

④

BEYOND STOCHASTIC

CONTROL...

(and MFG...!)

I INTRODUCTION

II BAYESIAN VS PARTIAL INFORMATION

III CONDITIONAL PROCESSES

(some extracts from this year Cdf course
more details may be downloaded...)

I INTRODUCTION

- Bayesian learning and stochastic control

- (ex. ads ...)

show to formulate and solve the problems?

links with partial information problems ...

- Optimal control

- natural models

- how to formulate and solve the problems?

- feedback vs general controls

- more in the context of MFB (instead of control pbs. ...)

to be continued ...

II BAYESIAN VS PARTIAL INFORMATION

II.1 . EX.

$$dX_t = a \alpha_t dt + dW_t$$

a unknown parameter

α_t control ("adapted to X_t ")

W_t B-motion

only observation: X_t

B. rule: no initial guess on a (pudca)

$$\mu_{t+h} = \frac{e^{-\frac{|dX - a\alpha_t|^2}{2h}} \mu_t}{\int e^{-\frac{|dX - b\alpha_t|^2}{2h}} \mu_t db}$$

$$P(A|B) = P(B|A) \frac{P(A)}{P(B)}$$

$$(B) d\mu_t = (a - \int b \mu_t) \mu_t \alpha_t dX_t - \int b \mu_t (a - \int b \mu_t) \mu_t \alpha_t^2 dt \quad (4)$$

Prop: $\exists!$ sol. given by $\mu_t = \frac{f_t}{\int f_t d\omega}$ where $f_0 = \mu_0$ and f_t solves the (Z) eq.

$$df_t = a f_t (\alpha_t dX_t)$$

$$(f_t = f_0 \exp(a \int_0^t \alpha_s dX_s - \frac{1}{2} a^2 \int_0^t \alpha_s^2 ds))$$

Remarks:

i) $\mu_0 = f_0$ Gaussian $\Rightarrow \mu_t, f_t$ "Gaussian" hence reduced equations for mean and variance

$$ii) \mu_0 = f_0 = \sum_{i=1}^M \Theta^i \delta_{a_i} \Rightarrow f_t = \sum_{i=1}^M \Theta^i(t) \delta_{a_i}$$

$$d\Theta^i = a_i \Theta^i \alpha_t dX_t$$

iii) If $\alpha_t \equiv \alpha$, $dX_t = a_0 \alpha dt + dW_t$, $\mu_t \rightarrow \delta_{a_0}$ unless $a_0 \in \text{Supp}(\mu_0 = f_0)$. In fact μ_t concentrates on the set of minima of $\int \ln(|a - a_0| / |a \in \text{Supp}(\mu_0)|)$

(5)

II.2 How to combine with stochastic control?

(inf. hor., $\rho > 0$, cost. $L(x, \alpha)$)

"pick randomly α_t according to μ_t hence $dx, d\mu$ and average the cost with μ_t " dynamic programming?

better to rephrase everything in terms of path info.

$$dx_t = A x_t dt + dw_t \quad A \text{ in } dt \text{ of } W \text{ unknown}$$

observation X_t , α_t adapted to X_t

$$E \left[\int_0^\infty e^{-\rho t} L(x_t, \alpha_t) dt \right] = E \left[\int_0^\infty e^{-\rho t} L(x_t, \alpha_t) e^{\int_0^t A x_s ds - \frac{1}{2} \int_0^t A^2 x_s^2 ds} \right]$$

$$\text{now } dx_t = dw_t = E \left[\int_0^\infty e^{-\rho t} L(x_t, \alpha_t) E \left[e^{\int_0^t A x_s ds - \frac{1}{2} \int_0^t A^2 x_s^2 ds} \middle| \mathcal{F}_t \right] \right]$$

where $\mathcal{F}_t = \sigma(X_s / 0 \leq s \leq t)$.

Zakai: introduce f_t (random measure adapted to \mathcal{F}_t)

$$\int \varphi(A) f_t(A) d\alpha = E \left[\varphi(A) e^{\int_0^t A x_s ds - \frac{1}{2} \int_0^t A^2 x_s^2 ds} \middle| \mathcal{F}_t \right]$$

$$(\Sigma) df_t = a f_t \alpha_t dx_t$$

Conclusion: $V(x, b) = \inf_{\alpha_t} E \int_0^\infty e^{-\beta t} L(x_t, \alpha_t) dt$ (6)

$$dx_t = \alpha_t dt, \quad d\beta_t = b \beta_t \alpha_t dW_t, \quad x_0 = x, \quad \beta_0 = \beta \in \mathbb{M}_b^+$$

$\infty \supset \text{HJB (PL}^2 \text{ --) well posed instance}$
 of $\alpha_t \rightarrow A$ bounded (closed) set of \mathbb{R}^k .

Finite D reduction (specific to ex.) for β

$$\int \beta_t = \int \beta \left(\exp \left(b \int_0^t \alpha_s dW_s - \frac{b^2}{2} \int_0^t \alpha_s^2 ds \right) dt \right)$$

introduce $\psi(\lambda, \mu) = \int \beta \exp(\lambda b - \mu \frac{b^2}{2})$

$$d\lambda_t = \alpha_t dW_t, \quad d\mu_t = \alpha_t^2 dt$$

Prop. $V(x, \beta) = V(x, \lambda, \mu) = \inf_{\alpha_t} E \left[\int_0^\infty e^{-\beta t} L(x_t, \alpha_t) \psi(\lambda_t, \mu_t) \right]$

formally $\delta V - \frac{1}{2} \frac{\partial^2 V}{\partial x^2} + \sup_{\alpha \in A} \left\{ \frac{1}{2} \alpha^2 \frac{\partial^2 V}{\partial \lambda^2} - \alpha \frac{\partial^2 V}{\partial x \partial \lambda} - \alpha^2 \frac{\partial V}{\partial \mu} - L(x, \alpha) \psi \right\} = 0$

singular ψ unbounded ("exp." in λ)

$$\left[\begin{array}{l} \text{observe that } \frac{\partial^2 \psi}{\partial \lambda^2} = -\frac{1}{2} \frac{\partial \psi}{\partial \mu} \text{ and} \\ \text{use } U : V = U \psi \end{array} \right]$$

(7)

then the equation for U is

$$\int U - \frac{1}{2} \frac{\partial^2 U}{\partial x^2} + \sup_{\alpha \in A} \left\{ -\frac{1}{2} \alpha^2 \frac{\partial^2 U}{\partial \lambda^2} - \alpha \frac{\partial^2 U}{\partial x \partial \lambda} - \alpha^2 \frac{\partial U}{\partial \mu} - L(x, \alpha) \right. \\ \left. - \alpha^2 \left(\frac{\partial}{\partial \lambda} \log \psi \right) \frac{\partial U}{\partial \lambda} - \alpha \left(\frac{\partial}{\partial \lambda} \log \psi \right) \frac{\partial U}{\partial x} \right\} = 0$$

for all $x, \lambda, \mu \geq 0$ (no BC at $\mu = 0$)

Prop. If $\left| \frac{\partial}{\partial \lambda} \log \psi \right| \leq C(1 + |\lambda|)$ (or if ψ decays at least like a G.), then $\exists!$ viscosity solution U .

Remark: Most general situation is

$$dX_t = \sigma(X_t, \kappa_t) dW_t + b(X_t, \kappa_t) dt. \quad (\text{observed})$$

$$dY_t = \gamma(X_t, Y_t, \kappa_t) dW_t + \delta(X_t, Y_t, \kappa_t) dZ_t + \beta(X_t, Y_t, \kappa_t) dt \\ (\text{not observed})$$

W, Z with B .

then f_t solves a SPDE ...

(optimal control of SPDE, HJB \leftrightarrow MFG)

III CONDITIONAL PROCESSES

III.1 Introduction

- motivation: modelling issue!
- static / dynamic
- condition. by no exit. : domain D how?
 ($D \uparrow \mathbb{R}^d$ recovering classical dyn. prog.?)

III.2 Two examples

$$dX_t = \alpha_t dt + dW_t \quad X_0 = x_0 \in \bar{D} \quad (\text{smooth in } \mathbb{R}^d \text{ domain})$$

$$\textcircled{1} \inf_{|\alpha_t| \leq L} \mathbb{E}_x [g(X_T) / \tau_2 \geq T] \quad (= \frac{\mathbb{E}_x(g(X_T) \mathbb{1}_{\tau_2 \geq T})}{\mathbb{P}(\tau_2 \geq T)})$$

$$\textcircled{2} \inf_{\alpha_t} \int_0^T \mathbb{E}_x [f(X_t) + \frac{1}{2}|\alpha_t|^2 / \tau_2 \geq T] dt + \mathbb{E}_x [g(X_T) / \tau_2 \geq T]$$

- feedbacks : $\alpha_t = \alpha(t, x)$
- or
- general possibly stochastic controls

?

III.3 Feedbacks

$$dX_t = \alpha(t, X_t) dt + dW_t, \quad X_0 = x_0 \in \bar{D}$$

$$\textcircled{1} \text{ inf } E_{x_0} [g(X_T) / \tau_x \geq T] \quad (L > 0)$$

$$|\alpha| \leq L$$

$$E_x [g(X_T) \mathbb{1}_{(\tau_x \geq T)}] / P(\tau_x \geq T)$$

$$= \frac{\int P(T, y) g(y) dy}{\int P(T, y) dy}$$

$$\begin{cases} \frac{\partial P}{\partial t} - \frac{1}{2} \Delta P + dW(\alpha P) = 0, & P|_{t=0} = P_0 \text{ (ex. } \delta_x) \\ \mu = 0 \text{ on } \partial D \end{cases}$$

$$\text{Min}_{|\alpha| \leq L} \left\{ \frac{\int P(T, y) g(y) dy}{\int P(T, y) dy} / \frac{\partial P}{\partial t} \dots \right\}$$

Prop. \exists optimal control and for any optimal control, $\exists u$ solving

$$-\frac{\partial u}{\partial t} - \frac{1}{2} \Delta u + |\nabla u| = 0, \quad u|_{t=T} = \frac{g}{\int P} - \frac{\int g P}{(\int P)^2}$$

and $\alpha = -\frac{\nabla u}{|\nabla u|}$ if $\nabla u \neq 0$.

(Opt. control of FP eqs and MF6!)

Sketch: $\int_{\mathcal{P}} g - \frac{\int_{\mathcal{P}} f_{\mathcal{P}}}{(\int_{\mathcal{P}})^2} \geq 0$ (10)

$\delta_{\mathcal{P}} = q - p$ $q \leftrightarrow \beta$ control $\delta\alpha = \beta - \alpha$

$\frac{\delta \delta_{\mathcal{P}}}{\delta r} - \frac{1}{2} \Delta \delta_{\mathcal{P}} + \text{div}(\delta\alpha p + \alpha \delta p) = 0$, $\delta p|_{t=0} = 0$

adjoint state u : $-\frac{\partial u}{\partial r} - \frac{1}{2} \Delta u = A$, $u|_{t=T} = \frac{q}{\int_{\mathcal{P}}} - \frac{\int_{\mathcal{P}} p}{(\int_{\mathcal{P}})^2}$

$0 \leq \int u \delta_{\mathcal{P}} = - \iint A \delta_{\mathcal{P}} + (\delta\alpha p + \alpha \delta p) \cdot \nabla u$

choose $A = +\alpha \nabla u = + \iint (\beta - \alpha) p \cdot \nabla u$ $\forall |\beta| \leq 1$.

hence $\alpha = - \frac{\nabla u}{|\nabla u|}$.

(2) Min $\int_0^T \frac{\int (\beta + \frac{1}{2} |\alpha|^2) p}{\int p} dt + \frac{\int q p(T)}{\int p}$

Prop.: \exists optimal control and, for any optimal control, $\exists u$

satisfying: $u|_{t=T} = \frac{q}{\int p} - \frac{\int q p}{(\int p)^2}$

$-\frac{\partial u}{\partial r} - \frac{1}{2} \Delta u + \frac{1}{2} (\int p) |\nabla u|^2 = \frac{q}{\int p} - \frac{\int q p}{(\int p)^2} - \frac{1}{2} \int |\nabla u|^2 p$

and $\alpha = - (\int p) (\nabla u)$.

Rk nonuniqueness! $g \equiv 0$!

(11)

III.4 Relaxing the conditioning

$$D = B_R \quad R \rightarrow +\infty$$

$$\alpha_R \leftrightarrow -\nabla \tilde{\alpha}_R$$

where $\tilde{\alpha}_R = u_R + c_R$ for any constant c_R

$$\text{and } u_R = \frac{g}{\int P_R} - c_R \text{ at time } T \quad (\text{Ex. ①})$$

and $\int P_R \rightarrow 1$ as $R \rightarrow \infty$, hence $\tilde{\alpha}_R$ goes to

the solution of HJB (decoupled from the p.p. i.e.

MF6 \rightarrow HJB + FP decoupled ... !)

III. General controls

Case (1) for instance: "cond. law" S^{PDE}

$$d\varphi + \left(-\frac{1}{2} \Delta \varphi + \text{div}(\alpha \varphi)\right) dt = \nabla \varphi dW$$

$$p=0 \text{ on } \partial D, \varphi|_{t=0} = p_0$$

and

$$\text{Min}_{|\alpha| \leq 1} \frac{E\left(\int_0^T g(y) p(T, y, \omega) dy\right)}{E(p(T, y, \omega))}$$

(FB stochastic system for optimal controls \leftrightarrow MFG)

or HJB approach $\text{Min} = \Phi(T, p_0)$ and Φ

Solves

$$0 = \frac{\partial \Phi}{\partial t} - \frac{1}{2} \frac{\partial^2 \Phi}{\partial p^2} (\nabla_p, \nabla_p) + \sup_{\|\alpha\| \leq 1} \left\{ \left\langle \frac{\partial \Phi}{\partial p}, -\frac{1}{2} \Delta \varphi + \text{div}(\alpha \varphi) \right\rangle \right\}$$

$$\text{with } \Phi|_{t=0} = \frac{\int g \varphi}{\int \varphi}$$

Remarks: 1) feedbacks $\alpha(t, x)$ lead to the same HJB eq.

without the 2nd order term

$$2) \alpha = - \frac{\nabla_x \frac{\partial \Phi}{\partial p}}{\frac{1}{2} \frac{\partial^2 \Phi}{\partial p^2}}$$

(13)

"THM" If g is not constant, the two minima are not equal in general (i.e. Min. G.C. < Min. F.C. in general).

$$0 \stackrel{?}{=} \frac{\delta^2 \Phi}{\delta p^2} (\nabla p, \nabla p)$$

yes at time T : $\Phi = \int_{\mathcal{D}} g p$, $\frac{\delta^2 \Phi}{\delta p^2} = -2 \frac{\int g \nabla p \cdot \nabla p}{(\int p)^2}$

and $\int \nabla p = 0$ ($p=0$ on $\partial \mathcal{D}$).

but $\frac{\partial}{\partial t} \frac{\delta^2 \Phi}{\delta p^2} (\nabla p, \nabla p) \Big|_{t=0} \neq 0$: because of a piece

$$\Phi_1 = \frac{\int g p \int -\Delta p}{\int p^2}$$

and $\frac{\delta^2 \Phi_1}{\delta p^2} (\nabla p, \nabla p) = \frac{2 \int g \nabla p \cdot \nabla (-\Delta p)}{\int p^2} \neq 0$ for some p

if $\int g \nabla p \neq 0$ for some p i.e. g non constant...

III $T \rightarrow +\infty$

(14)

Formally if α becomes time indt then

$$p \sim e^{-\lambda_1 t} m \int \rho \psi$$

where ψ, m are the 1st eigenf., λ_1 1st eigenv

$$-\frac{1}{2} \Delta m + dw(\alpha m) = \lambda_1 m, m > 0, \int m = 1$$

$$-\frac{1}{2} \Delta \psi - \alpha \nabla \psi = \lambda_1 \psi, \psi > 0, \int \psi = 1$$

and $m = \psi = 0$ on ∂D .

And we may expect to obtain the following

problem as $T \rightarrow \infty$ (for example 1)

$$\text{Min } \int \rho m \quad / \quad \left. \begin{array}{l} -\frac{1}{2} \Delta m + dw(\alpha m) = \lambda_1 m \\ m > 0, \int m = 1, m = 0 \text{ on } \partial D \end{array} \right\}$$

Justification (see also MFG $T \rightarrow \infty$)

(15)

General tool : generalized inv. and QI measures
for time dependent coeff.!

$$\underline{Rk1} \quad \alpha(t_n + \cdot, \cdot) \xrightarrow{n} \alpha(\beta, x) \in L^\infty(\underline{\mathbb{R}_t \times \mathbb{D}})$$

Rk2 from my course on ergodic problems (+2),
valid for general uniformly elliptic operators / diffusion processes
with time dependent coefficients. Ex. 1) general case

III $\exists!$ $m > 0$ "bounded" in (x, t)

$$\text{solution of } \begin{cases} \frac{\partial m}{\partial t} + A(t)^{\alpha} m = 0 & \text{in } \mathbb{D} \times \mathbb{R}_t \\ \int m(t) dx = 1, \quad \forall t \in \mathbb{R} \end{cases}$$

Cor: if A indt of t , m indt of t ; periodic / a. per. /

stationary $\Rightarrow m$ periodic / a. per. / stationary

In the course (16-17), extension to $\mathcal{Q} \cap \mathbb{R}^m$

$$\forall \alpha \in L_{x,t}^\infty$$

TH i) $\exists!$ (m, λ) "bounded" in $t \in \mathbb{R}$

solution of

$$\left\{ \begin{array}{l} \frac{\partial m}{\partial r} - \frac{1}{2} \Delta m + d\bar{w}(\alpha m) = b m \quad \text{for } t \in \mathbb{R}, r \in \mathbb{R} \\ m > 0, \int_{\mathcal{D}} m = 1 \quad \forall t \in \mathbb{R}, \quad m|_{\partial \mathcal{D}} = 0 \\ \lambda \text{ bdd from below and from above on } \mathbb{R} \end{array} \right.$$

ii) $\exists!$ (φ, μ) "bounded" in $t \in \mathbb{R}$ solution of

$$\left\{ \begin{array}{l} \frac{\partial \varphi}{\partial r} - \frac{1}{2} \Delta \varphi - \alpha \nabla \varphi = \mu \varphi \quad \text{for } t \in \mathbb{R}, r \in \mathbb{R} \\ \varphi > 0, \int_{\mathcal{D}} \varphi m = 1, \quad \forall t \in \mathbb{R}, \quad \varphi|_{\partial \mathcal{D}} = 0 \end{array} \right.$$

and $\lambda \equiv \mu$.

$$((\varphi, \mu) \sim (\varphi e^{A(t)}, \mu + \dot{A}))$$

$T \rightarrow \infty$, limit pb is

$$\left[\begin{array}{l} \text{Min } \int_{\mathbb{R}} g_m(x) dx / \\ |\alpha| \leq L \text{ on } \mathbb{D} \times \mathbb{R} \\ \frac{\partial m}{\partial t} - \frac{1}{2} \Delta m + d \cdot \nabla (\alpha m) = \lambda m, m > 0, m|_{\partial \mathbb{D}} = 0, \int m = 1 \forall t \\ \lambda, \gamma_d \text{ bdd on } \mathbb{R} \end{array} \right.$$

or $\int (\mathbb{1} + \frac{1}{2} |\alpha|^2) m(x) dx$ (ex. 2)

Rk conditions for uniqueness $\Rightarrow \alpha$ ind of t !

(opt. cond. "MFG factor with \mathbb{D} . BC" ...)

for instance in ex. 2 if $\|\beta\| < \epsilon_0$, uniqueness!