- **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 decent 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

- $\mathbb{E}[y \mid x]$ 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 $x_i \in \mathcal{X}$

- In practice, when starting 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

Expectation on a FUNCTION

→ You can find expectation by averaging over sample

- Slide 17: Iterate 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

- Lost on Slide 21 Notes

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

→ For stochastic processes, you can create 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 risk

↦ Risk premium depends on variance and risk aversion

↦ Why are we risk averse?

↦ Our satisfaction to 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 $U(x) \Rightarrow \mathbb{E}[U(x)] < U(\mathbb{E}[x])$

↦ We define Certainty Equivalent Value:

$$x_{CE} : U^{-1}(\mathbb{E}[U(x)])$$

- Calculating Risk Premium:

↦ Let $\bar{x} \equiv \mathbb{E}[x]$

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

$$\approx U(\bar{x}) + U'(\bar{x}) \cdot (x - \bar{x})$$

- Take expectation to get:

... See slide 7 - 8

- $\pi_A \approx \frac{1}{2} A(\bar{x}) \cdot \sigma_x^2$

risk premium   risk aversion   variance

- 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 Martha's Portfolio Problem