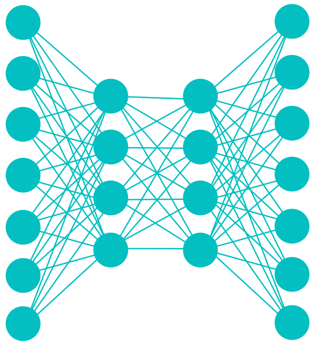
Lecture Notes for

Neural Networks and Machine Learning

Introduction to Reinforcement Learning

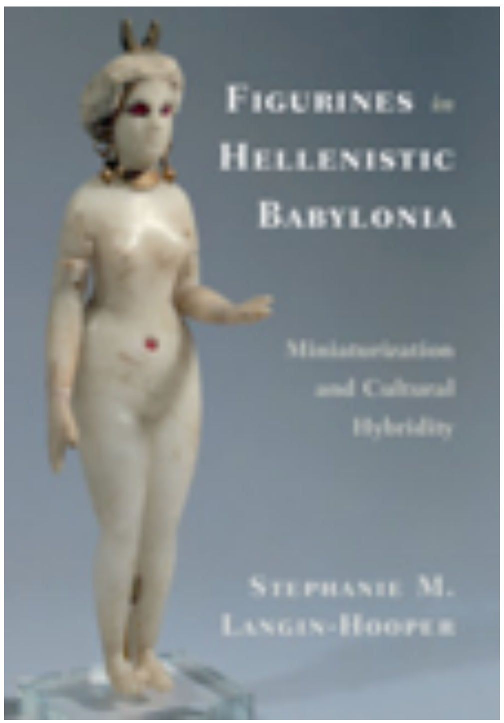


Logistics and Agenda

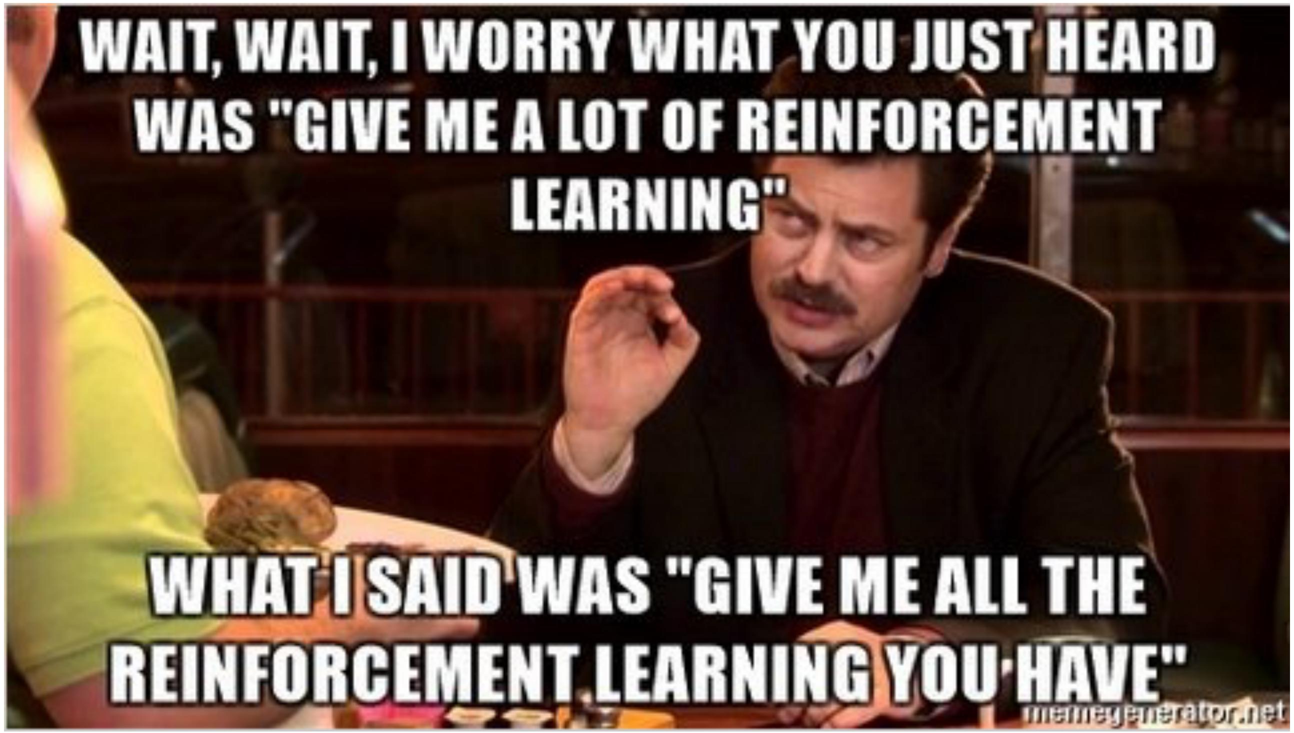
- Logistics
  - Lab Four: Cleaning up GANs
- Agenda
  - Final Projects
  - Basics of Reinforcment Learning
  - Markov Processes
  - Reinforcement Learning Categorization
  - OpenAI Gym

Final Project

One Idea from Professor Stephanie Langin-Hooper
SMU Meadows



Reinforcement Learning Basics



History of RL from Two Paths

- **Optimal Control**
  - Model processes via Markov property
  - Optimal paths through states calculated through dynamic programming
- **Animal Behavioral Learning (psychology)**
  - Animals learn by trial and error
  - Formalized by Thorndike, 1911. Strengthen through pleasure and weaken through pain
  - Pavlov and B.F. Skinner would conduct experiments proving that behavior could be influenced with RL
  - **Motivation for many pioneering Researchers:** Claude Shannon, J. Deutsch, Marvin Minsky, F. Rosenblatt, Widrow, Hoff


Edward Thorndike


B.F. Skinner


Ivan Pavlov

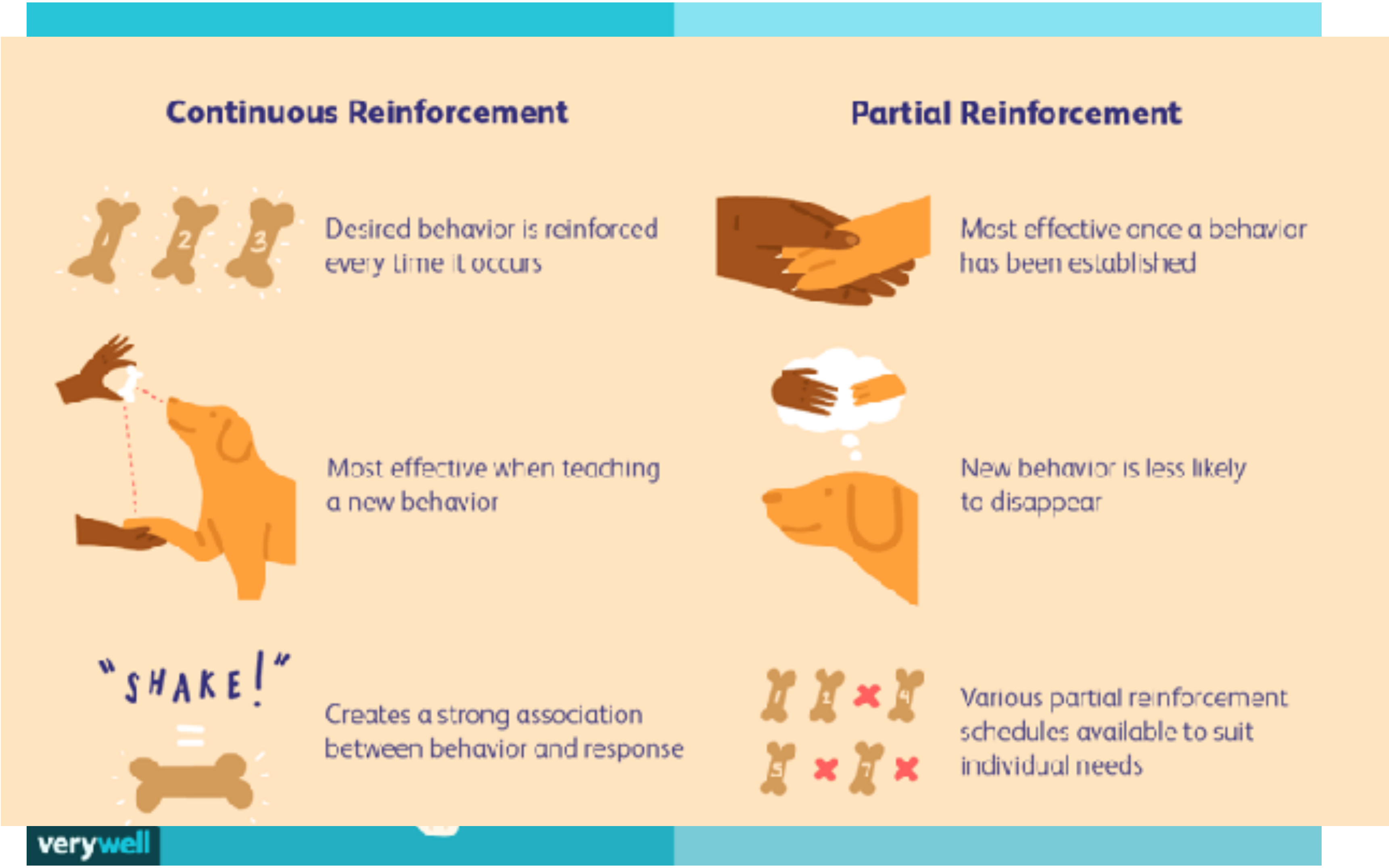

Bernard Widrow


Marvin Minsky


Ted Hoff


Claude Shannon

Conditioning, Skinner and Pavlov



https://www.verywellmind.com/classical-vs-operant-conditioning-2794861

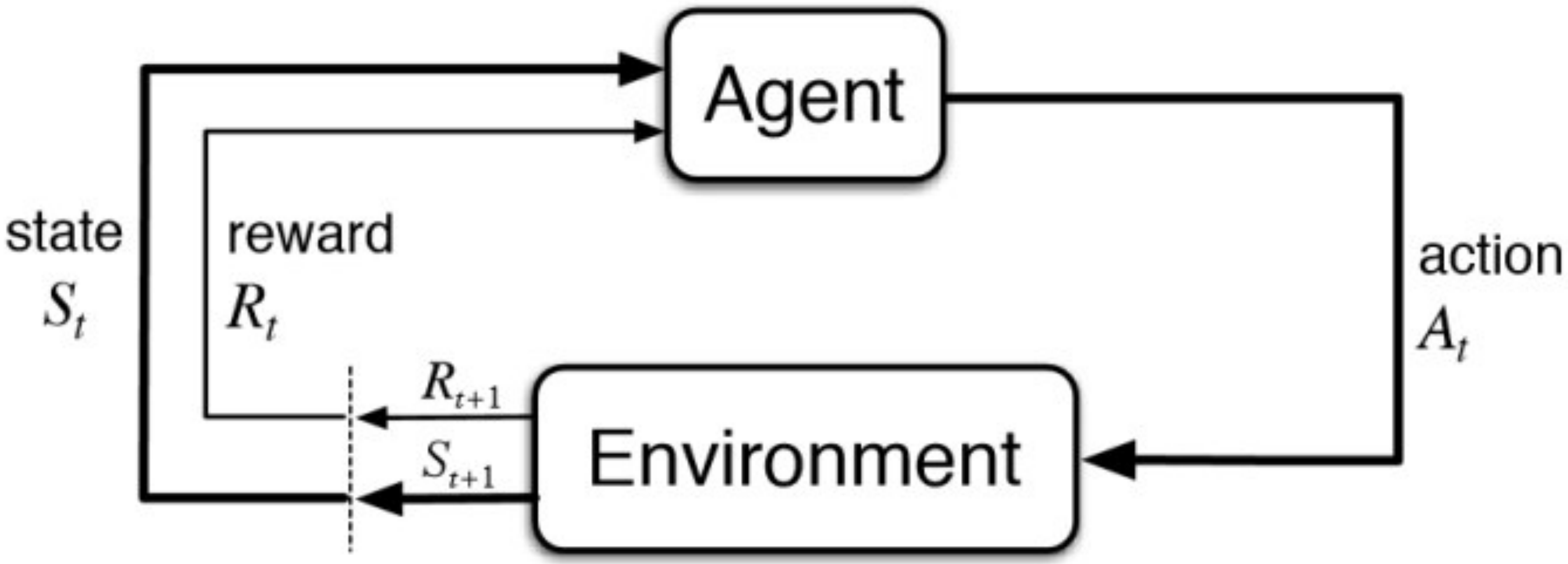
How to condition a machine learning model?

- Hybrid of **Supervised** and **Unsupervised** Learning
- **Reinforcement** Learning
  - Possibly specific labels given, but not necessarily with supervision for how labels are achieved
    - labels are typically stochastic
  - Uses many techniques from supervised learning, but applied towards a slightly different objective function
  - Rewards (positive and negative) are possible to assess behavior in an environment (just like with animals RL)
  - Not specific to Machine Learning community

RL Landscape

- **Agent**
  - Interacts with the environment. Your model guides the Agent's decisions
- **Environment**
  - Anything that is not the agent
- **Observations**
  - What the agent knows about the environemnt
- **Actions**
  - What an agent can perform with the given environment
- **Rewards**
  - Local measure of success
  - Can compound local rewards over time

Generic Reinforcement Learning



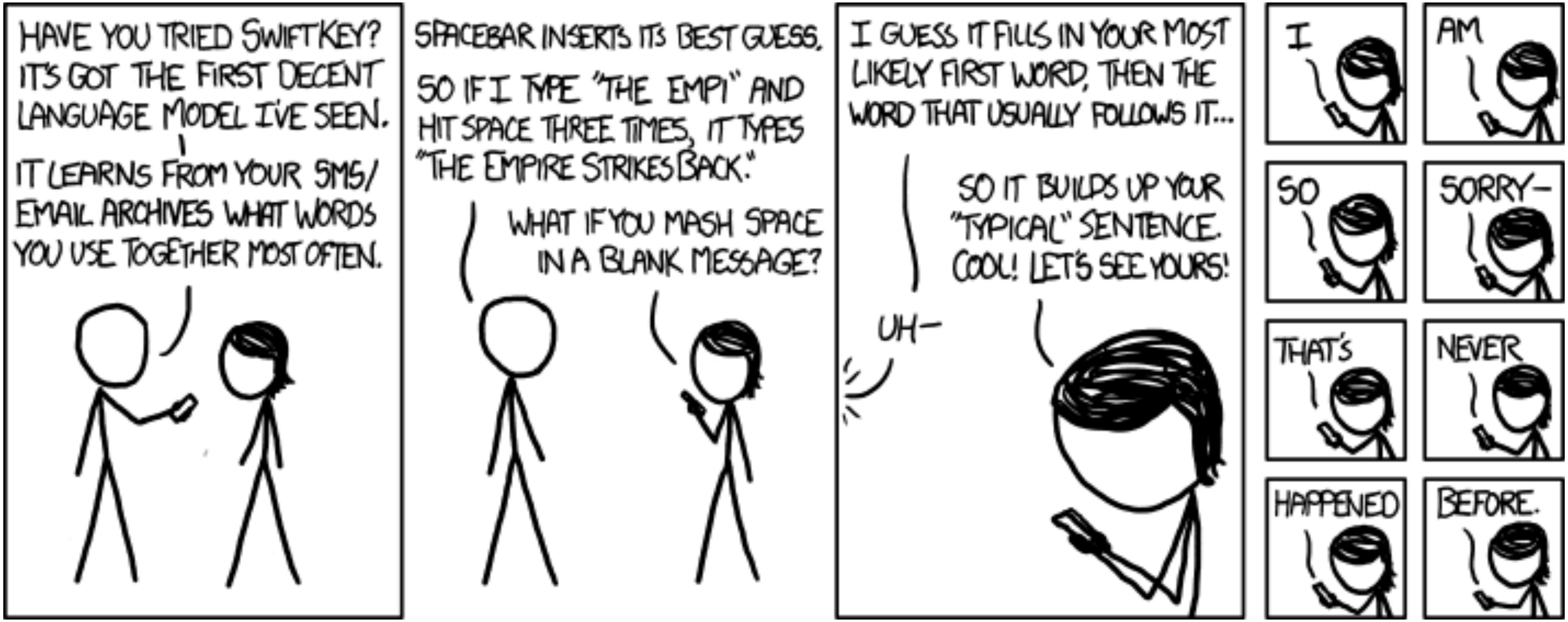
https://www.kdnuggets.com/2018/03/5-things-reinforcement-learning.html

RL Parameters in Psychology

- One model for some human behavior, such as **you all tell me**
- Agent:
- Environment (be specific):
- Observations:
- Actions:
- Reward:

Conclusion: The **complexity** of the process is entirely due to the **design** and **assumptions** made in creating the **environment**, **observation**, **actions** we can oversimplify many interactions

Markov Building Blocks



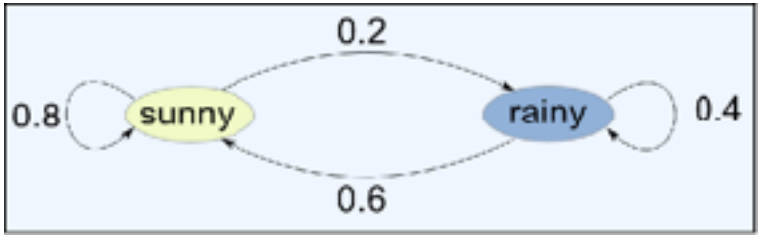
Markov Processes

- **Definition**: Any process that can be explained (or simplified) through a sequential set of states that depend only on the previous state
- **Practical Meaning**: For N states, there will be the probability of transition to any other state, encoded through an NxN transition matrix of discrete probabilities
- State sequences are not deterministic, they are sampled from these distributions
- Despite **simplicity**, they can model a number of real processes with **good enough** precision

Current State, s_t \ Next State, s_{t+1}					
	0.1	0.2	0.1	0.6	0.0
	0.9	0.0	0.1	0.0	0.0
	0.0	0.4	0.0	0.4	0.2
	0.0	0.4	0.2	0.0	0.4
	0.0	0.0	0.6	0.0	0.4

MP Example from Maxim Lapan

	Sunny’	Rainy’
Sunny	0.8	0.2
Rainy	0.6	0.4

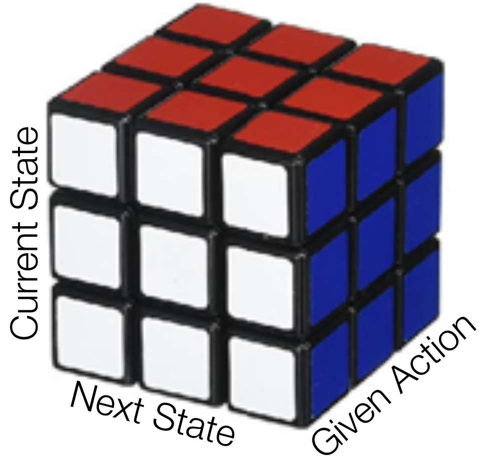


				...	
Sun+Summer					
Rainy+Summer					
Sun+Fall					
Rainy+Fall					
Sun+Else					
Rainy+Else					

Adding One Variable Can Have Drastic Effect on State Space Size

Markov Decision Processes (MDP)

- **New Definition**: any state to state transition can be altered by an action that is given by a Markov Process
- **Definition**: An MDP consists of:
  - Env. States, s_t
  - Actions for each state, $\boldsymbol{a}(s_t)$
  - Reward function for each state, $\boldsymbol{r}(s_t)$
  - A transition model, $P(s_{t+1}, s_t \mid a)$ a matrix of probabilities
    - Not ***guaranteed*** next state by given action



Markov Reward Process (MRP)

- **Total reward** is given by sum of all **future** rewards

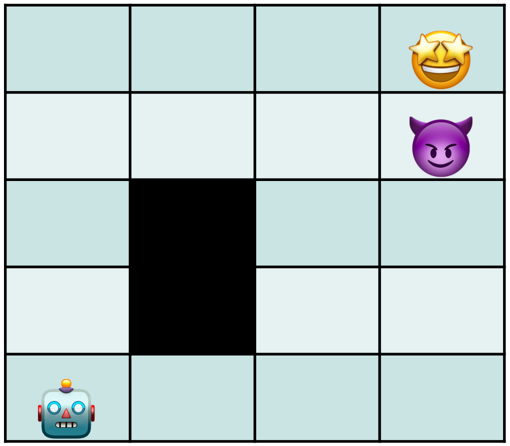
$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} \ldots = \sum_k \gamma^k R_{t+k+1}$$

- Gamma defines far- and short-sightedness
  - Common values are **0** (short), **0.9**, **0.99**, and **1** (far)
- This reward calculation can be used to estimate the "**Value**" of each state based upon the average total reward a state should give, $V(s) = \mathbf{E}[G \mid s_t=s]$
- Typically, this value must be estimated from the model over fixed sequences, otherwise some values can become arbitrarily large by looping actions

MDPs and MRPs

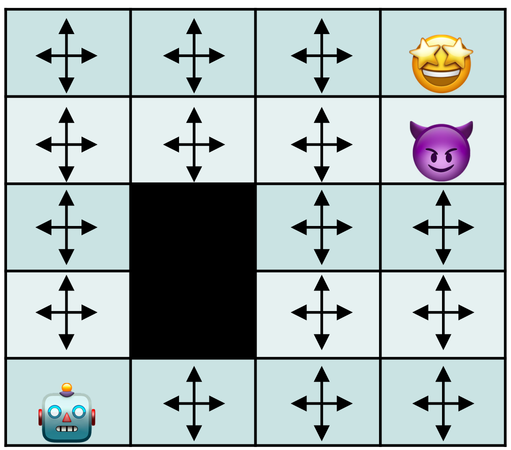
- The million dollar question:
  How do we select a good action given a current state?
- If γ is not 0, this can get really complicated as we need to look at all possible future actions to measure value
- Instead of defining what is optimal, let's instead setup a comparison of different actions we might take (**policy**)
- A **policy** is defined as $\pi(a, s) = P(a_t = a \mid s_t = s)$
  - Given the current state, we have a certain probability of selecting each action
  - Action selection is **probabilistic**, but easy to define **deterministic** actions (*set one action to 1.0, all others to 0.0*)
- Try different policies, select one with best average reward

An Illustrative Example: Grid World

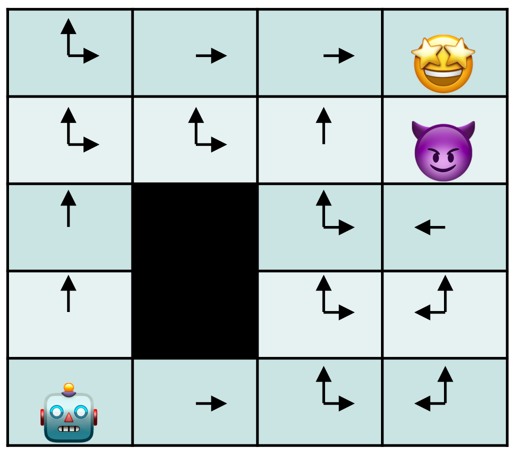


- **State**: Every square in grid
- **Action**: Move to make (l,r,u,d), *with probability*
- **Reward**: Goal, Death
- **Policy**: Given state, where should we move?
- **Optimal Policy**:

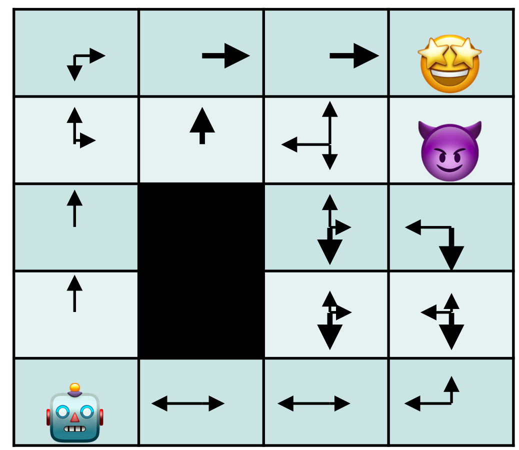
$$\pi^* = \arg\max_{\pi} \mathbf{E}\left[\sum_k \gamma^k R_{t+k+1} \,|\, \pi\right]$$



Random Policy

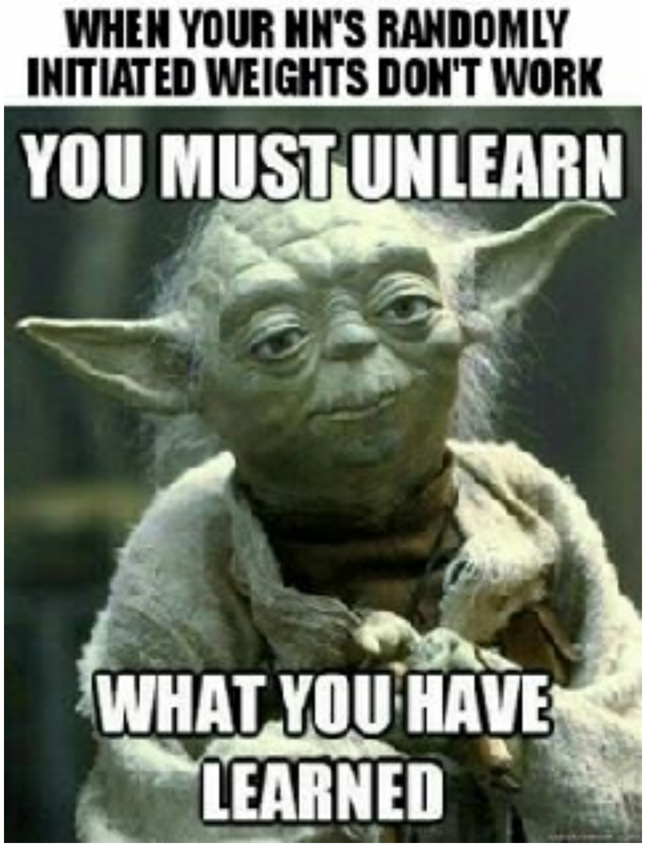


Another Policy



Another Policy

RL Categorization



Various Taxonomies

- Model-based versus Model-free
- Policy-based versus Value-based
- On-Policy, Off-Policy

- On-policy
  - We must interact with environment to learn a policy
- Off-policy
  - Can learn also from historical data or humans

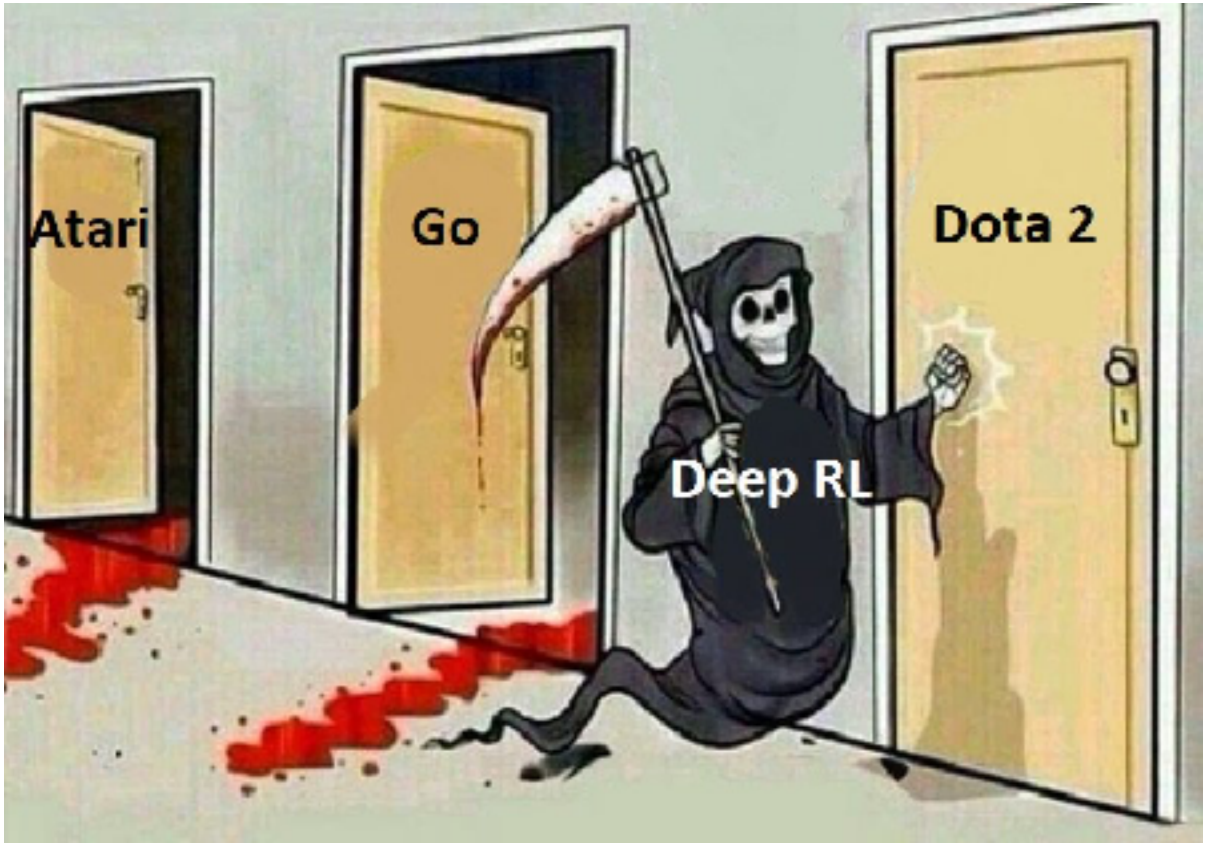
Model-based versus Model-free

- Model Based
  - Predict the next observation and reward based on an understanding (model) of the rules in environment
  - Often look a number of moves ahead (like in chess or similar game)
  - Hard to construct in complex environments
  - NOT what we will be studying… domain expertise
- Model Free
  - Don’t care what the environment is
  - Directly try to connect observations to actions (or values from which an action can be inferred)
  - Just use a neural network! That is our style!
- Mixed: Sure, like Alpha-Go

Policy Based versus Value Based

- Policy Based Learning
  - Directly approximate the policy of the agent
  - Policy is typically a probability distribution of actions that we sample from for next action
  - Could also be a “see this, do that” configuration
- Value Based
  - Calculate an intermediate value function for all possible actions
  - Policy becomes choosing the best action based on value function

OpenAI Gym



Object Oriented RL

- Basics:
  - Define object instance for Agent() and the Env()
  - Define what observations will return
  - Run env.step(action)
  - Get new observations and reward from env
- `action_space` and `observation_space`
  - Possible actions to execute, Observations to get
  - Discrete or continuous?
  - Can actions be given simultaneously?

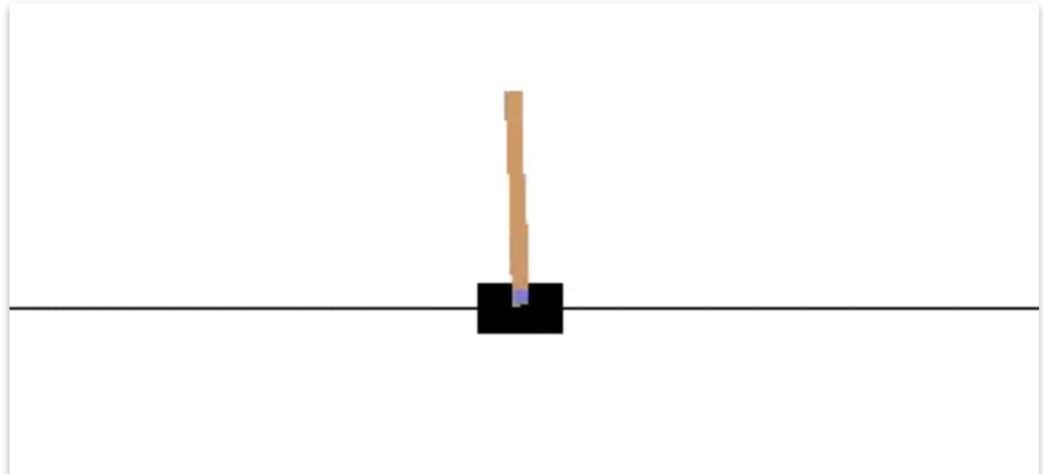
Basics of Cartpole

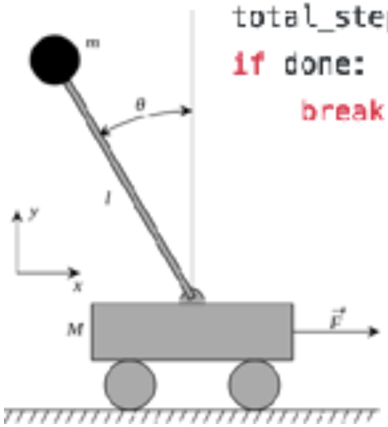
```python
import gym


if __name__ == "__main__":
    env = gym.make("CartPole-v0")

    total_reward = 0.0
    total_steps = 0
    obs = env.reset()

    while True:
        action = env.action_space.sample()
        obs, reward, done, _ = env.step(action)
        total_reward += reward
        total_steps += 1
        if done:
            break
```





Action Space: One input, [0, 1] pull left or pull right

Obs Space: Dynamic state variables (continuous and four dimensional)

End: When more than 15 degrees off or too far from center

Reward: +1 for each time step

Wrapping the Environment

- When you want some extra action, observation, reward processing
- Expose function with `ActionWrapper`, `RewardWrapper`, `ObservationWrapper`

```
class RandomActionWrapper(gym.ActionWrapper):
    def __init__(self, env, epsilon=0.1):
        super(RandomActionWrapper, self).__init__(env)
        self.epsilon = epsilon

    def action(self, action):
        if random.random() < self.epsilon:
            print("Random!")
            return self.env.action_space.sample()
        return action
```

```
if __name__ == "__main__":
    env = RandomActionWrapper(gym.make("CartPole-v0"))

    obs = env.reset()
    total_reward = 0.0

    while True:
        obs, reward, done, _ = env.step(0)
        total_reward += reward
        if done:
            break
```

Might return different action than user supplied with small probability

OpenAI Gym

https://gym.openai.com

We provide the environment; you provide the algorithm. You can write your agent using your existing numerical computation library, such as TensorFlow or Theano.

Lecture Notes for

Neural Networks and Machine Learning

Intro to Reinforcement Learning

Next Time:
CrossEntropy and Q-Learning

Reading: Lamar CH4-CH6