

Reinforcement Learning (RL)

Chapter 7:
Value Function Approximation (VFA)

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Aim of this chapter:

- ✓ Understanding the general concepts of the Value Function Approximation and loss function to find proper weights for reinforcement learning networks.

Value Function Approximation

Idea - Challenge

- ✓ In all previous approaches we considered **tabular representation** for **value function V** or **state-action function** (Q-value)
 - In form of array, vector, matrix, or lookup table
- ✓ In many problems the state **space and/or action spaces** is **very large**:
 - Very slow to learn the value of each state individually
 - All possible state-values or Q-values may not fit in the memory

Value Function Approximation

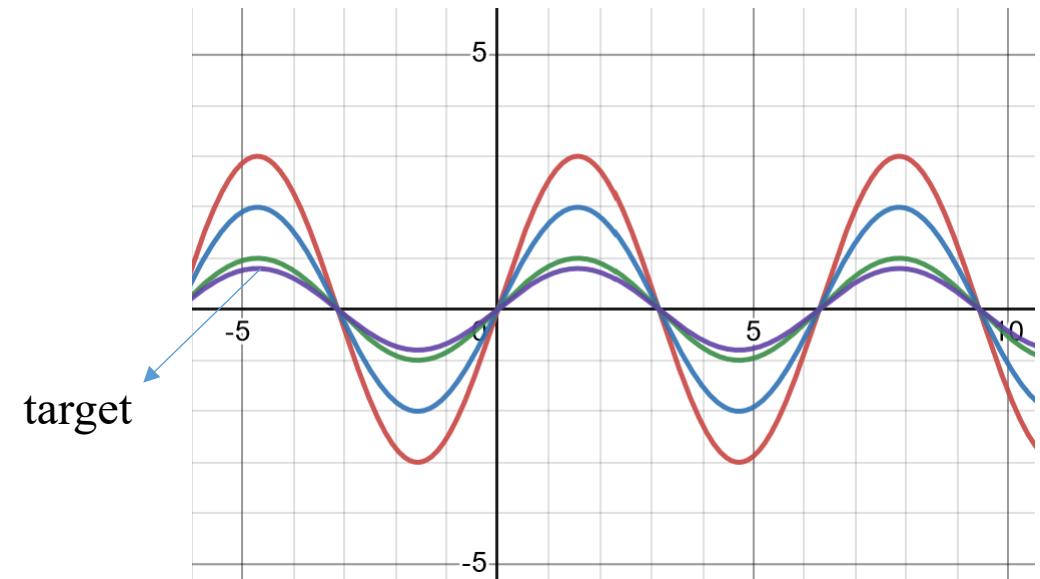
Solution if MDP is big

- ✓ Find a way to **parameterize the value function** and **remove tables** as storage.

What does parameterization mean?

$$w \sin x$$
$$1 \sin x$$
$$2 \sin x$$
$$3 \sin x$$

↓
w



Value Function Approximation

- ✓ We can Estimate **value** with **value function approximation**
- ✓ We usually represents the state-value or Q-value function with a parameterized function (\hat{Q} or \hat{V}).

$$V_\pi(s) \approx \hat{V}(s, w)$$

$$Q_\pi(s, a) \approx \hat{Q}(s, a, w)$$

Value Function Approximation

- ✓ Lets consider state s is indicated by set of observations $s = (x_1, x_2, \dots, x_n)^T$

If we write a simple **linear approximation**:

For state-value function:

$$\hat{V}(s, w) = \sum_{i=1}^n w_i x_i(s)$$

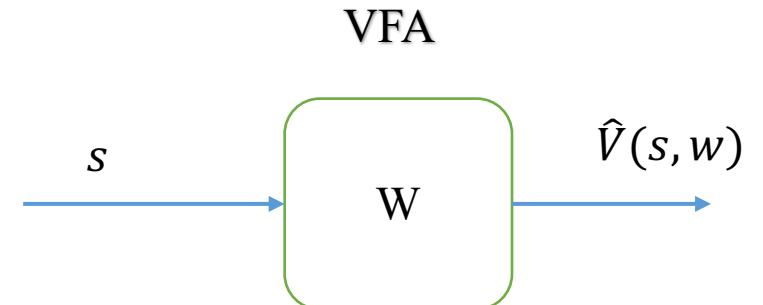
For state-action function:

$$\hat{Q}(s, a, w) = \sum_{i=1}^n w_{ai} x_i$$

Value Function Approximation

- ✓ Also can be represented as:

$$\hat{V}(s, w) \approx V_\pi(s)$$



$$\hat{Q}(s, a, w) \approx Q_\pi(s, a)$$

Usually **Neural Network** is the most proper option among different function approximators.

Value Function Approximation

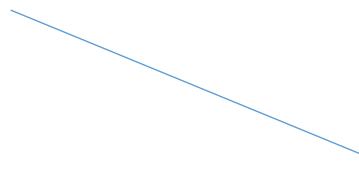
If we write a simple **Non-linear approximation**:

For state-value function:

$$\hat{V}(s, w) = g(x; w)$$

For state-action function:

$$\hat{Q}(s, a, w) = g(x; w)$$



e.g. Neural Network

Value Function Approximation

- ✓ Therefore we can define an **objective function** $E(w)$ (also known as $J(w)$) as **minimizing loss** between **target value** and **predicted value**.

$$E(w) = \mathbb{E}_{\pi}[(V_{\pi}(s) - \hat{V}(s, w))^2]$$

- ✓ This is an optimization problem (find parameter vector w to minimize MSE).
- ✓ For instance **Stochastic gradient descent (SGD)** algorithm can be used to solve it.

Value Function Approximation

How to calculate target and predicted values for VFA?

- ✓ There can be multiple solutions
- ✓ The most common way is to use TD
- ✓ For instance we can use Q-learning

$$E(w) = \mathbb{E}_\pi[(V_\pi(s) - \hat{V}(s, w))^2]$$

VFA as Q-learning

$$E(w) = \mathbb{E}[(R(s_t, a_t) + \gamma \text{Max}_a[\hat{Q}(s_{t+1}, a_{t+1}; w)] - \hat{Q}(s_t, a_t; w))^2]$$

$$\Delta w = \alpha[R(s_t, a_t) + \gamma \text{Max}_a[\hat{Q}(s_{t+1}, a_{t+1}; w)] - \hat{Q}(s_t, a_t; w)] \nabla_w \hat{Q}(s_t, a_t; w)$$

objective function

Gradient (Nabla)

Note: The real target value $Q(s_{t+1}, a_{t+1})$ in practice is also prediction from model as $\hat{Q}(s_{t+1}, a_{t+1}; w)$.

Value Function Approximation

How to calculate target and predicted values for VFA?

VFA as SARSA

$$E(w) = \mathbb{E}_\pi[(V_\pi(s) - \hat{V}(s, w))^2]$$

$$E(w) = \mathbb{E}[((R(s_t, a_t) + \gamma \hat{Q}(s_{t+1}, a_{t+1}; w) - \hat{Q}(s_t, a_t; w))^2]$$

$$\Delta w = \alpha[R(s_t, a_t) + \gamma \hat{Q}(s_{t+1}, a_{t+1}; w) - \hat{Q}(s_t, a_t; w) \nabla_w \hat{Q}(s_t, a_t; w)]$$

Value Function Approximation

How to calculate target and predicted values for VFA?

VFA as ESARSA

$$E(w) = \mathbb{E}_\pi[(V_\pi(s) - \hat{V}(s, w))^2]$$

$$E(w) = \mathbb{E}[((R(s_t, a_t) + \gamma \hat{Q}(s_{t+1}, a_{t+1}; w) - \hat{Q}(s_t, a_t; w))^2]$$

$$\Delta w = \alpha [R(s_t, a_t) + \gamma \sum \hat{\pi}(a|s_{t+1}) \hat{Q}(s_{t+1}, a_{t+1}; w) - \hat{Q}(s_t, a_t; w) \nabla_w \hat{Q}(s_t, a_t; w)]$$

Note:

We also can apply MC, TD(0), TD(λ) as VFAs.

Value Function Approximation

Advantage

Solving memory problem

- ✓ State action pair table is very big

Generalization

- ✓ For non-seen states there can be approximation of some actions

Continues

- ✓ More applicable for continues environments