

Recall:

1. system state equation

$$Y_s(\omega) : [t, T] \times \Omega \rightarrow \mathbb{R}^d$$

$$\begin{cases} dY_s = f(Y_s, \alpha_s, s) ds + \sigma(Y_s, \alpha_s, s) dB_s, & s \geq t \\ Y_t = x, & \text{a.s.} \end{cases} \quad (2.3b)$$

filtered probability space $(\Omega, \mathcal{F}, \{\mathcal{F}_s\}_{s \geq t}, P)$.

2. the set of admissible control:

$$\mathcal{A}_{t,T} = \{ \alpha_s(\omega) : [t, T] \times \Omega \rightarrow A \subset \mathbb{R}^m \mid \alpha_s \text{ is adapted to the filtration } \{\mathcal{F}_s\}_{s \geq t} \}.$$

3. existence and uniqueness of strong solution (s.s.) to (2.3b)

Supposing σ & f satisfy usual bounds + continuity condition, then for any given initial condition (x, t) and $\alpha_s(\omega)$, (2.3b) $\exists!$ strong solution.

3. Value function & dynamic programming principle

Assumptions: $\begin{cases} g(\cdot) \\ r \end{cases}$ satisfies $\begin{matrix} (H_1) \\ (H_2) \end{matrix}$ given in last Tuesday

$\Rightarrow$

• objective function

$$J_{x,t}(\alpha(\cdot)) = E \left[\int_t^T r(Y_s, \alpha_s, s) ds + g(Y_T) \mid Y_t = x \right] < +\infty$$

★ ocp is to maximize (or minimize) the objective function over all admissible controls

$\Rightarrow$

• Value function

$$u(x, t) = \max_{\alpha \in \mathcal{A}_{t,T}} E \left[\underbrace{\int_t^T r(Y_s, \alpha_s, s) ds}_{\text{running payoff}} + \underbrace{g(Y_T)}_{\text{terminal payoff}} \mid Y_t = x \right] \quad (2.39)$$

• DPP

for any stopping time $\tau \in [t, T]$,

$$u(x, t) = \max_{\alpha \in \mathcal{A}_{t,\tau}} E \left[\int_t^\tau r(Y_s, \alpha_s, s) ds + u(Y_\tau, \tau) \mid Y_t = x \right] \quad (2.41)$$

4. The Hamilton-Jacobi-Bellman equation (HJBe)

Assume $u(x, t) \in C^{2,1}(\mathbb{R}^d \times [0, T])$. formally derive

$$u_t(x, t) + \max_{a \in A} \left[r(x, a, t) + \frac{1}{2} \text{tr} (D^2 u(x, t) \sigma(x, a, t) \sigma^T(x, a, t)) + f(x, a, t) \cdot \nabla u(x, t) \right] = 0$$

!!

$\frac{\partial}{\partial x} u$

$$H(D^2 u, Du, x, t)$$

the second order differential operator

$\Leftrightarrow$

$$u_t(x, t) + H(D^2 u, Du, x, t) = 0 \quad (2.47)$$

总结:

Why need HJB: find an optimal control α^* s.t. $u(x, t) = J_{x, t}(\alpha^*)$.

有两种框架去 find optimal control:

★ way 1: in classical PDE approach: here a priori assumption: $u(x, t) \in C^{2,1}$

way 2: in viscosity solution approach: weaker assumption: $u(x, t)$ locally bdd

Today,

I. The classical PDE approach

(that is the)

Verification theorem (see P47 -book- pham)

- Assumptions:
- ① $w(x, t) \in C^{2,1}(\mathbb{R}^d \times [0, T]) \cap C^0(\mathbb{R}^d \times [0, T])$
 - ② $w(x, t): \exists$ a constant $C > 0$ s.t. $\rightarrow$ growth condition
 $|w(x, t)| \leq C(1 + |x|^2), \forall (x, t) \in [0, T] \times \mathbb{R}^d$
 - ③ $w(x, T) = g(x) \rightarrow$ terminal payoff
 - ④ $\exists$ a measurable function $\hat{\alpha}(x, t): \mathbb{R}^d \times [0, T] \rightarrow A \subset \mathbb{R}^m$

s.t.

$$w_t + \max_{a \in A} [r(x, a, t) + \mathcal{L}^a w(x, t)] = 0, \text{ and } \max_{a \in A} [r(x, a, t) + \mathcal{L}^a w(x, t)] = r(x, \hat{\alpha}(t) + \mathcal{L}^{\hat{\alpha}} w(x, t))$$

(i.e., $\exists$ a function $\hat{\alpha}(x, t)$, s.t. $w(x, t)$ satisfies HJB)

$$\textcircled{5} \text{ The SDE } \begin{cases} dY_s = f(Y_s, \hat{\alpha}_s, s) ds + \sigma(Y_s, \hat{\alpha}_s, s) dB_s \\ Y_t = x \end{cases}$$

$\exists!$ solution, denoted by $\hat{Y}_s^{t, x}$:

And the control $\{\hat{\alpha}(\hat{Y}_s^{t, x}, s)\}_{s \geq t} \in A_{t, T}$.

Conclusion:

- ① $J_{x, t}(\hat{\alpha}) = w(x, t) = u(x, t)$
- ② $\therefore \hat{\alpha}$ is an optimal control.

HJB 的解不一定有这么好

正则性. $\therefore$ 引入粘性解的框架.

总结: the classical approach, 就是

step 1. obtain the existence of smooth solution to HJB for some $\hat{\alpha}$

step 2. By verification thm, show this smooth solution is the value function

step 3. obtain the optimal control $\hat{\alpha}$

Step 3. obtain the optimal control $\hat{\alpha}$

II. Example:

1. System state equation

Consider a wealth (bond & stock) process evolves according to

$$\begin{cases} dX_s = X_s [\underbrace{\alpha_s \mu + (1-\alpha_s)r}_{f} ds + \underbrace{\alpha_s \sigma}_{\text{the stock proportion of wealth}} dB_s, & s \geq t, t \in [0, T] \\ X_t = x \end{cases} \quad \text{SDE}$$

μ, r, σ - constants
the bond proportion

2. admissible control set

The investor faces the portfolio constraint, i.e.

$$A := \left\{ \begin{array}{l} \alpha_s: [0, T] \times \Omega \longrightarrow A \subset \mathbb{R}, \text{ } A \text{ is a closed convex subset} \\ \alpha_s \text{ is progressively measurable, s.t. } \int_0^T |\alpha_s|^2 ds < \infty \end{array} \right\}$$

investor portfolio constraint

integrability

i.e. for all $s \in [t, T]$, α_s is $\mathcal{B} \otimes \mathcal{F}_s$ measurable.

3. objective function:

the expected utility from terminal wealth at T

$$J_{x,t}(\alpha(\cdot)) = E[g(X_T^{t,x})], (t,x) \in [0,T] \times \mathbb{R}^+$$

with

$$g(x) = \frac{x^p}{p}, x \geq 0, p < 1, p \neq 0.$$

$\therefore$ running payoff $r \equiv 0$.

4. Value function

$$V(x,t) = \max_{\alpha \in A} E[g(X_T^{t,x})] \quad (1)$$

5. HJB for the stochastic C.P. (1)

$$V_t + \max_{\alpha \in A} [\underbrace{r(x,\alpha,t)}_{\in \mathbb{R}^+} + \frac{1}{2} \text{tr} (D^2 W(x,t) \underbrace{\sigma(x,\alpha,t)}_{1 \text{ dimensional}} \underbrace{\sigma^T(x,\alpha,t)}_{1 \text{ dimensional}}) + f \cdot \nabla W] = 0$$

$$W(x,T) = g(x), x \in \mathbb{R}^+$$

terminal condition

$$\mathcal{L}^\alpha = b(x,t) \cdot \nabla W + \frac{1}{2} \text{tr} (D^2 W \sigma \cdot \sigma^T)$$

$\Rightarrow$

$$V_t + \max_{\alpha \in A} [x(\alpha\mu + (1-\alpha)r)W_x + \frac{1}{2} x^2 \alpha^2 \sigma^2 W_{xx}] = 0$$

!!
va ...

random walk (2)

!! $\downarrow$ Random walk (2) $\checkmark$
 $\mathbb{E}^a w(x, t)$ never reach boundary, need the boundary condition.
 $w(x, T) = g(x) = \frac{x^p}{p} > 0, x \in \mathbb{R}^+, p < 1, p \neq 0$
 for (2) find optimal control α , $p=0$, need the boundary condition
 $g(x) = \lim_{p \rightarrow 0} \left(\frac{x^p}{p} - \frac{1}{p} \right)$

Step 1. find a smooth solution of (2) for some $\hat{\alpha}$

1) assume the smooth solution in the form

$$w(x, t) = \phi(t) g(x) \text{ for some } \phi(t) > 0.$$

$$g(x) = \frac{x^p}{p}$$

$$\Rightarrow w_t = \phi_t g(x)$$

$$g_{xx}(x) = p \cdot (p-1) x^{p-2}$$

$$\begin{aligned} \mathbb{E}^a w(x, t) &= x(a\mu + (1-a)r)\phi(t)g(x) + \frac{1}{2}x^2a^2\beta^2\phi(t)g_{xx}(x) \\ &= x x^{p-1} [a(\mu-r) + r] \phi(t) + \frac{1}{2}a^2\beta^2\phi(t) \cdot x^2 \cdot (p-1) \cdot x^{p-2} \\ &= p g(x) [a(\mu-r) + r] \phi(t) + \frac{1}{2}(p-1)a^2\beta^2\phi(t) \cdot p g(x) \\ &= p \phi(t) g(x) [a(\mu-r) + r - \frac{1}{2}(1-p)a^2\beta^2] \\ &=: p \phi(t) g(x) F(a) \end{aligned}$$

$$w(x, T) = \phi(T) g(x) = g(x)$$

$$\Leftrightarrow \begin{cases} \phi_t g(x) + p \max_{a \in A} [F(a) \phi(t) g(x)] = 0 \\ \phi(T) g(x) = g(x) \end{cases} \quad (3)$$

$$\text{with } F(a) = a(\mu-r) + r - \frac{1}{2}(1-p)a^2\beta^2.$$

$$g(x) > 0 \Rightarrow g(x) = \frac{x^p}{p} > 0, \text{ terminal function}$$

a new ODE:

$$\begin{cases} \phi_t + p \max_{a \in A} [F(a)] \phi(t) = 0 \\ \phi(T) = 1 \end{cases} \quad (4)$$

$$\Rightarrow \phi(t) = e^{\int_t^T q(s) ds}$$

$$\begin{aligned} \therefore w(x, t) &= e^{\int_t^T q(s) ds} \cdot g(x), (x, t) \in \mathbb{R}^+ \times [0, T] \\ &= e^{\int_t^T q(s) ds} \cdot \frac{x^p}{p} \in C^{2,1}(\mathbb{R}^+ \times [0, T]), \end{aligned}$$

$$\text{with } q = p \max_{a \in A} [F(a)].$$

$$\Rightarrow w(x, t) = e^{\int_t^T q(s) ds} \frac{x^p}{p} \text{ is a smooth solution of HJBe (3):}$$

$$\begin{cases} w_t + \max_{a \in A} [F(a) p w(x, t)] = 0, (x, t) \in \mathbb{R}^+ \times [0, T]. \end{cases}$$

$$\begin{cases} W_t + \max_{a \in A} [F(a) p w(x,t)] = 0, & (x,t) \in \mathbb{R}^+ \times [0, T), \\ W(x, T) = g(x) \end{cases} \quad (5)$$

$\max_{a \in A} \mathbb{E}^a W(x,t)$

$x \in \mathbb{R}^+$

2) 实际上, 对于这个 red term, $\exists \hat{a} \in A$, s.t. red term = $F(\hat{a}) p w(x,t)$:

$$2) \because F(a) = a(\mu - r) + r - \frac{1}{2} a^2 (1-p) \beta^2$$

$$\Rightarrow F'(a) = \mu - r - a(1-p)\beta^2$$

$$F''(a) = -(1-p)\beta^2 < 0 \quad (\because p < 1) \rightarrow \text{Concave function}$$

and A is a closed convex set

$$\therefore \exists \hat{a} \in A, \text{ s.t. } \max_{a \in A} F(a) = F(\hat{a}).$$

$$\therefore W(x,t) = \phi(t) g(x) > 0$$

$$\begin{aligned} \therefore \max_{a \in A} \mathbb{E}^a (W(x,t)) &= p \max_{a \in A} [F(a) \cdot \phi(t) g(x)] \\ &= p \cdot F(\hat{a}) \phi(t) g(x). \end{aligned}$$

$\therefore$ for this $\hat{a}$, HJB eq (3) $\exists$ a smooth solution

$$\begin{aligned} W(x,t) &= e^{p F(\hat{a})(T-t)} \cdot \frac{x^p}{p}, \\ &\leq e^{p F(\hat{a})T} \cdot \frac{1}{p} x^p, \quad p < 1 \\ &\leq \begin{cases} e^{p F(\hat{a})T} \cdot \frac{1}{p} x^2, & \text{for any } x \geq 1 \\ e^{p F(\hat{a})T} \cdot \frac{1}{p} + x^2, & 0 < x < 1 \end{cases} \end{aligned}$$

here $w(x,t)$ satisfies growth condition.

Step 2. for this constant control $\hat{a}$, consider the system state equation

$$\begin{cases} dX_s = X_s [\hat{a} \mu + (1-\hat{a})r] ds + X_s \hat{a} \beta dB_s, & s \geq t, t \in [0, T] \\ X_t = x \end{cases}$$

here $\begin{cases} f(x, a) = x[a\mu + (1-a)r] \\ r(x, a) = x a \beta \end{cases}$ satisfies Lipschitz and linear growth

$\Rightarrow$ the SDE $\exists$ strong solution $\hat{X}_s^{t,x}$

$$\hat{a} \in A.$$

Verification
theorem

$$J_{x,t}(\hat{a}) = W(x,t) = w(x,t)$$

$\Rightarrow$ the maximum point $a = \hat{a} \in A$ for $F(a) = a(\mu - r) + r - \frac{1}{2} a^2 (1-p) \beta^2$.

$\Rightarrow$ the maximum point $\alpha = \hat{\alpha} \in A$ for $F(\alpha) = \alpha(\mu - r) + r - \frac{1}{2}\alpha^2(\sigma^2)\beta^2$,
is the optimal control. #.

Remark.

1. To use verification theorem, the uniqueness of smooth solution to HJB need to get.

$\therefore$ Generally, we need consider

$\left\{ \begin{array}{l} \text{HJB} \\ \text{terminal condition} \\ \text{boundary condition} \end{array} \right.$

but, here, there is no boundary condition in the example. This is because:

1) the second order coefficient of $I^{\alpha} w := x(\alpha\mu + (1-\alpha)r)w_x + \frac{1}{2}x^2\alpha^2\beta^2 w_{xx}$ is $\frac{1}{2}x^2\alpha^2\beta^2$;

2) $\tilde{m}$ random walk never reach boundary.