10: Reinforcement Learning * Slide - 48 belong to the many by boto becomes · For infinite horizon, just like Va(s), we get a system of equations for Q* (s,a). The equations are not exactly linear because of the max () function terms * Slide - 55 · Now, we could calculate the states / measure the state of soil fairly accurately maybe by using moisture servous or other parameters. We could also determine the set of actions we can take. But, in real title life, the transition model & cot forming the remard function in so easy or you could say it isn't so vanilla.

Exploration: - means we are trying to understand the system or process by trying to do things de random de analyse the results of these actions.

Exploitation: - Trying to do the best thing. (Not necessarily to plant the in the soil) In general to do an action which yeiths the highest reward

One option to choose the tradeoff is use an \(\xi - \text{greedy} \)

Strategy. This \(\xi - \text{greedy} \) is basically as Bernoulli random variable. \(\chi = \xi - \xi \)

\[\xi - \xi \) explore, \(\xi \) = 1-\(\xi \)

\[\xi \) explore, \(\xi \) = \(\xi \)

- Oneway in which we can learn Q is by estimating the transition model T&R (reward function)
- S to be equally likely. Hence, probability of getting to a random S is ISI

Hence, $\hat{T}(s,a,\hat{s}) = 1$. Since all to be $\frac{1}{s}$ bound both.

The 'a' indicates initial value.

- has been taken, R(s,a) = 0
- The select action () functions chooses an action based on what we want to do. If we choose an &-greedy strategy, we would choose to exploit 100. (1-8) times out of 100 times at explore, 100. & of out 100 times. If we choose to exploit, out hunchion would depend on Q i.e. we would choose the best action based on Q. If we choose to explore, our function wont depend on Q & would choose any action randomly uniformly.
- The execute() Purchion executes the action & the nature returns the output state & reward.