RL WORKSHOP

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DATA SCIENCE CLUB

Schedule

1. RL intro
2. MDP’s
3. Policy Iteration
4. MC learning
5. Function approx
6. Policy gradient methods
7. Self play
8. Env

RL Intro

- What is RL?
  - At a very high level, RL is the process of learning to act and accomplish goals in **dynamic** environments
  - This is inspired by some ideas in psychology that behavior is reinforced by through the idea that behaviors that result in praise/pleasure tend to repeat and behaviors that bring “pain” go extinct
  - This leads to RL being a “trial and error” learning paradigm
- Agents receive rewards for working towards a goal
- Different representations of rewards and goals can alter the agents ability to perform well in specific scenarios found in RL (online learning, stochastic policies, etc)

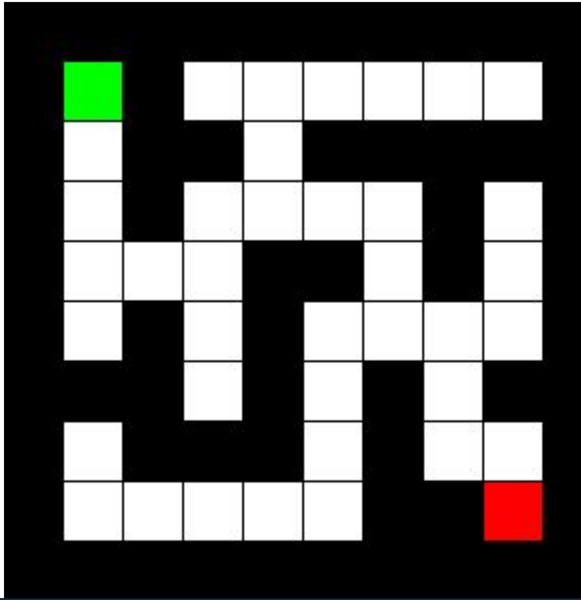
MDP'S: Formalizing RL problem spaces

- The MDP representation of the RL process is built on the Markov assumption: that all information needed to make an a acting given your current state is all encoded within your current state, no explicit access to previous states is needed

$$\mathbb{P}\left[R_{t+1} = r, S_{t+1} = s' \,|\, S_0, A_0, R_1, \ldots, A_{t-1}, R_t, S_t, A_t\right] = \mathbb{P}\left[R_{t+1} = r, S_{t+1} = s' \,|\, S_t, A_t\right]$$

MDP'S: Formalizing RL problem spaces

- Represented often times by 5 main items
  - State Space (S): Representation of all possible states to be in
  - Action Space (A): Representations of all possible actions to take
  - Transition Function (T:SxSxA → Real): Given state and action, take action
    - Represents P(s'|s, a): Probability of ending up in new state given state action pair
  - Reward Function (R:SxA → Real): Reward for specific state action pair
  - The last two can be mixed
    - P(s', r|s, a) - Transition function can include reward
  - Policy (denoted by π) (π: S → A): Maps states to actions to take, what the agent uses to make decisions



MDP'S: Cont

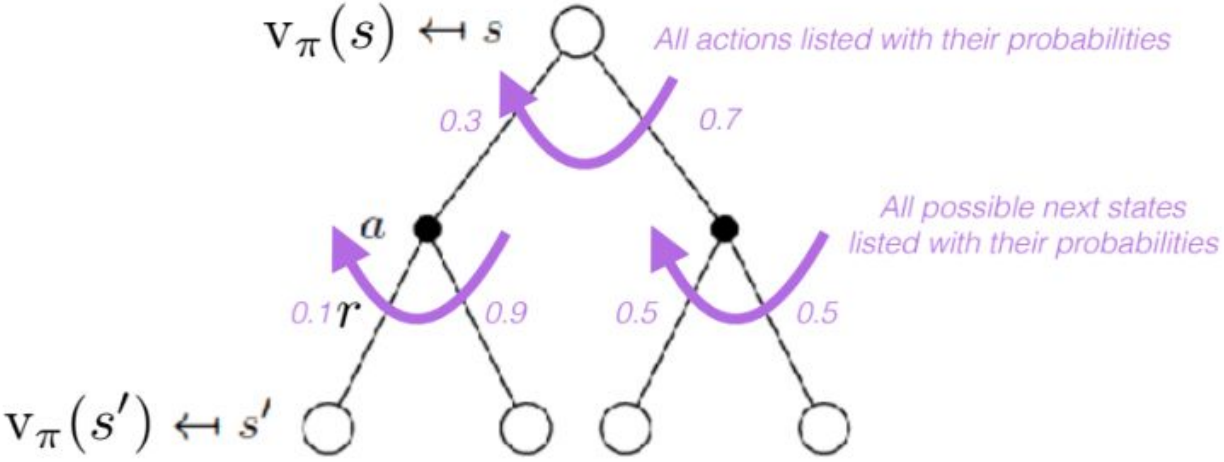
- So how can we act on this representation?
- Goal - Learn optimal policy: π* S → A
  - Maximize discounted reward
  - Gain best possible performance in an environment

$$v_\pi(s) = E_{a\sim\pi}[q_\pi(s,a)|S_t = s, A_t = a] = \sum_a \pi(a|s) \sum_{s',r} p(s',r|s,a)\left[r + \gamma v_\pi(s')\right]$$

- How can we judge the quality of a policy?
  - Value/ Q-value functions
- Value function (V:S → Real):
  - Represents the estimated value of being in a state while following policy
- Q-Value function (Q:SxA → Real):
  - Represents the estimated value of being in a state and taking an action, then following policy

$$q(s,a) = \mathbb{E}[R_{t+1} + \gamma v(s')|S_t = s, A_t = a] = \sum_{r,s'} (r + \gamma v(s'))p(s',r|s,a)\ .$$

MDP'S: Value function visualization



$$v_\pi(s) = \sum_a \pi(a\,|\,s) \sum_{s',r} p\left(s', r\,|\,s, a\right) \left[r + \gamma v_\pi(s')\right]$$

Policy Iteration: Optimizing policy with the value function

- Policy Iteration
  - Evaluate policy by estimating the values of each step till convergence
  - Improve your policy using reward and estimated values
- Major assumption: we know the *reward* and *transition* functions

Policy Iteration: Pseudocode

Policy Iteration (using iterative policy evaluation) for estimating $\pi \approx \pi_*$

1. Initialization
   $V(s) \in \mathbb{R}$ and $\pi(s) \in \mathcal{A}(s)$ arbitrarily for all $s \in \mathcal{S}$

2. Policy Evaluation
   Loop:
   $\quad \Delta \leftarrow 0$
   $\quad$ Loop for each $s \in \mathcal{S}$:
   $\quad\quad v \leftarrow V(s)$
   $\quad\quad V(s) \leftarrow \sum_{s',r} p(s', r \,|\, s, \pi(s))\big[r + \gamma V(s')\big]$
   $\quad\quad \Delta \leftarrow \max(\Delta, |v - V(s)|)$
   until $\Delta < \theta$ (a small positive number determining the accuracy of estimation)

3. Policy Improvement
   policy-stable $\leftarrow$ *true*
   For each $s \in \mathcal{S}$:
   $\quad$ *old-action* $\leftarrow \pi(s)$
   $\quad \pi(s) \leftarrow \arg\max_a \sum_{s',r} p(s', r \,|\, s, a)\big[r + \gamma V(s')\big]$
   $\quad$ If *old-action* $\neq \pi(s)$, then *policy-stable* $\leftarrow$ *false*
   If *policy-stable*, then stop and return $V \approx v_*$ and $\pi \approx \pi_*$; else go to 2

Figure 1: Policy iteration, taken from Section 4.3 of Sutton & Barto's RL book (2018).

MC methods: Dynamics free learning

- Policy iteration was built using the assumption of environmental dynamics (transition function, reward functions,etc)
    - How can we still learn a policy assuming we don't have those dynamics?
- One method is plausible: Monte carlo learning
    - Core idea: instead of using the dynamics of the function to determine what state we end up and the rewards we get from that, we use our own experiences in the environment
    - We update the value of a state after simulation an entire episode starting from that state

MC methods: Dynamics free learning

- Goal: learn $v_\pi(s)$ from episodes of experience under policy π:

$$S_1, A_1, R_2, ..., S_k \sim \pi$$

- Remember that the return is the total discounted reward:

$$G_t = R_{t+1} + \gamma R_{t+2} + ... + \gamma^{T-1} R_T$$

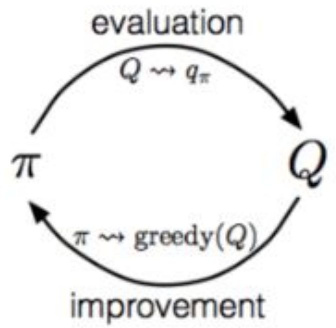
- Remember that the value function is the expected return:

$$v_\pi(s) = \mathbb{E}_\pi \left[G_t \mid S_t = s \right]$$

- Monte-Carlo policy evaluation **uses empirical mean return instead of expected return**

MC Learning Cont

$$\pi_0 \xrightarrow{\text{E}} q_{\pi_0} \xrightarrow{\text{I}} \pi_1 \xrightarrow{\text{E}} q_{\pi_1} \xrightarrow{\text{I}} \pi_2 \xrightarrow{\text{E}} \cdots \xrightarrow{\text{I}} \pi_* \xrightarrow{\text{E}} q_*$$



- MC policy iteration step: Policy evaluation using MC methods followed by policy improvement
- Policy improvement step: greedify with respect to value (or action-value) function

MC Learning: Pseudocode

First-visit MC prediction, for estimating $V \approx v_\pi$

Input: a policy π to be evaluated

Initialize:
  $V(s) \in \mathbb{R}$, arbitrarily, for all $s \in \mathcal{S}$
  $Returns(s) \leftarrow$ an empty list, for all $s \in \mathcal{S}$

Loop forever (for each episode):
  Generate an episode following π: $S_0, A_0, R_1, S_1, A_1, R_2, \ldots, S_{T-1}, A_{T-1}, R_T$
  $G \leftarrow 0$
  Loop for each step of episode, $t = T-1, T-2, \ldots, 0$:
    $G \leftarrow G + R_{t+1}$
    Unless S_t appears in $S_0, S_1, \ldots, S_{t-1}$:
      Append G to $Returns(S_t)$
      $V(S_t) \leftarrow \text{average}(Returns(S_t))$

FA: moving on from tabular methods

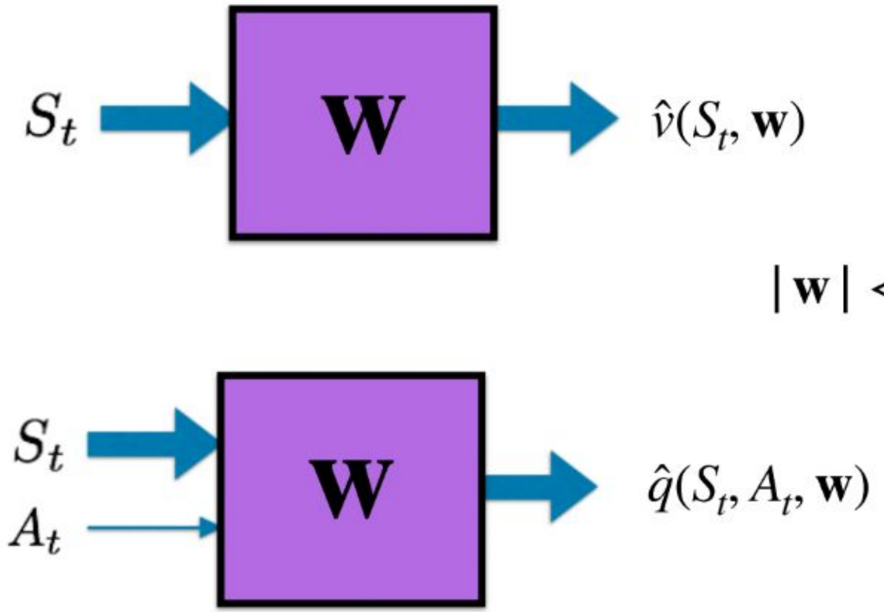
- In both previous RL methods we continuously update each states value function through various methods
  - Policy iteration: we update by sampling every possible next state given an action
  - MC-learning: update state value with bootstrapped estimate return
- But with FA we instead parameterize the value function with specific weights instead to better generalize learning of policy
- From there we can use any linear function approximator to utilize GD to improve the weights performance in accuracy in relation to an objective function

FA: moving on from tabular methods

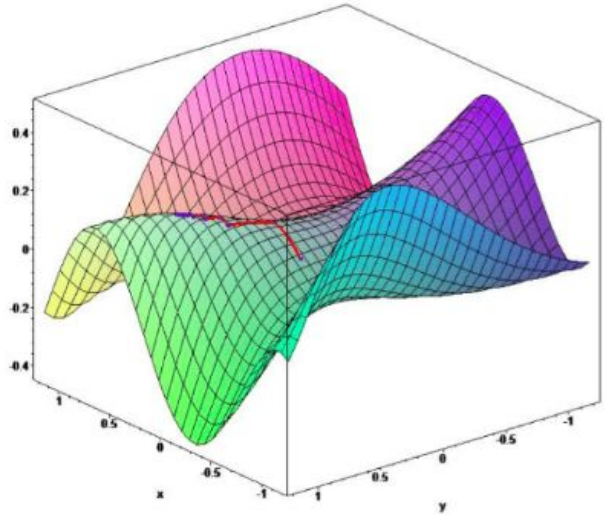
- Goal: find parameter vector w minimizing mean-squared error between the true value function $v_\pi(S)$ and its approximation $\hat{v}(S, \mathbf{w})$:

$$J(\mathbf{w}) = \mathbb{E}_\pi\left[\left(v_\pi(S) - \hat{v}(S, \mathbf{w})\right)^2\right]$$

FA: moving on from tabular methods



$$|\mathbf{w}| << |\mathcal{S}|$$



Gradient descent

- To find a local minimum of J(w), adjust w in direction of the negative gradient:

$$\Delta \mathbf{w} = -\frac{1}{2}\alpha \nabla_{\mathbf{w}} J(\mathbf{w})$$

- Starting from a guess $\mathbf{w}_0$
- We consider the sequence $\mathbf{w}_0, \mathbf{w}_1, \mathbf{w}_2, \ldots$ s.t. : $\mathbf{w}_{n+1} = \mathbf{w}_n - \frac{1}{2}\alpha \nabla_{\mathbf{w}} J(\mathbf{w}_n)$
- We then have $J(\mathbf{w}_0) \geq J(\mathbf{w}_1) \geq J(\mathbf{w}_2) \geq \ldots$

Gradient descent

- Let J(w) be a differentiable function of parameter vector w
- Define the gradient of J(w) to be:

$$\nabla_{\mathbf{w}} J(\mathbf{w}) = \begin{pmatrix} \frac{\partial J(\mathbf{w})}{\partial \mathbf{w}_1} \\ \vdots \\ \frac{\partial J(\mathbf{w})}{\partial \mathbf{w}_n} \end{pmatrix}$$

FA: example: TD learning w/O FA

Tabular TD(0) for estimating v_π

Input: the policy π to be evaluated
Algorithm parameter: step size $\alpha \in (0, 1]$
Initialize $V(s)$, for all $s \in \mathcal{S}^+$, arbitrarily except that $V(terminal) = 0$

Loop for each episode:
    Initialize S
    Loop for each step of episode:
        $A \leftarrow$ action given by π for S
        Take action A, observe R, S'
        $V(S) \leftarrow V(S) + \alpha\big[R + \gamma V(S') - V(S)\big]$
        $S \leftarrow S'$
    until S is terminal

FA: TD learning with FA

Semi-gradient TD(0) for estimating $\hat{v} \approx v_\pi$

Input: the policy π to be evaluated
Input: a differentiable function $\hat{v} : \mathcal{S}^+ \times \mathbb{R}^n \to \mathbb{R}$ such that $\hat{v}(\text{terminal},\cdot) = 0$

Initialize value-function weights $\boldsymbol{\theta}$ arbitrarily (e.g., $\boldsymbol{\theta} = \mathbf{0}$)
Repeat (for each episode):
  Initialize S
  Repeat (for each step of episode):
    Choose $A \sim \pi(\cdot|S)$
    Take action A, observe R, S'
    $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha\big[R + \gamma\hat{v}(S',\boldsymbol{\theta}) - \hat{v}(S,\boldsymbol{\theta})\big]\nabla\hat{v}(S,\boldsymbol{\theta})$
    $S \leftarrow S'$
  until S' is terminal

Policy gradient methods: A new paradigm

- Instead of parameterizing the value function of the state, parameterize the state and as a larger result the policy itself, removing the need for value functions
- This means we can parameterize the policy along whatever lines we want, including, including having the policy parameters be the parameters of a probability distribution, allowing for probabilistic optimal policies, ideal for situations like poker where actions are sampled from this distribution

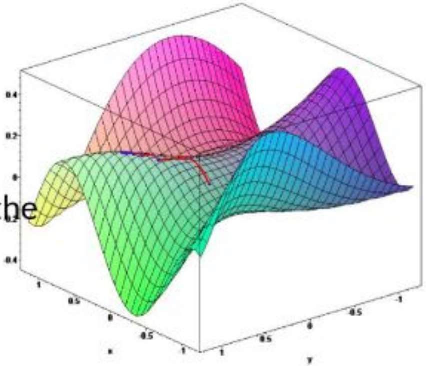
Policy optimization

- Let $U(\Theta)$ be a policy objective (loss) function
- General policy optimization pseudocode goes as such
    - Initialize policy parameters (Θ)
    - Sample trajectories by deploying policy with current parameterization
    - Compute gradient vector $\nabla U(\Theta)$
    - Update policy parameters as such: $\Theta + \alpha\nabla U(\Theta)$ (where α is step size)

Policy optimization: an alternate view

Policy Gradient

- Let U(θ) be any policy objective function
- Policy gradient algorithms search for a local maximum in U(θ) by ascending the gradient of the policy, w.r.t. parameters θ



$$\theta_{new} = \theta_{old} + \Delta\theta$$

$$\Delta\theta = \alpha \nabla_\theta U(\theta)$$

α is a step-size parameter (learning rate)

is the policy gradient

$$\nabla_\theta U(\theta) = \begin{pmatrix} \frac{\partial U(\theta)}{\partial \theta_1} \\ \vdots \\ \frac{\partial U(\theta)}{\partial \theta_n} \end{pmatrix}$$

Policy gradient: the gradient of the policy objective w.r.t. the parameters of the policy

Types of policy parameterizations

Policy functions

deterministic continuous policy

$a = \pi_\theta(s)$

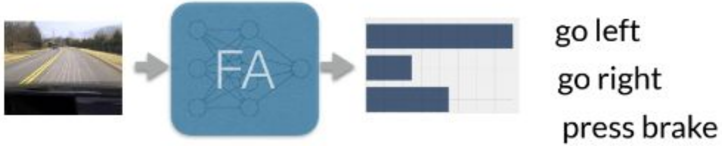
e.g. outputs a steering angle directly

stochastic continuous policy

$a \sim \mathcal{N}(\mu_\theta(s), \sigma^2_\theta(s))$

FA for stochastic multimodal continuous policies is an active area of research

(stochastic) policy over discrete actions



Outputs a distribution over a discrete set of actions

REINFORCE: taking advantage of policy gradients

From this method, as well as deriving a specific gradient we can state the final algorithm for this workshop using Policy gradients

0. Initialize policy parameters θ

1. Sample trajectories $\{\tau_i = \{s_t^i, a_t^i\}_{t=0}^{T}\}$ by deploying the current policy $\pi_\theta(a_t \mid s_t)$.

2. Compute gradient vector $\nabla_\theta U(\theta) \approx \hat{g} = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(a_t^{(i)} \mid s_t^{(i)}) G_t^{(i)}$

3. $\theta \leftarrow \theta + \alpha \nabla_\theta U(\theta)$

REINFORCE: taking advantage of policy gradients

Algorithm 1 REINFORCE

procedure REINFORCE
    Start with policy model π_θ
    repeat:
        Generate an episode $S_0, A_0, r_0, \ldots, S_{T-1}, A_{T-1}, r_{T-1}$ *following* $\pi_\theta(\cdot)$
        for t *from* $T-1$ *to* 0:
            $G_t = \sum_{k=t}^{T-1} \gamma^{k-t} r_k$
        $L(\theta) = \frac{1}{T} \sum_{t=0}^{T-1} G_t \log \pi_\theta(A_t|S_t)$
        Optimize π_θ *using* $\nabla L(\theta)$
end procedure

MISC Topics

Gymnasium

- Environment Collection: Gym is a Python library offering a range of environments for testing reinforcement learning algorithms.

- OpenAI Support: Developed by OpenAI, Gym ensures quality environments compatible with various reinforcement learning techniques.

- Simplified Usage: Gym provides a user-friendly interface, streamlining the process of experimenting with reinforcement learning algorithms.

Gymnasium: env

- Environment Interface: The env class in Gym defines a common interface for interacting with reinforcement learning environments.

- Unified Interaction: It abstracts the interaction between agents and environments, providing consistent methods for actions, observations, and rewards.
  - Some methods include, env.step, env.display
  - Some fields include: action_space, observation_space
- Good to look through documentation

Self Play

- Self-Play Concept: Self-play is a reinforcement learning technique where an agent learns by playing against itself rather than against fixed opponents or a pre-existing dataset.
- Dynamic Opponent: In self-play, the agent's opponent evolves alongside its own learning process, adapting to the agent's current capabilities and strategies.
- Continuous Improvement: Through iterative self-play, agents can continuously improve their strategies, leading to robust and adaptive behavior in a variety of environments or games.

Similar(ish) example: Generative adversarial Imitation learning(GAIL)

Activity

Complete (and correct) and implementation of the REINFORCE Algorithm

Collab link:
https://tinyurl.com/2s4fskcj