

Lee. 20 (Last!!)

Completely observable case (i.e.,  $y \equiv x$ )

Deterministic HJB

Problem:  $\min_{\gamma(\cdot) \in \Gamma} \phi(\underline{x}(T), T) + \int_0^T L(t, \underline{x}, u) dt$

s.t.  $\dot{\underline{x}} = \underline{f}(\underline{x}, \underline{u}, t)$ ,  $\underline{x} \in \mathcal{X} \subseteq \mathbb{R}^n$   
 $\underline{u} \in \mathcal{U} \subseteq \mathbb{R}^m$

Find  $u^*(\underline{x}, t) = \gamma^*(\underline{x}, t)$

PDE for the value function  $V(\underline{x}, t)$  is called HJB PDE

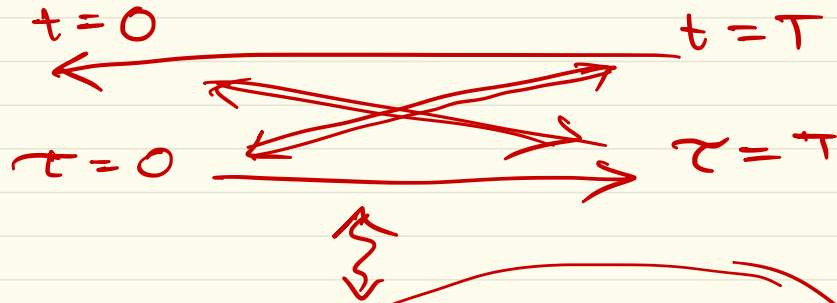
$$\frac{\partial V}{\partial t} + \min_{\underline{u} \in \mathcal{U}} \left\{ L(t, \underline{x}, \underline{u}) + \left\langle \frac{\partial V}{\partial \underline{x}}, \underline{f}(t, \underline{x}, \underline{u}) \right\rangle \right\} = 0, \text{ s.t. } V(\underline{x}(T), T) = \phi(\underline{x}(T), T)$$



$$\frac{\partial V}{\partial t} + H_{\text{opt}}(t, \underline{x}, \frac{\partial V}{\partial \underline{x}}) = 0 \text{ s.t. (copy)}$$

1<sup>st</sup> order PDE, nonlinear PDE

Terminal value problem  $\Leftrightarrow$  IVP by  $\tau := T - t$



IVP!

$$\frac{\partial V}{\partial \tau} + H_{\text{opt}} \left( \tau, \underline{x}, \frac{\partial V}{\partial \underline{x}} \right) = 0$$

s.t.  $V(\tau=0, \underline{x}) = \phi(\underline{x})$

How to solve: Numerical sol<sup>n</sup>: Method of characteristics

Analytical:  $V(t, \underline{x}) \equiv \frac{1}{2} \underline{x}^T P(t) \underline{x}$  (quels)

e.g. LQR Derive Riccati ODE etc.  
Kalman gain

$\hookrightarrow$  Moral: Guess can help solve this PDE.

Analytical: (no guess)

Suppose OCP is time invariant.

Suppose also that  $H_{\text{opt}}$  is indep. of  $\underline{x}$ .

(i.e.)  $H_{\text{opt}}(\cdot) \equiv H_{\text{opt}}\left(\frac{\partial V}{\partial \underline{x}}\right)$

AND  $H_{\text{opt}}(\underline{z})$  is convex in  $\underline{z}$

AND  $H_{\text{opt}}(\underline{z})$  is 1-coercive, (i.e.)  $\lim_{\|\underline{z}\| \rightarrow \infty} \frac{H(\underline{z})}{\|\underline{z}\|} = +\infty$   
(superlinear)  $\swarrow$

Then we can give  
semi-analytical variational formula

for  $V(\tau, \underline{x})$

# Hopf-Lax Representation Formula:

$$V(\tau, \underline{x}) = \min_{\underline{y} \in \mathbb{R}^n} \left\{ \phi(\underline{y}) + \tau H_{\text{opt}}^* \left( \frac{\underline{x} - \underline{y}}{\tau} \right) \right\}$$

$$H^*(\underline{a}) := \max_{\underline{z} \in \mathbb{R}^n} \left\{ \underline{a}^T \underline{z} - H(\underline{z}) \right\}$$

||  
Lagrangian  
(L)

Legendre-Fenchel conjugate  
or convex conjugate of  $H(\cdot)$

Example: If HJB PDE:  $\frac{\partial V}{\partial t} + \frac{1}{2} \left\| \frac{\partial V}{\partial \underline{x}} \right\|_2^2 = 0$

$$H(\underline{z}) = \frac{1}{2} \underline{z}^T \underline{z}$$

$$\text{Then } H^*(\underline{a}) = \frac{1}{2} \underline{a}^T \underline{a} \Rightarrow \therefore \tau H_{\text{opt}}^* \left( \frac{\underline{x} - \underline{y}}{\tau} \right) = \frac{1}{2\tau} \|\underline{x} - \underline{y}\|_2^2$$

∴ By Hopf-Lax:

$$\begin{aligned} V(\underline{x}, \tau) &= \min_{\underline{y} \in \mathbb{R}^n} \left\{ \phi(\underline{y}) + \frac{1}{2\tau} \|\underline{x} - \underline{y}\|_2^2 \right\} \\ &= \frac{1}{\tau} \min_{\underline{y} \in \mathbb{R}^n} \left\{ \frac{1}{2} \|\underline{x} - \underline{y}\|_2^2 + \tau \phi(\underline{y}) \right\} \\ &= \frac{1}{\tau} \underbrace{\text{prox}_{\tau\phi}^{\|\cdot\|_2}(\underline{x})}_{\text{Moreau-Yosida proximal operator}} \end{aligned}$$

Moreau-Yosida proximal  
operator

Stochastic HJB (SDE completely observed):

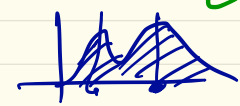
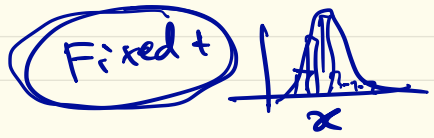
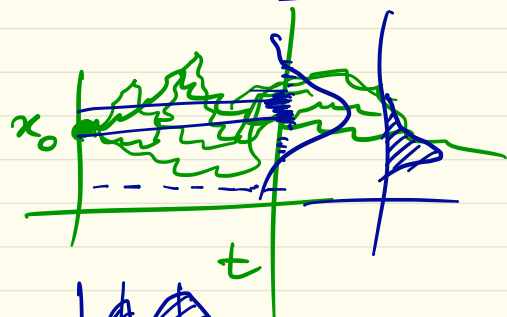
$$\underline{\dot{x}} = f(t, \underline{x}, u) + g(t, \underline{x}, u) \times \text{noise}$$

$$\Leftrightarrow \underline{d\mathbf{x}} = \underbrace{f(t, \underline{x}, u)}_{\substack{n \times 1 \\ \text{Stochastic} \\ \text{differential} \\ \text{coeff.}}} dt + \underbrace{g(t, \underline{x}, u)}_{\substack{n \times p \\ \text{Diffusion} \\ \text{coeff.}}} \underbrace{d\omega}_{\substack{\text{process noise} \\ d\omega \sim N(0, Idt)}}$$

Objective

$$\min_{\gamma \in \Gamma(\cdot)} E \left[ \phi(\underline{x}(T), T) + \int_0^T L(\underline{x}, u, t) dt \right]$$

s.t.  $\rightarrow$  this dynamics.  
 Find  $u^* = \gamma^*(\underline{x}, t)$



# Stochastic HJB :

Define Hamiltonian :

$$H(\underline{x}, \underline{u}, t, V, \underbrace{\frac{\partial V}{\partial \underline{x}}}_{\underline{W}}, \underbrace{\frac{\partial^2 V}{\partial \underline{x}^2}}_{\text{Hess}(V)})$$

(Remember:  
Here, we have  
no PMP)

$$:= L(t, \underline{x}, \underline{u}) + \left\langle \frac{\partial V}{\partial \underline{x}}, f(t, \underline{x}, \underline{u}) \right\rangle +$$

$$\frac{1}{2} \text{tr} \left( \underbrace{g^T(t, \underline{x}, \underline{u})}_{p \times n} \underbrace{\text{Hess}(V)}_{n \times n} \underbrace{g(t, \underline{x}, \underline{u})}_{n \times p} \right)$$

$$\frac{1}{2} \text{tr} \left( \underbrace{g g^T}_{n \times n} \text{Hess}(V) \right)$$

Diffusion  
tensor

Stoc. HJB:

$$\frac{\partial V}{\partial t} + \min_{u \in \mathcal{U}} H(t, \underline{x}, \underline{u}, V, \frac{\partial V}{\partial \underline{x}}, \frac{\partial^2 V}{\partial \underline{x} \partial \underline{x}^T}) = 0$$

$$\Leftrightarrow \frac{\partial V}{\partial t} + H_{\text{opt}}(t, \underline{x}, V, \frac{\partial V}{\partial \underline{x}}, \frac{\partial^2 V}{\partial \underline{x} \partial \underline{x}^T}) = 0,$$

2<sup>nd</sup> order nonlinear PDE

$$V(\underline{x}(T), T) = \phi(\underline{x})$$

Side remark:

$$d\underline{x} = \underline{f}(\underline{x}, t) dt + \underline{g}(\underline{x}, t) d\underline{w}$$

$$\underline{y}: \mathbb{R}^n \mapsto \mathbb{R} \quad \underline{y} = \underline{y}(\underline{x}, t) \leftarrow \text{Deterministic function}$$

Ito's Lemma:

$$d\underline{y} = \frac{\partial \underline{y}}{\partial t} dt + (\nabla \underline{y})^T d\underline{x} + \frac{1}{2} (d\underline{x})^T (\text{Hess}(\underline{y}))^T d\underline{x}$$
$$= \left\{ \frac{\partial \underline{y}}{\partial t} + (\nabla \underline{y})^T \underline{f}(\underline{x}, t) + \frac{1}{2} \text{tr}(\underline{g}^T \text{Hess}(\underline{y}) \underline{g}) \right\} dt + (\nabla \underline{y})^T \underline{g}(\underline{x}, t) d\underline{w}$$



Fokker-Planck or Kolmogorov Forward PDE:

$$\frac{\partial p}{\partial t} = -\nabla \cdot (p f) + \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \frac{\partial^2}{\partial x_i \partial x_j} (g g^T p)$$

$$p(x, t=0) = p_0(x)$$

$$\Leftrightarrow \frac{\partial p}{\partial t} = \mathcal{L}_{\text{Fokker-Planck}} p$$

or  $\mathcal{L}_{\text{Forward Kolmogorov}} p$

Backward Kolmogorov PDE

$$\frac{\partial p}{\partial s} = \mathcal{L}_{\text{Backward Kolmogorov}} p$$

$$= \left\langle \frac{\partial p}{\partial x}, f \right\rangle + \frac{1}{2} \text{tr}(g g^T \text{Hess}(p))$$

Formally,

Backward Kol.

$= \mathcal{L}_{\text{Forward}}$

adjoint

$$\langle \mathcal{L} p, v \rangle = \langle p, \mathcal{L}^* v \rangle \quad \forall p, v \in L^2$$

Stochastic HJB:

$$\frac{\partial V}{\partial t} + \min_{u \in U} \left\{ L(t, x, u) + \underbrace{\mathcal{L} V}_{\substack{\text{Backward} \\ \text{Kolmogorov}}} \right\} = 0$$