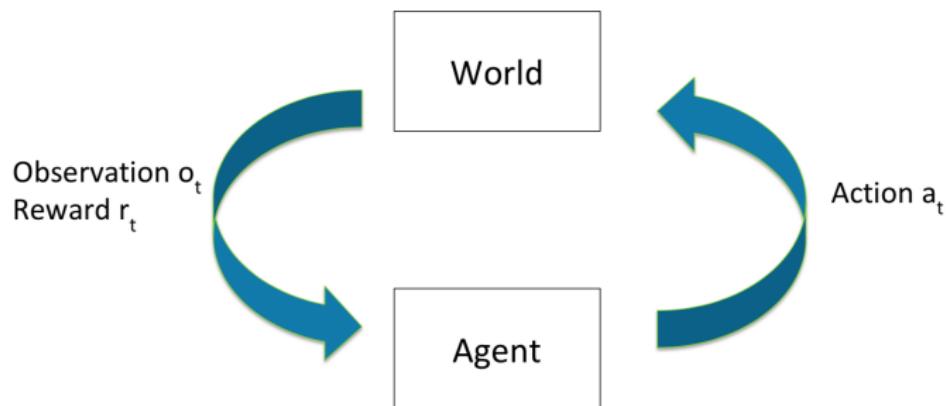
- Can always be satisfied
  - Setting state as history always Markov:  $s_t = h_t$
- In practice often assume most recent observation is sufficient statistic of history:  $s_t = o_t$
- State representation has big implications for:
  - Computational complexity
  - Data required
  - Resulting performance

# Full Observability / Markov Decision Process (MDP)



- Environment and world state  $s_t = o_t$

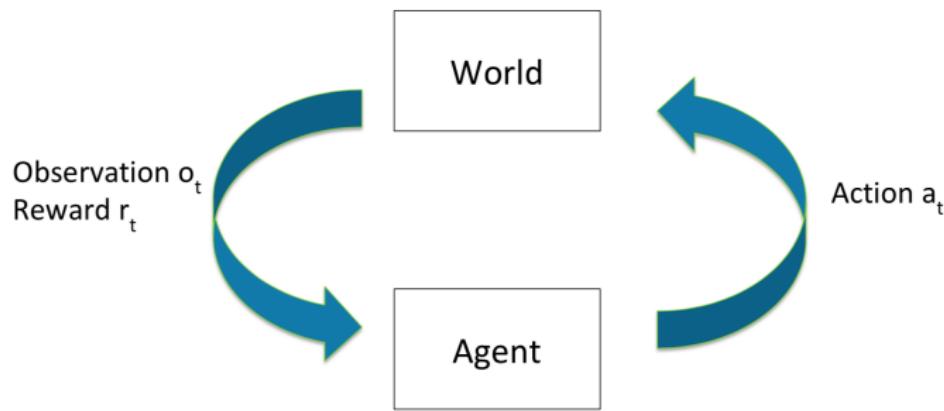
# Partial Observability / Partially Observable Markov Decision Process (POMDP)



- Agent state is not the same as the world state
- Agent constructs its own state, e.g.
  - Use history  $s_t = h_t$ , or beliefs of world state, or RNN, ...

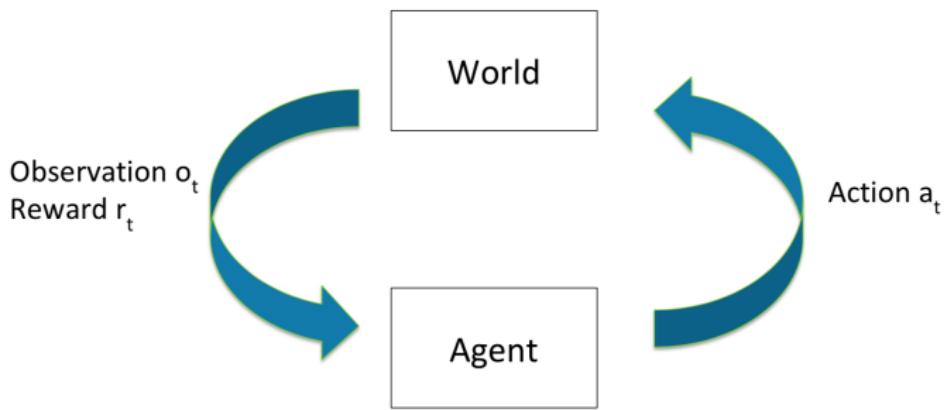
# Partial Observability Examples

- Poker player (only sees own cards)
- Healthcare (don't see all physiological processes)



- Agent state is not the same as the world state
- Agent constructs its own state, e.g.
  - Use history  $s_t = h_t$ , or beliefs of world state, or RNN, ...

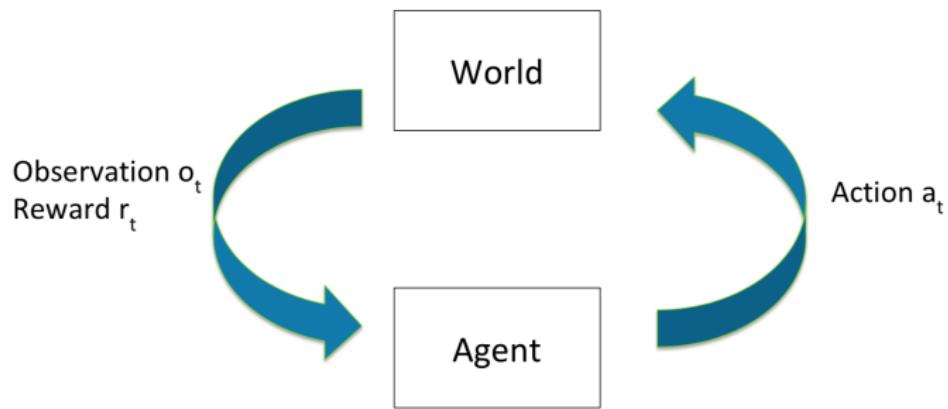
# Types of Sequential Decision Processes: Bandits



Bandits: very simple MDP

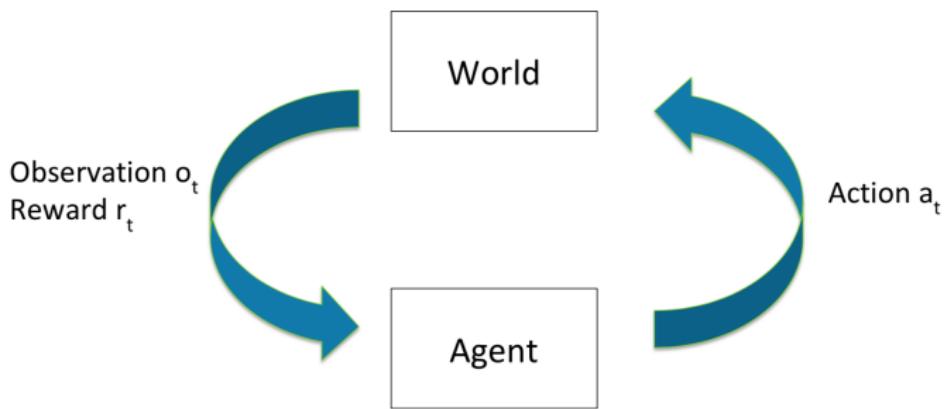
- Bandits: actions have no influence on next observations
- No delayed rewards

# Types of Sequential Decision Processes: MDPs and POMDPs



- Actions influence future observations
- Credit assignment and strategic actions may be needed

# Types of Sequential Decision Processes: How the World Changes



- **Deterministic:** Given history & action, single observation & reward
  - Common assumption in robotics and controls
- **Stochastic:** Given history & action, many potential observations & rewards
  - Common assumption for customers, patients, hard to model domains

# Example: Mars Rover as a Particular Markov Decision Process

$s_1$	$s_2$	$s_3$	$s_4$	$s_5$	$s_6$	$s_7$
			 A photograph of a Mars rover, likely Spirit or Opportunity, on the reddish-brown surface of Mars. The rover has a solar panel array and scientific instruments mounted on its deck.			

Figure: Mars rover image: NASA/JPL-Caltech

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

# RL Algorithm Components

- Often include one or more of
  - **Model:** Representation of how the world changes in response to agent's action
  - **Policy:** function mapping agent's states to action
  - **Value function:** Future rewards from being in a state and/or action when following a particular policy

# Model

- Agent's representation of how the world changes in response to 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

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

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

# Policy

- Policy  $\pi$  determines how the agent chooses actions
- $\pi : S \rightarrow A$ , 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

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

- Policy represented by arrow
- $\pi(s_1) = \pi(s_2) = \dots = \pi(s_7) = \text{right}$
- Quick check: is this a deterministic policy or a stochastic policy?

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

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

- Discount factor  $\gamma$  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,  $\gamma = 0$
- $\pi(s_1) = \pi(s_2) = \dots = \pi(s_7) = \text{right}$
- 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

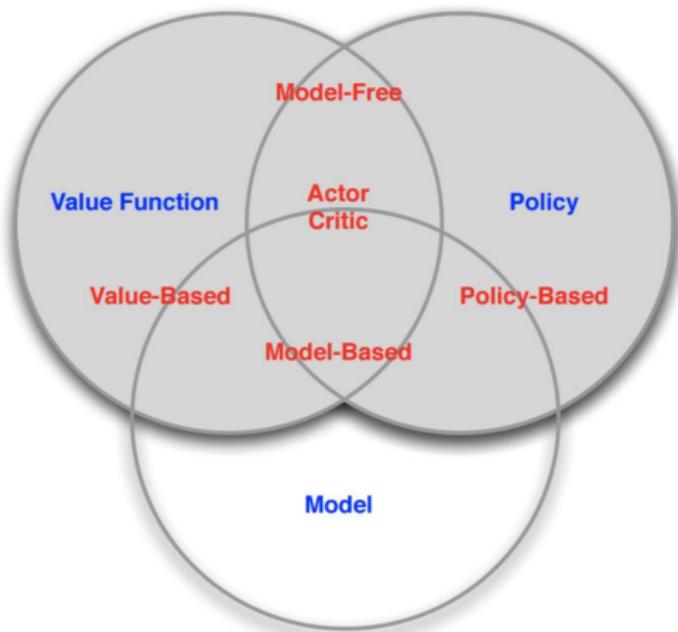


Figure: Figure from David Silver's RL course

# Key Challenges in Learning to Make Sequences of Good Decisions

- Planning (Agent's internal computation)
  - Given model of how the world works
    - Dynamics and reward model
  - Algorithm computes how to act in order to maximize expected reward
    - With no interaction with real environment

# Key Challenges in Learning to Make Sequences of Good Decisions

- Planning (Agent's internal computation)
  - Given model of how the world works
    - Dynamics and reward model
  - Algorithm computes how to act in order to maximize expected reward
    - With no interaction with real environment
- Reinforcement learning
  - Agent doesn't know how world works
  - Interacts with world to implicitly/explicitly learn how world works
  - Agent improves policy (may involve planning)

# Planning Example

- Solitaire: single player card game
- Know all rules of game / perfect model
- If take action  $a$  from state  $s$ 
  - Can compute probability distribution over next state
  - Can compute potential score
- Can plan ahead to decide on optimal action
  - E.g. dynamic programming, tree search, ...

# Reinforcement Learning Example

- Solitaire with no rule book
- Learn directly by taking actions and seeing what happens
- Try to find a good policy over time (that yields high reward)

# Exploration and Exploitation

- Agent only experiences what happens for the actions it tries
  - Mars rover trying to drive left learns the reward and next state for trying to drive left, but not for trying to drive right
  - Obvious! But leads to a dilemma

# Exploration and Exploitation

- Agent only experiences what happens for the actions it tries
- How should an RL agent balance its actions?
  - Exploration: trying new things that might enable the agent to make better decisions in the future
  - Exploitation: choosing actions that are expected to yield good reward given past experience
- Often there may be an exploration-exploitation tradeoff
  - May have to sacrifice reward in order to explore & learn about potentially better policy

# Exploration and Exploitation Examples

- Movies
  - Exploitation: Watch a favorite movie you've seen before
  - Exploration: Watch a new movie
- Advertising
  - Exploitation: Show most effective ad so far
  - Exploration: Show a different ad
- Driving
  - Exploitation: Try fastest route given prior experience
  - Exploration: Try a different route

# 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

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

- Policy represented by arrows
- $\pi(s_1) = \pi(s_2) = \dots = \pi(s_7) = \text{right}$
- Discount factor,  $\gamma = 0$
- What is the value of this policy?

## Example: Mars Rover Policy Control

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

- Discount factor,  $\gamma = 0$
- What is the policy that optimizes the expected discounted sum of rewards?

# Course Outline

- Markov decision processes & planning
- Model-free policy evaluation
- Model-free control
- Reinforcement learning with function approximation & Deep RL
- Policy Search
- Exploration
- Advanced Topics

See website for more details

# Summary

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

# Types of RL Agents: What the Agent (Algorithm) Learns

- Model-based
  - Explicit: Model
  - Implicit: Policy and/or value function (can use model to plan: compute a policy and/or value function)
- Value-based
  - Explicit: Value function
  - Implicit: Policy (can derive a policy from value function)
- Policy-based
  - Explicit: Policy
  - No value function
- Actor-Critic
  - Explicit: Policy
  - Explicit: Value function
- Algorithms can also have an explicit model, value and policy.