Bootcamp 6: Reinforcement Learning

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Machine Learning at Berkeley

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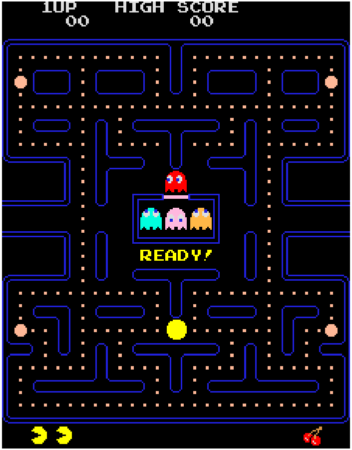
Overview

Problem: ML for Pacman.

How would you solve pacman with machine learning?

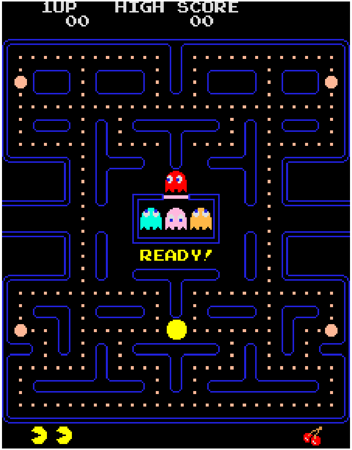


Problem: ML for Pacman.

How would you solve pacman with machine learning?

Find a model which takes screen pixels to actions:

$$\pi_\theta : s_t \mapsto a_t.$$



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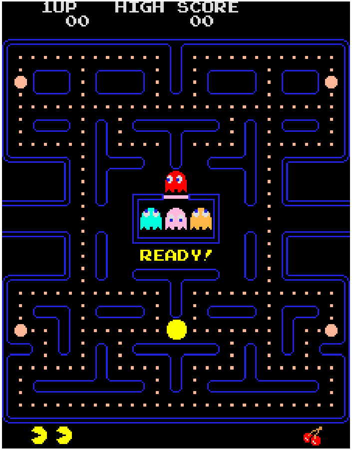
What is your loss function? Data?



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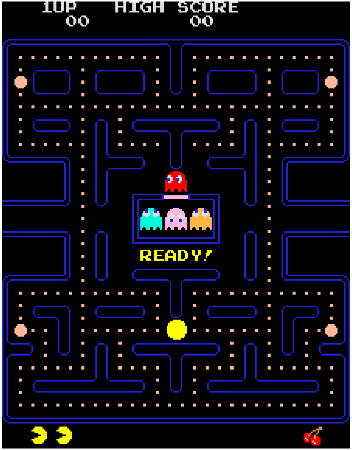
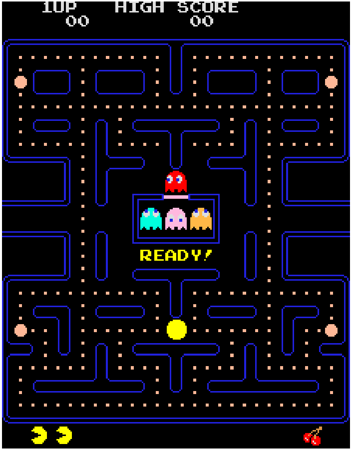


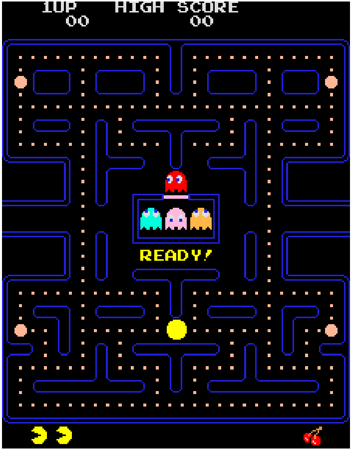
Solution: Reinforcement Learning

- Supervised learning is *not* the most general formulation of learning.



Solution: Reinforcement Learning

- Supervised learning is *not* the most general formulation of learning.
- Humans learn through reward and penalty



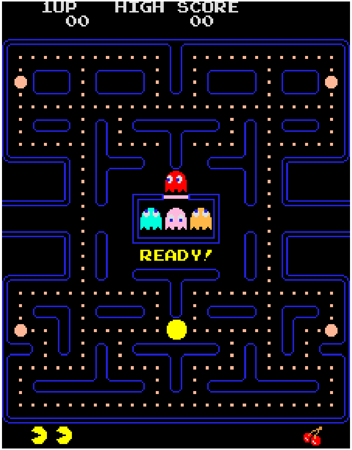
Solution: Reinforcement Learning

- Can we make algorithms which improve with crude reward signals?

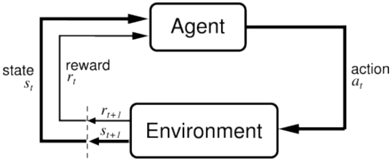
Machine learning without explicit objective functions

$\Downarrow$

Reinforcement Learning (RL)



The Core Idea



- Models (agents) take action a_t in some environment.
- Environment provides state s_t, reward r_t.
- Models learn to maximize reward r_t, $\forall t$.

Markov Decision Process (MDP)

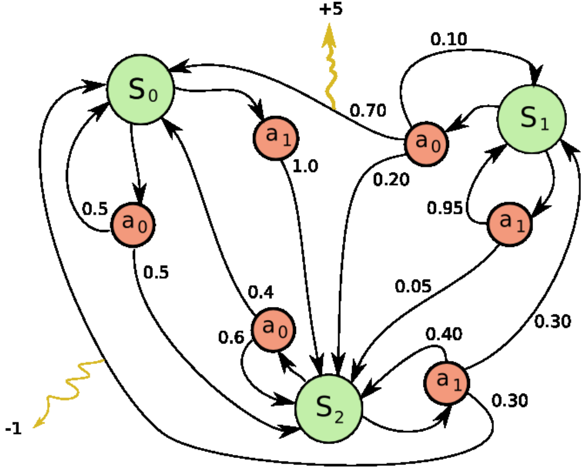
Environment, $E = (\mathcal{S}, \mathcal{A}, \mathcal{R}, \rho, r)$.

1. State space, $\mathcal{S}$
2. Action space, $\mathcal{A}$
3. Reward space, $\mathcal{R}$
4. Transition distribution, $\rho(s' \mid s, a)$. Given a previous state s and action a, environment gives s'.
5. Reward function $r(s, a) \in \mathcal{R}$.

Markov Property: $\rho(s' \mid s, a)$ depends only on s, a not previous states!

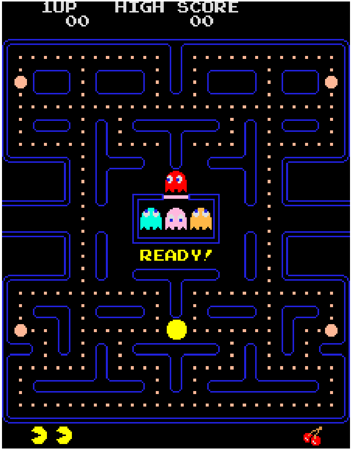
Markov Decision Process (MDP)

Example MDP



Pacman as an MDP

- $\mathcal{S} = \mathbb{R}^{256\times256}$, images as state space.
- $\mathcal{A} = \{\uparrow, \downarrow, \rightarrow, \leftarrow\}$, joystick as action space.
- $r(s_t, a_t)$ = change in score.
- $\rho(s_{t+1} \mid s_t, a_t)$ = next frame of game after joystick action a_t.



Policies/Agents

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Two different types of agents

- Deterministic policy $a = \pi(s)$ acts in E.
- Stochastic policy $a \sim \pi(a|s)$ gives a probability distibution over actions.

Policy Trajectories

$$s_1 \xrightarrow{\pi} a_1 \xrightarrow{\rho, r} s_2, r_2 \xrightarrow{\pi} a_2 \xrightarrow{\rho, r} \cdots$$

Value under a policy

The **state value** is a function of a given state for an agent π defined as

$$V^{\pi}(s_t) = \mathbb{E}\left[\sum_{n=t+1}^{\infty} \gamma^n r(s_n, \pi(s_n))\right]$$

1. γ is the discount factor
2. $\pi(s_n)$ is the action the agent π makes after seeing state s_n.
3. $r(s_n, \pi(s_n))$ is the reward the agent gets from taking that action.

Value under a policy

The **state-action value** for an agent π is defined such that

$$Q^\pi(s_t, a_t) = \mathbb{E}\left[\underbrace{r(s_t, a_t)}_{\text{reward for } a_t} + V^\pi(s_t)\right]$$

- Given some state s_t, the *best* agent, π^* is one that take action

$$a_t = \underset{a}{\operatorname{argmax}}\, Q(s_t, a).$$

Problems in Reinforcement Learning

- **Policy Optimization:** maximize the expected reward with respect to a policy π;

$$\pi^* = \underset{\pi}{\operatorname{argmax}}\, \mathbb{E}\left[\sum_{t=0}^{\infty} r_t\right]$$

- **Policy Evaluation:** Given some fixed policy π compute expected return.
  - Computing Q^π, V^π, and other expectations on policy rollout.
  - Lets us perform policy optimization!

Behavioral Cloning

Behavioral Cloning: Supervised learning in MDPs using and expert agent expert π^*!

Given expert examples $\mathcal{D} = (s_t, a_t = \pi^*(s_t))$ and a model π_θ find θ^* st

$$\theta^* = \operatorname*{argmin}_\theta \mathcal{L}(a_t, \pi_\theta(s_t)).$$

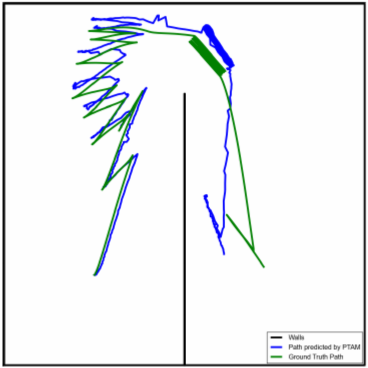
where $\mathcal{L}$ is some loss function.

- Show, don't tell!
- No complicated machinery, just standard ML.

Issue: Compounding Error

Given some irreducible error $\epsilon = 0.001$

- $\mathcal{L}(a_0, \pi(s_0)) = \epsilon$
- $\mathcal{L}(a_1, \pi(s_1)) = 2\epsilon$
- $\mathcal{L}(a_2, \pi(s_2)) = 3\epsilon$
- $\mathcal{L}(a_3, \pi(s_3)) = 4\epsilon$
- $\mathcal{L}(a_4, \pi(s_4)) = 5\epsilon$



The action-value function (simplified).

1. The future expected reward of an agent π is

$$Q^\pi(s_t, a_t) = \underbrace{r(s_t, a_t)}_{\text{reward for } a_t} + \sum_{n=t+1}^{\infty} \gamma^n r(s_n, \pi(s_n))$$

2. The Bellman equation gives us

$$Q^\pi(s_t, a_t) = r_t + \gamma Q^\pi(s_{t+1}, \pi(s_{t+1}))$$

''

3. Given some state s_t, the **best** agent, π^* is one that take action

$$a_t = \arg\max_a Q(s_t, a).$$

Q-Learning (State-action Value Iteration)

TODO: DO THESE SLIDES The action-value function (simplified).

1. The Q function for π^* is

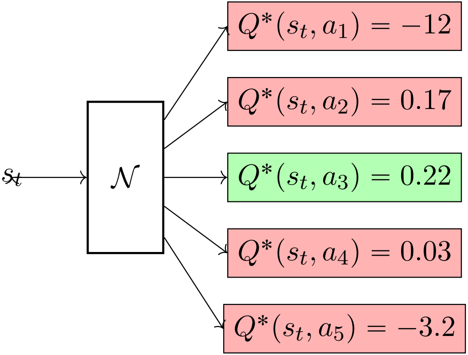
$$Q^*(s_t, a_t) = r_t + \gamma \arg\max_a Q^\pi(s_{t+1}, a).$$

2. We can *approximate* this with deep learning!
   1. Make a neural network $\mathcal{N} : \mathcal{S} \to \mathbb{R}^n$ which predicts the future reward of taking each possible action

$$\mathcal{N}(s_t) = \begin{pmatrix} Q^*(s_t, a_1) \\ Q^*(s_t, a_2) \\ \vdots \\ Q^*(s_t, a_n) \end{pmatrix}$$

Q-Learning (State-action Value Iteration)

Deep Q-Learning



$$\pi(s_t) = \arg\max_a \mathcal{N}(s_t)$$

Policy Iteration

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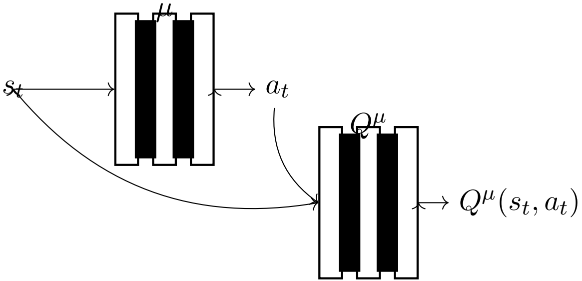
Deep Determisitic Policy Gradient

1. Actor neural network $\mu : \mathcal{S} \to \mathcal{A}$
2. Critic network $Q^\mu : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$
3. Performance of μ is $Q^\mu(s_t, \mu(s_t))$. **Maximize performance!** $\nabla_W Q^\mu(s_t, a_t) = \nabla_a Q^\mu(s_t, a) \cdot \nabla_W \mu(s_t)$



Questions?