Reinforcement Learning for CPS Safety Engineering

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Motivations

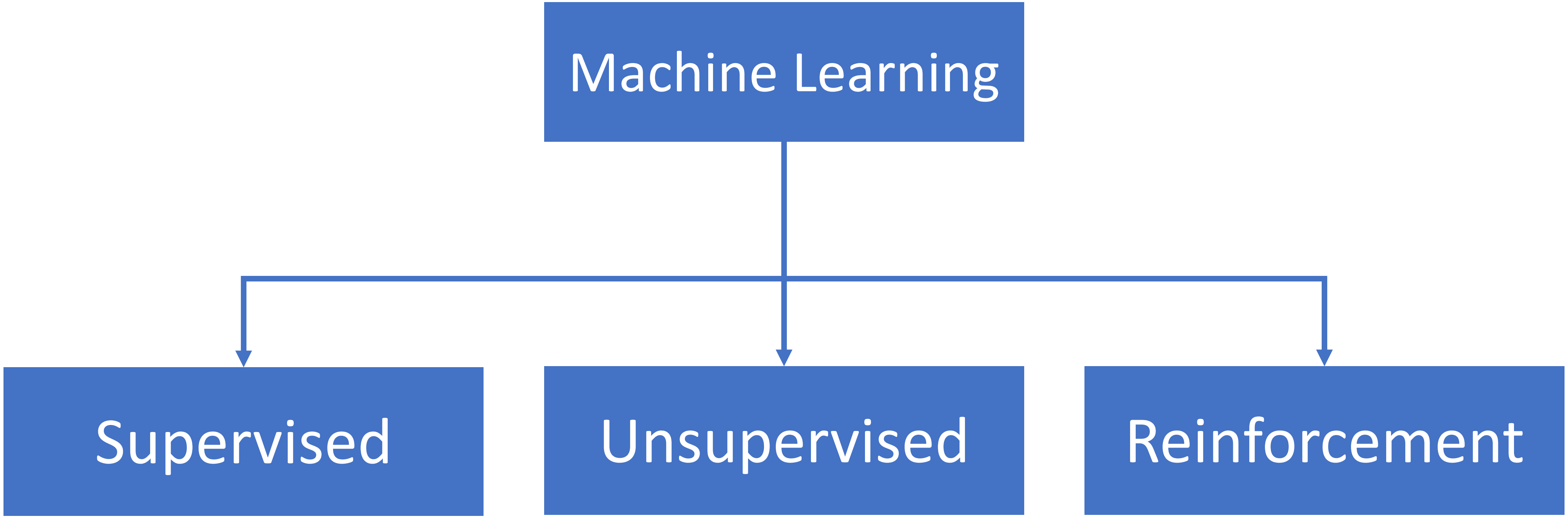
Safety-critical duties desired by CPS?

- Autonomous vehicle control: UAV, passenger vehicles, delivery trucks
- Automatically responding to, or preventing, damage
- Industrial robot control for use around humans
- Large process automation
  - E.g., optimization of factory

Reinforcement Learning

Georgia Tech, https://www.youtube.com/watch?v=f2at-cqaJMM

Deepmind, https://arxiv.org/abs/1707.02286


Machine Learning
Supervised
Unsupervised
Reinforcement

Introduction to RL

- A computational approach to **learning from interaction**
  - Established in the 1980s
  - Objective is to take actions to maximize a reward (or minimize a cost)
  - Seen as a path toward Artificial General Intelligence
- RL is at the intersection between
  - Psychology
  - Control Theory
  - Computer Science/AI
- Resurgence with advent of deep learning methods

Advances in RL since 2015

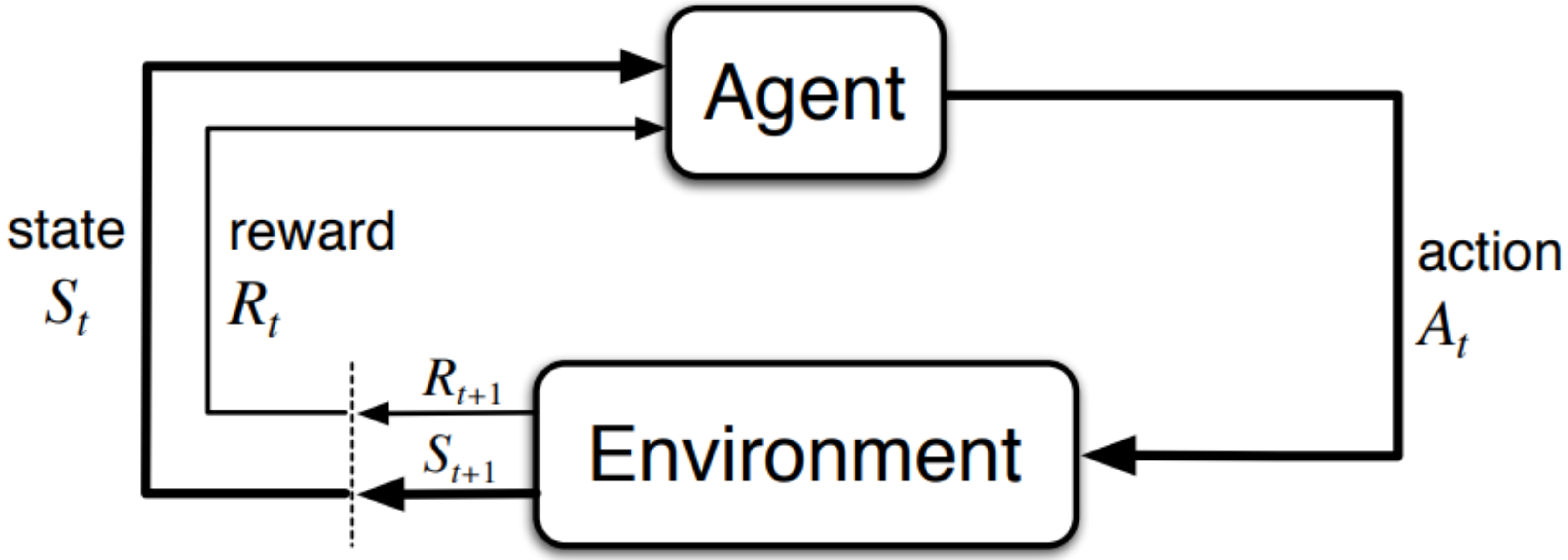
	Method	Training Time	Mean	Median
2015	DQN	8 days on GPU	121.9%	47.5%
2015	Gorila	4 days, 100 machines	215.2%	71.3%
2015	D-DQN	8 days on GPU	332.9%	110.9%
2015	Dueling D-DQN	8 days on GPU	343.8%	117.1%
2015	Prioritized DQN	8 days on GPU	463.6%	127.6%
2016	A3C, FF	1 day on CPU	344.1%	68.2%
2016	A3C, FF	4 days on CPU	496.8%	116.6%
2016	A3C, LSTM	4 days on CPU	623.0%	112.6%

Table 1. Mean and median human-normalized scores on 57 Atari games using the human starts evaluation metric.

[Mnih, et al. Asynchronous Methods for Deep Reinforcement Learning, 2016]

Terminology

- *Agent* – The thing we are learning to control
- *Environment* – All the factors affecting the agent
- *Action* – Performed by agent in an attempt to affect change on the environment
- *Reward* – Returned by the environment to the agent after the agent makes an action. Used to help the agent learn.
  - AKA the negative *cost*



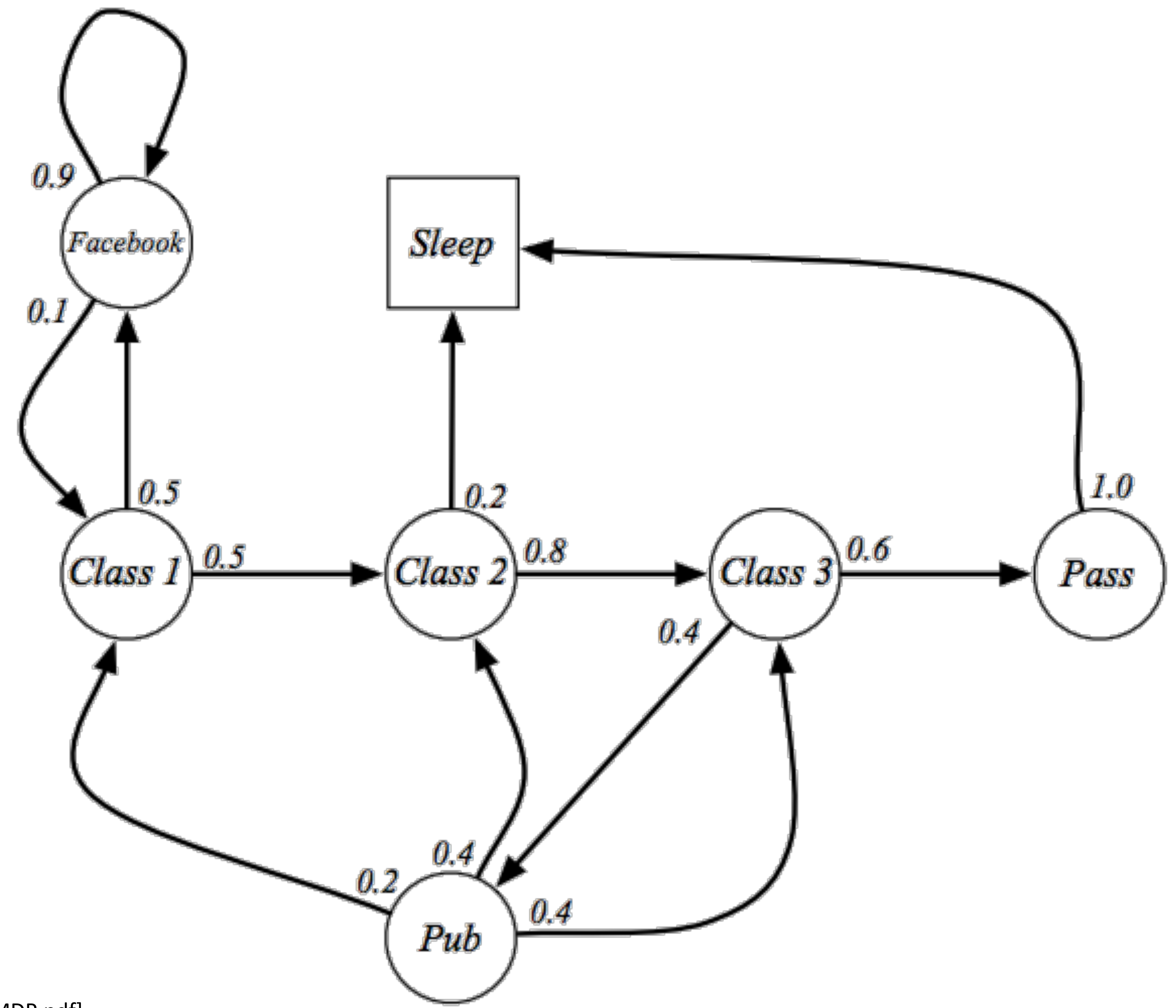
[R. Sutton, and A. Barto. Reinforcement Learning: An Introduction. 2016]

Markov Decision Process

- What RL solves
- Environments where agent's decisions are only dependent on present
  - An object in flight
  - Self-driving car
  - Manufacturing process
  - Robot control
- It's not that the past doesn't matter, but the laws of physics guarantee certain things, e.g. momentum
- Methods also exist to solve approximate MDP

Example: Student Markov Chain

Start here at the beginning of each ***episode***



[http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching_files/MDP.pdf]

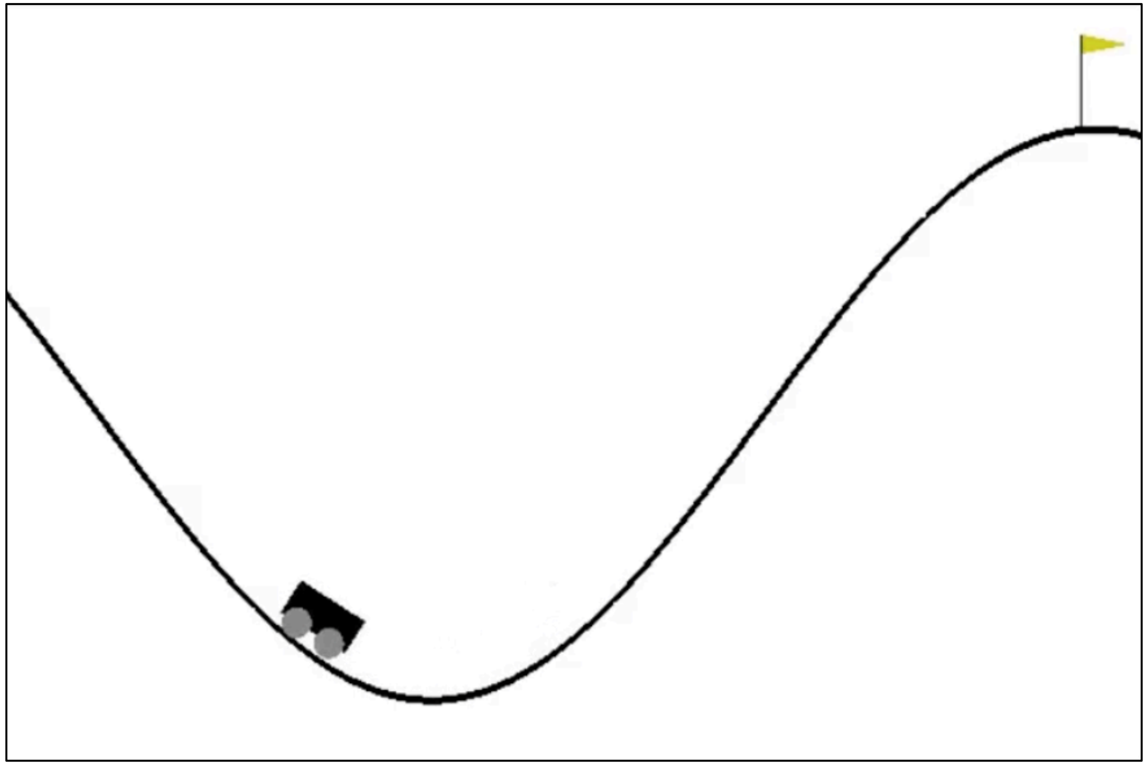
RL for CPS Safety Engineering

- Interdisciplinary natures makes RL interesting for CPS engineering
  - AI, ML (Math, Statistics)
  - Mechanics design and simulation (ME, Physics, CS)
  - Programming and implementation (CS, EE)

Mountain Car Example

Canonical example: Mountain Car

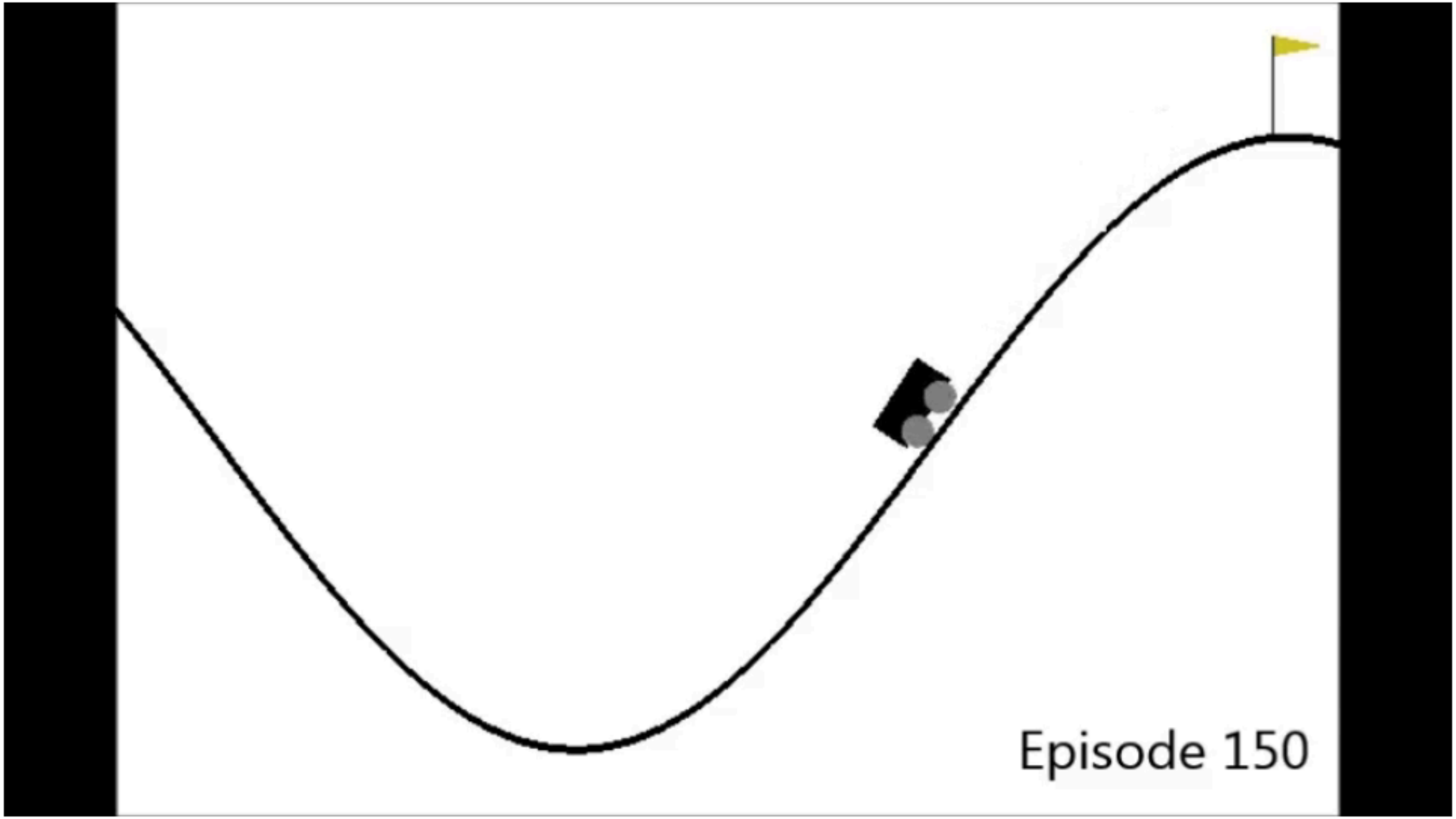
- Agent is an underpowered car with 3 actions:
  - Backward, Neutral, Forward
- Reward := -1 per timestep
  - Implicit goal := Reach the flag as fast as possible
- State := x-pos and velocity



[R. Sutton, and A. Barto. Reinforcement Learning: An Introduction. 2016]

Model-Free Control via Policy-Based RL

- A simple physics model determines the behavior of car
  - Captures position of the car on the hill
  - Captures effect of limited engine power
- Using a physics model simplifies approach
  - Use an efficient traditional controller
- But in many scenarios the model is not available or too complex
  - Amazon package delivery drone
- Solve mountain car using sophisticated method as toy example
  - Directly train a neural network-based policy


Episode 150

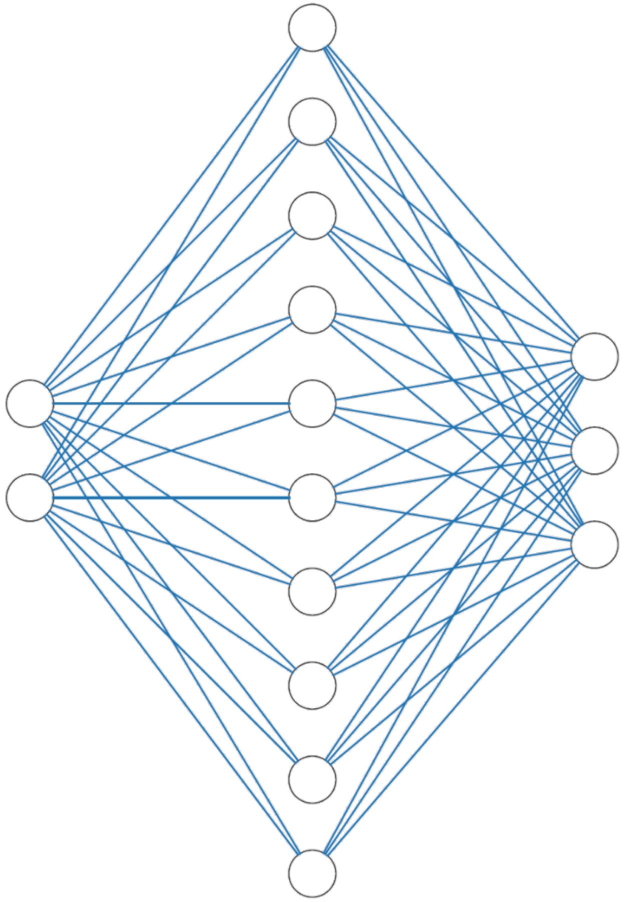
RL Terminology and Notation

- S_t – State of the environment at time t
  - x-axis position and velocity
- A_t – Action taken by agent at time t
  - Backward, Neutral, Forward
- π – The policy function; returns the next action to take. Stochastic in this example
- θ – A parameter vector for the policy; i.e. the weights learned in a neural network

Putting everything together:
$A_{t+1} \sim \pi_\theta(A_t, S_t) = P(A_t | S_t, \theta)$

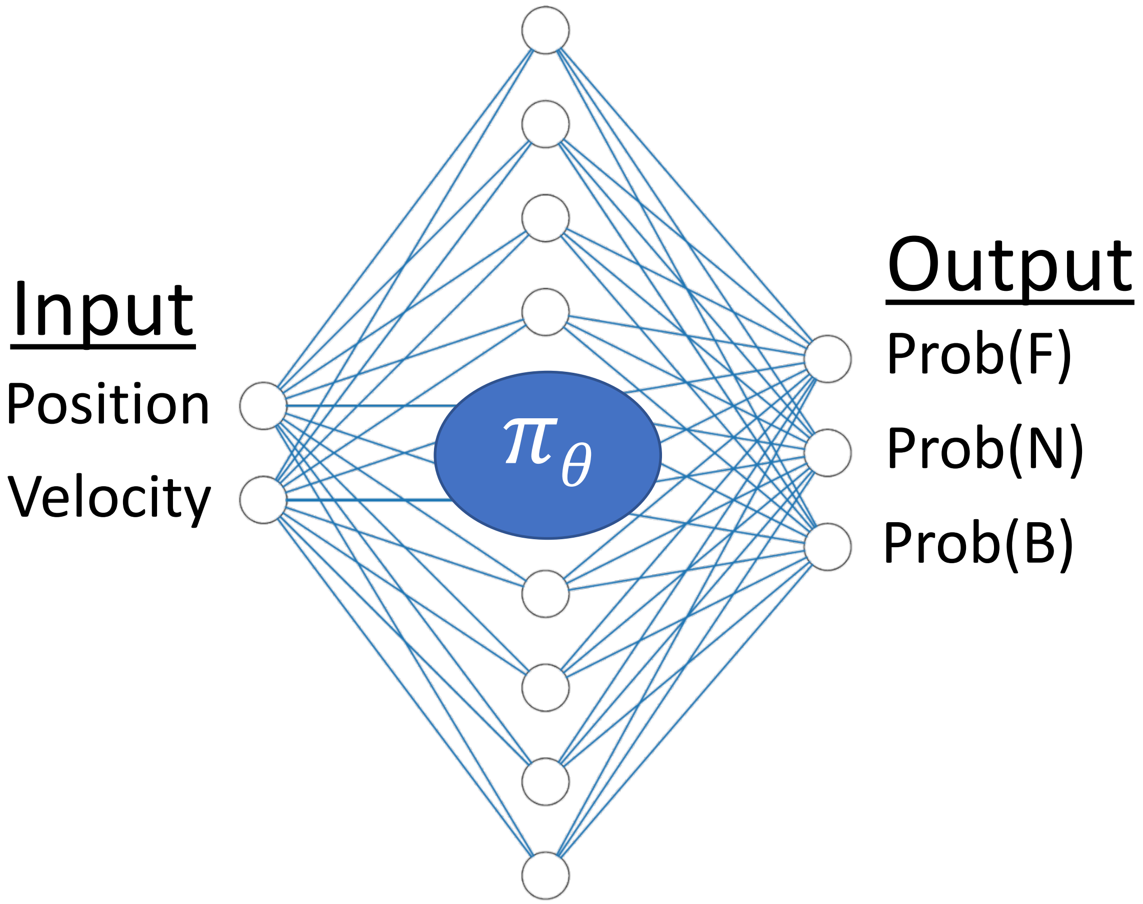
The policy π_θ

- π_θ is often approximated
- Deep neural networks are power for approximation
- We will use gradient ascent to optimize the DNN



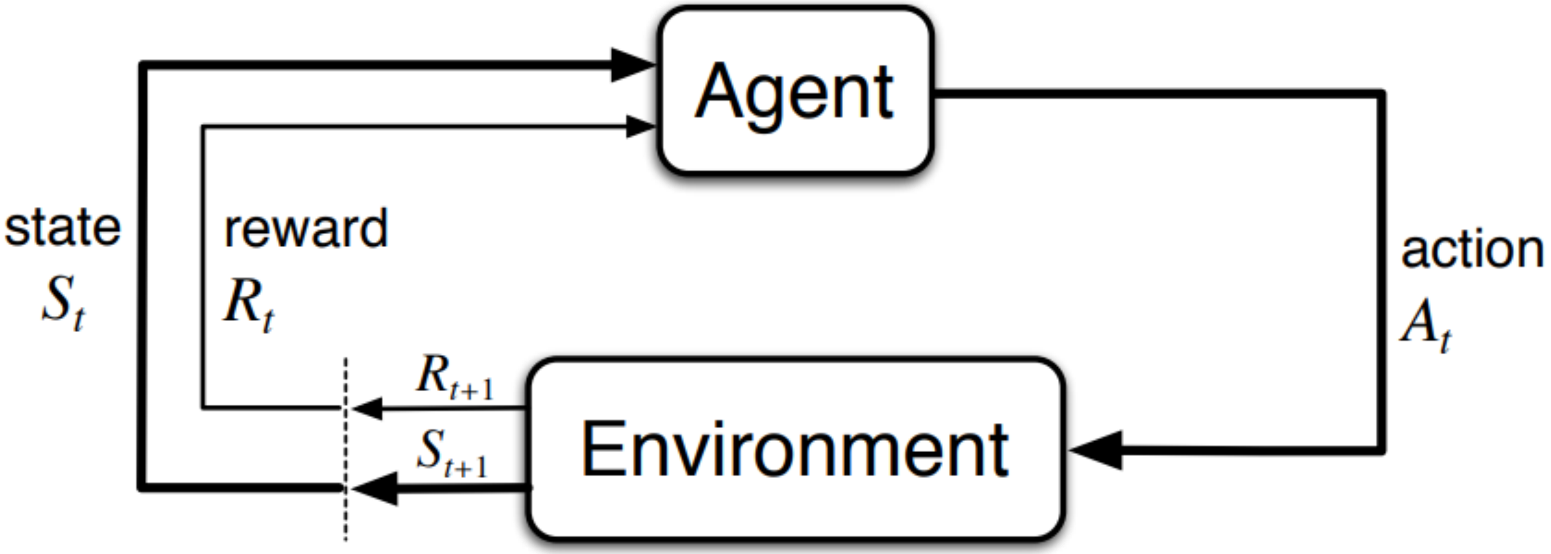
The policy function π_θ, approximated by NN

- State information at time t:
  - Position and Velocity
- Action options at time t:
  - Forward acceleration
  - Neutral
  - Backward acceleration



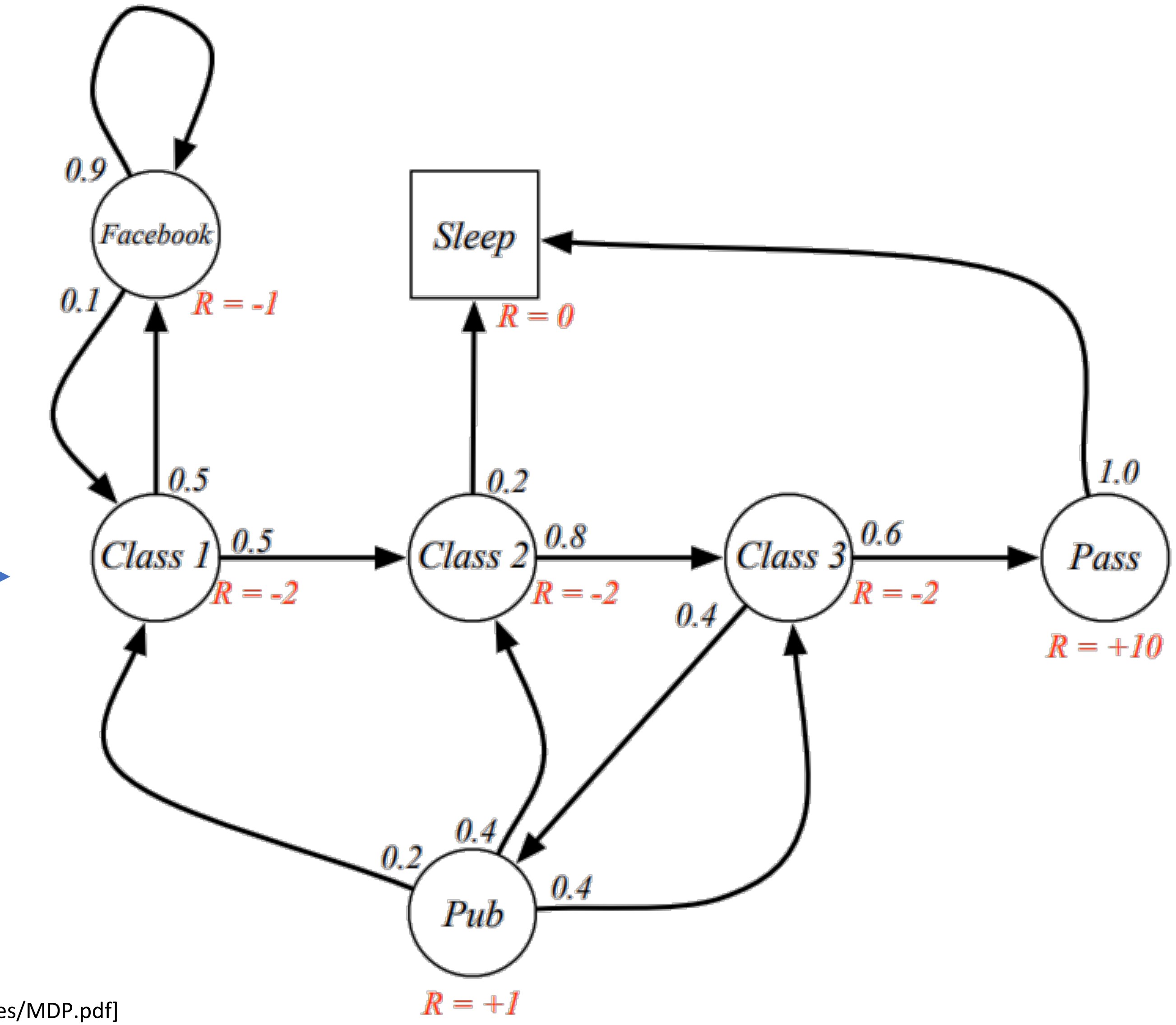
Reward function

- At every time step take an action
  - Forward, neutral, backward
  - Each action has a reward of -1
  - Train agent to reach the flag in minimum time steps



Example: Markov Reward Process

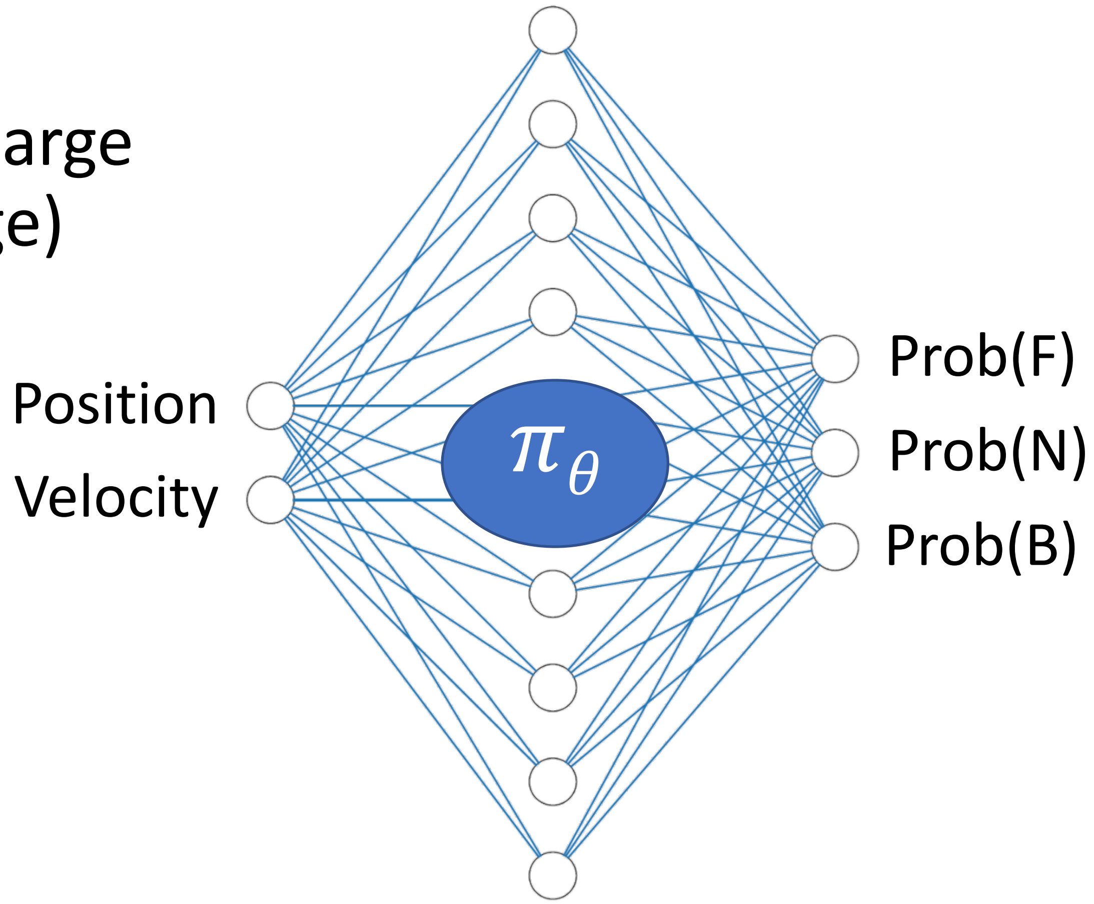
Start here at the beginning of each episode



[http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching_files/MDP.pdf]

How to train the NN?

- Small networks can be effectively trained with genetic algorithms
- Genetic algorithms work poorly with large networks (parameter space is too large)
- Gradient-ascent optimization works with large parameter space



Monte-Carlo Policy Gradient (REINFORCE)

- Find DNN parameter vector θ such that π_θ maximizes the reward
- For every episode, until flag is reached
  - Get state information (position & velocity) from environment
  - Feed NN with state information
  - NN will output a probability for (F)orward, (N)eutral, and (B)ackward
  - Randomly select action F, N, and B (using the above probabilities)
  - Store the state information and action taken
- Once flag is reached
  - Assign the most reward to the last action … least reward to the first action
  - Update θ s.t. actions made at the end are more probable

[http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html]

Monte-Carlo Policy Gradient

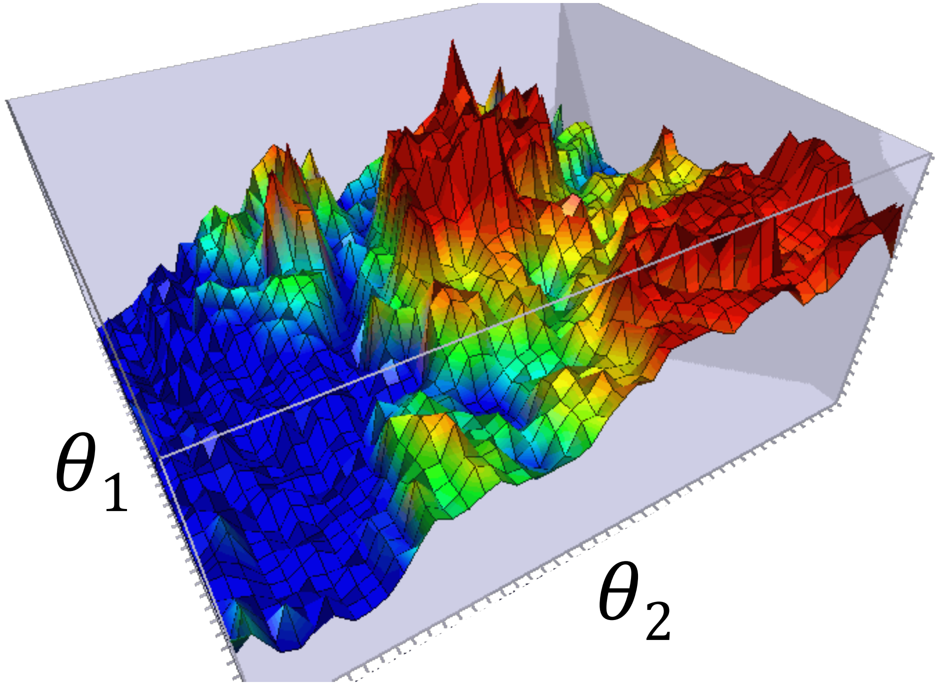
- Method leverages methods created for supervised learning
  - Inputs ≔ the state information (position, velocity)
  - Predictions := forward, neutral, or backward action taken
  - Labels (“ground truth”) := After the episode was over, assign most value to the last actions. Assign least value to the first actions
- Run many episodes, after each episode finishes (flag is reached) strengthen the network such that the last moves become more probable

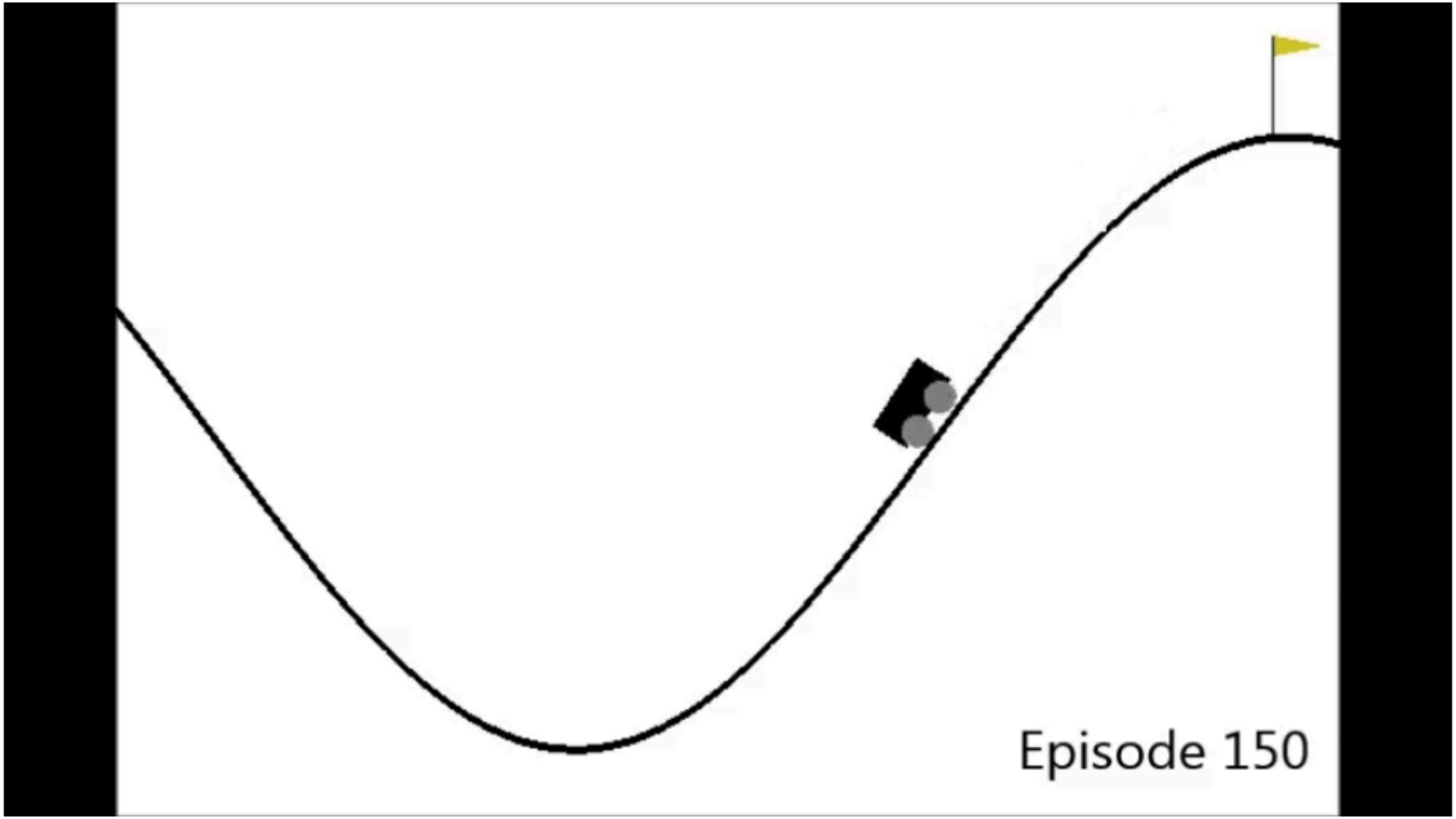
[http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html]

Gradient-ascent

- Gradient algorithms find a local extremum
- At end of each episode, adjust each parameter in θ s.t. actions made near the end are strengthened
- How much and in which direction to move each parameter is determined by the backpropagation method

Episode Rewards




Episode 150

Caveats

- Deep RL is usually slow to learn
- Transferring knowledge from one problem to another is difficult
- Reward function can be complex

Safety and Security Considerations

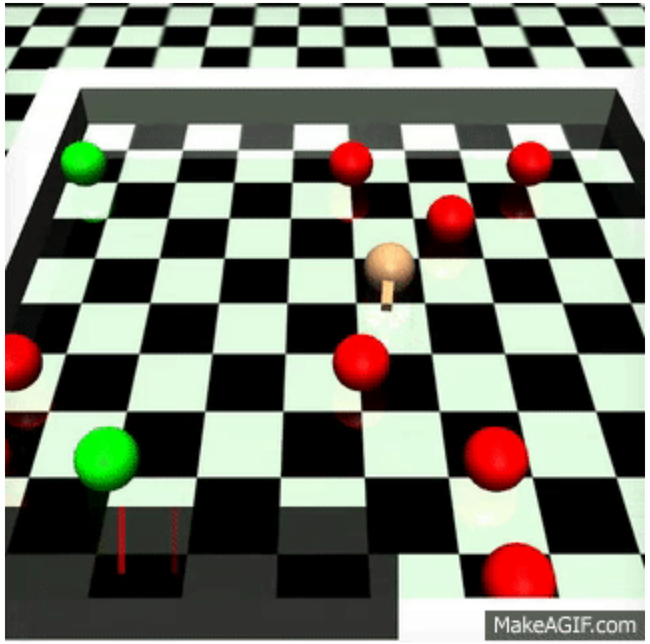

Adversarial Examples In The Physical World
Kurakin A., Goodfellow I., Bengio S., 2016

Safety and Security Considerations

- DNNs are black-box models
  - Possible to give an input which causes DNN to provide wild output
- Efforts to mitigate this limitation
  - E.g. Constrained Policy Optimization

Constrained Policy Optimization

- School-book RL specifies only the reward function
  - Problem: when an agent is learning, it may try anything
  - Potentially unsafe when training is in physical environment
- Constraints can be added to the objective function



[Achiam et al. “Constrained Policy Optimization”, 2017]

Current Efforts

Developing RL for Quadcopter Control

- Good case study for complex autonomous CPS
  - Collision avoidance
  - Target tracking
  - Package delivery
- Using open source firmware and hardware

Using Microsoft AirSim for 1st-order learning

[S. Shah et al. AirSim: High-Fidelity Visual and Physical Simulation for Autonomous Vehicles. 2017.]

Conclusions

- RL is a generalizable method to tackle many CPS decision making problems
  - High-capacity models can make sophisticated decisions

- Good approach for CPS education, because of interdisciplinary nature

- Open problems when using black-box functions for safety applications

Questions?