

## OPTIMAL ASSET ALLOCATION IN DISCRETE TIME

STANFORD UNIVERSITY - CME 241: SOLUTION TO ASSIGNMENT PROBLEM

We are given wealth  $W_0$  at time 0. At each of discrete time steps labeled  $t = 0, 1, \dots, T$ , we are allowed to allocate the current wealth  $W_t$  in a risky asset and a riskless asset in an unconstrained, frictionless manner. The risky asset yields a random rate of return  $\sim N(\mu, \sigma^2)$  over each single time step. The riskless asset yields a rate of return denoted by  $r$  over each single time step.

Our goal is to maximize the Utility of Wealth at the final time step  $t = T$  by dynamically allocating  $x_t$  in the risky asset and the remaining  $W_t - x_t$  in the riskless asset for each  $t = 0, 1, \dots, T - 1$  (assume no transaction costs and no restrictions on going long or short in either asset). Assume the single-time-step discount factor is  $\gamma$  and the Utility of Wealth at the final time step  $t = T$  is  $U(W_T) = -\frac{e^{-aW_T}}{a}$  for some fixed  $a > 0$ .

- **Formulate this problem as a *Continuous States, Continuous Actions* MDP by specifying it's *State Transitions, Rewards* and *Discount Factor*. The problem then is to find the *Optimal Policy*.**

*State* will be represented as  $(t, W_t)$ . Assume our decision (*Action*) at any time step  $t$  is given by the quantity of investment in the risky asset at time step  $t = 0, 1, \dots, T - 1$  and is denoted by  $x_t$  (hence, quantity of investment in the riskless asset at time  $t$  will be  $W_t - x_t$ ). We denote the policy as  $\pi$ , so  $\pi((t, W_t)) = x_t$ . Denote the random variable for the return of the risky asset as  $R \sim N(\mu, \sigma^2)$  and the excess return of the risky asset (over riskless return  $r$ ) as  $S = R - r$ . So,

$$W_{t+1} = x_t(1 + R) + (W_t - x_t)(1 + r) = x_t S + W_t(1 + r)$$

The *Reward* is always 0 for all  $t = 0, 1, \dots, T - 1$  and the *Reward* at the terminal time step  $t = T$  is  $U(W_T) = -\frac{e^{-aW_T}}{a}$ . The MDP discount factor is  $\gamma$ .

- **As always, we strive to find the Optimal Value Function. The first step in determining the Optimal Value Function is to write the Bellman Optimality Equation.**

We denote the Value Function for a given policy as:

$$V^\pi(t, W_t) = E_\pi[\gamma^{T-t} \cdot U(W_T) | (t, W_t)] = E_\pi[-\gamma^{T-t} \cdot \frac{e^{-aW_T}}{a} | (t, W_t)]$$

We denote the Optimal Value Function as:

$$V^*(t, W_t) = \max_{\pi} V^{\pi}(t, W_t) = \max_{\pi} E_{\pi}[-\gamma^{T-t} \cdot \frac{e^{-aW_T}}{a} | (t, W_t)]$$

The Bellman Optimality Equation is:

$$V^*(t, W_t) = \max_{x_t} (E_{R \sim N(\mu, \sigma^2)}[\gamma \cdot V^*(t+1, W_{t+1})])$$

- Assume the functional form for the Optimal Value Function is  $-b_t e^{-c_t W_t}$  where  $b_t, c_t$  are unknowns functions of only  $t$ . Express the Bellman Optimality Equation using this functional form for the Optimal Value Function.

$$\begin{aligned} V^*(t, W_t) &= \max_{x_t} (E_{R \sim N(\mu, \sigma^2)}[-\gamma \cdot b_{t+1} e^{-c_{t+1}(x_t S + W_t(1+r))}]) \\ &= \max_{x_t} (-\gamma \cdot b_{t+1} e^{-c_{t+1} W_t(1+r) - c_{t+1} x_t(\mu - r) + \frac{\sigma^2}{2} c_{t+1}^2 x_t^2}) \end{aligned}$$

- Since the right-hand-side of the Bellman Optimality Equation involves a max over  $x_t$ , we can say that the partial derivative of the term inside the max with respect to  $x_t$  is 0. This enables us to write the Optimal Allocation  $x_t^*$  in terms of  $c_{t+1}$ .

$$\frac{\partial V^*(t, W_t)}{\partial x_t} = 0 \Rightarrow -c_{t+1}(\mu - r) + \sigma^2 c_{t+1}^2 x_t^* = 0 \Rightarrow x_t^* = \frac{\mu - r}{\sigma^2 c_{t+1}}$$

- Substituting this maximizing  $x_t^*$  in the Bellman Optimality Equation enables us to express  $b_t$  and  $c_t$  as recursive equations in terms of  $b_{t+1}$  and  $c_{t+1}$  respectively.

Plugging in  $x_t^*$  in the above equation for  $V^*(t, W_t)$  gives:

$$V^*(t, W_t) = -\gamma \cdot b_{t+1} e^{-c_{t+1} W_t(1+r) - \frac{(\mu-r)^2}{2\sigma^2}}$$

But since

$$V^*(t, W_t) = -b_t e^{-c_t W_t}$$

we can write the following recursive equations for  $b_t$  and  $c_t$ .

$$\begin{aligned} b_t &= \gamma \cdot b_{t+1} e^{-\frac{(\mu-r)^2}{2\sigma^2}} \\ c_t &= c_{t+1}(1+r) \end{aligned}$$

- We know  $b_T$  and  $c_T$  from the knowledge of the MDP *Reward* at  $t = T$  (Utility of Terminal Wealth), which enables us to unroll the above recursions for  $b_t$  and  $c_t$ .

Since  $V^*(T, W_T) = -\frac{e^{-aW_T}}{a}$ ,  $b_T = \frac{1}{a}$ ,  $c_T = a$ . Therefore, we can unroll the above recursions for  $b_t$  and  $c_t$ .

$$b_t = \frac{\gamma^{T-t}}{a} e^{-\frac{(\mu-r)^2 \cdot (T-t)}{2\sigma^2}}$$

$$c_t = a \cdot (1+r)^{T-t}$$

- Solving  $b_t$  and  $c_t$  yields the Optimal Policy and the Optimal Value Function.

$$x_t^* = \frac{\mu - r}{\sigma^2 a (1+r)^{T-t-1}}$$

$$V^*(t, W_t) = -\frac{\gamma^{T-t}}{a} \cdot e^{-\frac{(\mu-r)^2 \cdot (T-t)}{2\sigma^2}} \cdot e^{-a \cdot (1+r)^{T-t} \cdot W_t}$$