

• 29 - Jan - 2021 Notes :

• Function Approximation :

@abstractmethod solve finds a best fit for iterables of x and y

@abstractmethod update : Improved function approximation with new data

• You can implement solve analytically or use the built-in stochastic gradient descent notes.

• Tabular methods (dicts of dicts) can be used with FunctionApprox

• Task : What is the average height of people in ten countries?

↳ X = Which country

↳ Y = Heights

↳ Table updated at each sample

• Evaluate looks up current averages in table

• Update adds samples to the averages.

↳ Incremental averaging

• solve runs update until samples get exhausted

• $\mathbb{E}[y|x]$ can include weights on samples in the average

• Tabular setting is compatible with FunctionApprox interface

↳ Special is a special case of linear function approximation

↳ Features ϕ_i as indicator functions for each $x_i \in X$

• In practice, when sharing averages, use estimated values coming from population/historical data/domain knowledge.

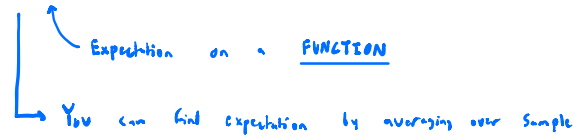
↳ Very rarely do we calculate averages from scratch

↳ Initial Values influence time to convergence

- Specializing Function Approx to Tabular gives normal MDP properties

↗ Check this, slide 14

- You can sample or find expectation of an arbitrary distribution



- Slide 17: Iterator on FunctionApprox is just to run diagnostics on approximations at different iterations

- Slide 18: iterate takes initial function approximation approx=0 and applies update to it over and over, produces iterator

- Approximate Value Iteration Interface: For MDP

- Look at Slide 21 Notes

- How do you get a good estimate of probability distribution of states? Use domain knowledge

↳ For stochastic processes, you can track samples

↳ Simulation = Stitch together samples one step at a time.

↳ You can always use sampling distribution as your distribution

↳ Backup choice: Create a uniform distribution

- Review code for function approximation

• Chapter 5: Utility Theory basics

↳ Intuition on Risk-Aversion and Risk Premium

↳ Risk Aversion is a personality-based trait

↳ Degree of fear for taking risks

→ Risk premium depends on variance and risk aversion

→ Why are we risk averse?

→ Our satisfaction in better outcomes grows nonlinearly

→ We refer to this as the Utility Function

→ See slide 4 for good illustration

→ Accumulated satisfaction is concave down

→ Degree of concavity is risk aversion

→ Concave $U(x) \Rightarrow E[U(x)] < U(E[x])$

→ We define Certainty Equivalent Value:

$$x_{ce} = U^{-1}(E[U(x)])$$

• Calculating Risk Premium:

→ Let $\bar{x} \equiv E[x]$

$$\begin{aligned}\therefore U(x) &\approx U(\bar{x}) + U'(\bar{x}) \cdot (x - \bar{x}) + \frac{1}{2} U''(\bar{x}) \cdot (x - \bar{x})^2 \\ &\approx U(\bar{x}) + U'(\bar{x}) \cdot (x - \bar{x})\end{aligned}$$

• Take expectation to get:

... See slide 7 - 8

$$\begin{array}{ccccc} \pi_A & \approx & \frac{1}{2} A(\bar{x}) \cdot \sigma_x^2 & & \\ \uparrow & & \uparrow & \nwarrow & \\ \text{risk premium} & & \text{risk aversion} & & \text{variance} \end{array}$$

• Relative risk premium = relative risk premium divided by the mean.

• Return and risk go together

• For every individual, there is a balance of risk and reward

- Constant absolute risk aversion (CARA)
- Read appendix 1, moment generating functions
- No testing on Stochastic calculus.
- Read chapter on Utility Theory before Wednesday. We will see Merton's Portfolio Problem