

Mean-Field Games

Lectures at the Imperial College London

3rd Lecture: Solving Mean-Field Games

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Part I. Revisiting McKean-Vlasov FBSDEs

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a. Within the framework of MFG

Program without common noise

- Make use of the results from the first chapter in order to characterize the optimal paths in the fixed point
 - in the FBSDE formulation of the optimization problem \leadsto replace the environment by the law of the solution
 - derive an FBSDE of the McKean-Vlasov type of the general form

$$X_t = \xi + \int_0^t b(X_s, \mathcal{L}(X_s), Y_s, Z_s) ds + \int_0^t \sigma(X_s, \mathcal{L}(X_s), Y_s) dW_s$$

$$Y_t = g(X_T, \mathcal{L}(X_T)) + \int_t^T f(X_s, \mathcal{L}(X_s), Y_s, Z_s) ds - \int_t^T Z_s dW_s$$

- Choose the coefficients accordingly and solve!

Program with common noise

- Make use of the results from the first chapter in order to characterize the optimal paths in the fixed point
 - in the FBSDE formulation of the optimization problem \leadsto replace the environment by the conditional law of the solution
 - derive an FBSDE of the McKean-Vlasov type of the general form

$$X_t = \xi + \int_0^t b(X_s, \mathcal{L}(X_s | \mathbf{W}^0), Y_s, Z_s) ds + \int_0^t \sigma(X_s, \mathcal{L}(X_s | \mathbf{W}^0), Y_s) dW_s + \sigma^0(X_s, \mathcal{L}(X_s | \mathbf{W}^0), Y_s) dW_s^0$$

$$Y_t = g(X_T, \mathcal{L}(X_T | \mathbf{W}^0)) + \int_t^T f(X_s, \mathcal{L}(X_s | \mathbf{W}^0), Y_s, Z_s) ds - \int_t^T Z_s dW_s - \int_t^T Z_s^0 dW_s^0$$

- Choose the coefficients accordingly and solve!

MKV FBSDE for the value function

- Consider, on $(\Omega, \mathbb{F}, \mathbb{P})$, the MKV FBSDE

$$\begin{aligned} X_t &= \xi \\ &+ \int_0^t b(X_s, \mathcal{L}(X_s), \alpha^*(X_s, \mathcal{L}(X_s), Z_s \sigma^{-1}(X_s, \mathcal{L}(X_s)))) ds \\ &+ \int_0^t \sigma(X_s, \mathcal{L}(X_s)) dW_s \end{aligned}$$

$$\begin{aligned} Y_t &= g(X_T, \mathcal{L}(X_T)) \\ &+ \int_t^T f(X_s, \mathcal{L}(X_s), \alpha^*(X_s, \mathcal{L}(X_s), Z_s \sigma^{-1}(X_s, \mathcal{L}(X_s)))) ds \\ &- \int_t^T Z_s dW_s \end{aligned}$$

◦ $\alpha^*(x, \mu, z)$ is the **unique minimizer** of $\alpha \mapsto H(x, \mu, \alpha, z)$

- Under assumptions of Chapter 1 \leadsto solution to MKV FBSDE is MFG equilibrium

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$$\begin{aligned} Y_t &= g(X_T, \mathcal{L}(X_T | \mathbf{W}^0)) \\ &+ \int_t^T f(X_s, \mathcal{L}(X_s | \mathbf{W}^0), \alpha^*(X_s, \mathcal{L}(X_s | \mathbf{W}^0), Z_s \sigma^{-1}(X_s, \mathcal{L}(X_s | \mathbf{W}^0)))) ds \\ &- \int_t^T Z_s dW_s - \int_t^T Z_s^0 dW_s^0 \end{aligned}$$

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MKV FBSDE for the Pontryagin principle

- Consider, on $(\Omega, \mathbb{F}, \mathbb{P})$, the **MKV FBSDE**

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- Under assumptions of Chapter 1 \leadsto solution to MKV FBSDE is MFG equilibrium

Existence and uniqueness in small time

- New two-point-boundary-problem \leadsto
 - Cauchy-Lipschitz theory in small time only
- Example when $\sigma^0 \equiv 0$

$$X_t = \xi + \int_0^t b(X_s, \mathcal{L}(X_s), Y_s, Z_s) + \int_0^t \sigma(X_s, \mathcal{L}(X_s), Y_s) dW_s$$

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- Lipschitz setting
 - b, σ, f and g L -Lipschitz continuous in (x, μ, y, z)
 - Lipschitz in $\mu \Leftrightarrow W_2$ Wasserstein distance
 - $(b, f, \sigma, \sigma^0, g)(t, 0, \delta_0, 0, 0)$ bounded
 - \Rightarrow existence and uniqueness provided that $T \leq c(L)$

Part III. McKean-Vlasov FBSDEs

b. Lions derivative over $\mathcal{P}_2(\mathbb{R}^d)$

Differentiation on $\mathcal{P}_2(\mathbb{R})$

- Consider $\mathcal{U} : \mathcal{P}_2(\mathbb{R}^d) \rightarrow \mathbb{R}$
- Lifted-version of \mathcal{U}

$$\hat{\mathcal{U}} : L^2(\Omega, \mathcal{A}, \mathbb{P}; \mathbb{R}^d) \ni X \mapsto \mathcal{U}(\text{Law}(X))$$

- \mathcal{U} differentiable if $\hat{\mathcal{U}}$ Fréchet differentiable (Lions)
 - independent of the choice of (Ω, \mathbb{P}) (rich enough)
- Differential of \mathcal{U}

- Fréchet derivative of $\hat{\mathcal{U}}$ with $\mu = \text{Law}(X)$

$$D\hat{\mathcal{U}}(X) = \partial_\mu \mathcal{U}(\mu)(X), \quad \partial_\mu \mathcal{U}(\mu) : \mathbb{R}^d \ni x \mapsto \partial_\mu \mathcal{U}(\mu)(x) \in \mathbb{R}^d$$

- Derivative of \mathcal{U} at $\mu \rightsquigarrow \partial_\mu \mathcal{U}(\mu) \in L^2(\mathbb{R}, \mu; \mathbb{R}^d)$

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- Derivative of \mathcal{U} at $\mu \rightsquigarrow \partial_\mu \mathcal{U}(\mu) \in L^2(\mathbb{R}, \mu; \mathbb{R}^d)$
- **Finite dimensional projection**

$$\partial_{x_i} \left[\mathcal{U} \left(\frac{1}{N} \sum_{j=1}^N \delta_{x_j} \right) \right] = \frac{1}{N} \partial_\mu \mathcal{U} \left(\frac{1}{N} \sum_{j=1}^N \delta_{x_j} \right) (x_i).$$

Examples

- 1st example: $\mathcal{U}(\mu) = \int_{\mathbb{R}^d} h(x) d\mu(x)$

- two r.v.'s X and Y with values in \mathbb{R}^d

$$\begin{aligned}\mathcal{U}(\mathcal{L}(X + \varepsilon Y)) &= \mathbb{E}[h(X + \varepsilon Y)] \\ &= \mathbb{E}[h(X)] + \varepsilon \mathbb{E}[\partial h(X)Y] + o(\varepsilon)\end{aligned}$$

- $\partial_{\mu} \mathcal{U}(\mu)(v) = \partial h(v)$

- 2nd example: $\mathcal{U}(\mu) = \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} h(x - y) d\mu(x) d\mu(y)$

- two r.v.'s X and Y with independent copies X' and Y'

$$\begin{aligned}\mathcal{U}(\mathcal{L}(X + \varepsilon Y)) &= \mathbb{E}[h(X - X' + \varepsilon(Y - Y'))] \\ &= \mathbb{E}[h(X - X')] + \varepsilon \mathbb{E}[\partial h(X - X')(Y - Y')] + o(\varepsilon) \\ &= \mathbb{E}[h(X - X')] + \varepsilon \mathbb{E}[\partial h(X - X')Y] - \varepsilon \mathbb{E}[\partial h(X' - X)Y] + o(\varepsilon)\end{aligned}$$

- $\partial_{\mu} \mathcal{U}(\mu)(v) = \int_{\mathbb{R}^d} \partial h(v - y) d\mu(y) - \int_{\mathbb{R}^d} \partial h(y - v) d\mu(y)$

Connection with W_2 distance

- Let \mathcal{U} be Lions-differentiable with

$$\underbrace{\mathbb{E}[|\partial_\mu U(\mu)(X)|^2]} \leq C^2, \quad \mathcal{L}(X) = \mu$$
$$\int_{\mathbb{R}^d} |\partial_\mu U(\mu)(v)|^2 d\mu(v)$$

- For $X, X' \in L^2(\Omega, \mathcal{A}, \mathbb{P}; \mathbb{R}^d)$

$$\begin{aligned} & \mathcal{U}(\mathcal{L}(X')) - \mathcal{U}(\mathcal{L}(X)) \\ &= \int_0^1 \frac{d}{dt} \mathcal{U}(\mathcal{L}(tX' + (1-t)X)) dt \\ &= \int_0^1 \frac{d}{dt} \hat{\mathcal{U}}(tX' + (1-t)X) dt \\ &= \int_0^1 \mathbb{E}[\partial_\mu \mathcal{U}(\mathcal{L}(tX' + (1-t)X))(tX' + (1-t)X)(X' - X)] dt \\ &\leq C \mathbb{E}[|X' - X|^2]^{1/2} \end{aligned}$$

- take inf over (X, X') with given laws \leadsto Lipschitz w.r.t. W_2

Part III. McKean-Vlasov FBSDEs

c. Control of McKean-Vlasov and potential games

Rough version of the Pontryagin principle

- **Controlled MKV processes** (no common noise)

$$dX_t = b(X_t, \mathcal{L}(X_t), \alpha_t)dt + \sigma(X_t, \mathcal{L}(X_t))dW_t$$

- optimize the cost $J(\alpha) = \mathbb{E}[g(X_T, \mathcal{L}(X_T)) + \int_0^T f(X_t, \mathcal{L}(X_t), \alpha_t)dt]$

- **Optimize w.r.t. the measure as well**

- Use the same H and the same $\hat{\alpha}(t, x, \mu, y)$

- Adjoint equations:

$$dX_t = b(X_t, \mu_t, \hat{\alpha}(t, X_t, \mathcal{L}X_t, Y_t))dt + \sigma dW_t$$

$$dY_t = -\partial_x H(X_t, \mathcal{L}(X_t), \hat{\alpha}(X_t, \mathcal{L}(X_t), Y_t), Y_t)dt$$

$$- \text{"}\partial_\mu H(X_t, \mathcal{L}(X_t), \hat{\alpha}(X_t, \mathcal{L}(X_t), Y_t), Y_t)\text{"}dt + Z_t dW_t$$

$$Y_T = \partial_x g(X_T, \mathcal{L}(X_T)) + \text{"}\partial_\mu g(X_T, \mathcal{L}(X_T))\text{"}$$

- What do $\text{"}\partial_\mu H\text{"}$ and $\text{"}\partial_\mu g\text{"}$ mean?

Right version of the Pontryagin principle

- Adjoint equations take the form

$$\begin{aligned}dX_t &= b(X_t, \mathcal{L}(X_t), \hat{\alpha}(t, X_t, \mathcal{L}(X_t), Y_t))dt + \sigma dW_t \\dY_t &= -\partial_x H(X_t, \mathcal{L}(X_t), \hat{\alpha}(t, X_t, \mathcal{L}(X_t), Y_t), Y_t)dt \\&\quad - \mathbb{E}'[\partial_\mu H(X'_t, \mathcal{L}(X_t), \hat{\alpha}(X'_t, \mathcal{L}(X_t), Y'_t))(X_t)]dt + Z_t dW_t \\Y_T &= \partial_x g(X_T, \mathcal{L}(X_T)) + \mathbb{E}'[\partial_\mu g(X'_T, \mathcal{L}(X_T))(X_T)]\end{aligned}$$

- (X'_t, Y'_t) independent copy of (X_t, Y_t) on $(\Omega', \mathbb{F}', \mathbb{P}')$

- **example** \rightsquigarrow **social optimization** with

- $f(\mu, \alpha) = \frac{1}{2} \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} f(x - y) d\mu(x) d\mu(y) + \frac{1}{2} |\alpha|^2$, f symmetric
- $g(\mu) = \frac{1}{2} \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} g(x - y) d\mu(x) d\mu(y)$, g symmetric
- $b(\alpha) = \alpha$

$$\partial_\mu H(\cdot) = \partial_\mu f(\mathcal{L}(X_t))(X_t) = \mathbb{E}'[\partial f(X_t - X'_t)] = \partial_{|x=X_t} \mathbb{E}'[f(x - X'_t)]$$

- **same equilibrium as MFG** with $\int_{\mathbb{R}^d} f(x - y) d\mu(y) + \frac{1}{2} |\alpha|^2 \rightsquigarrow$
potential game!

Part II. Solving MFG without common noise

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a. Schauder fixed point theorem

Objective

- Assume $\sigma^0 \equiv 0$ and provide solution to

$$X_t = \xi + \int_0^t b(X_s, \mathcal{L}(X_s), Y_s, Z_s) + \int_0^t \sigma(X_s, \mathcal{L}(X_s), Y_s) dW_s$$

$$Y_t = g(X_T, \mathcal{L}(X_T)) + \int_t^T f(X_s, \mathcal{L}(X_s), Y_s, Z_s) ds - \int_t^T Z_s dW_s$$

- Assumption that

when $(\mathcal{L}(X_t))_{0 \leq t \leq T}$ replaced by some fixed input $(\mu_t)_{0 \leq t \leq T}$
 \Rightarrow

existence and uniqueness of a solution to the FBSDE
in environment $(\mu_t)_{0 \leq t \leq T}$

- Example: implement the results from Chapter 1!
 - apply the two characterizations for stochastic optimal control

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- Example: implement the results from Chapter 1!
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How to attack existence?

- **Preliminary remark:** no hope for solving MFG by Picard fixed theorem
 - at least under classical Lipschitz assumptions only
 - expect small time
 - **need refined assumptions**
- First step \leadsto existence only
 - **forget about uniqueness!**
 - use a fixed point theorem without uniqueness!
- Use **Schauder's fixed point theorem**
 - see statement in the next slide
 - need a structure with a **compactness**
 - in the framework of MFG \leadsto fixed point is on probability measures \leadsto nice compactness criterion!

Statement of the Schauder fixed point theorem

- Generalisation of Brouwer's theorem from finite to infinite dimension
- Let $(V, \|\cdot\|)$ be a normed linear space
 - $\emptyset \neq E \subset V$ with E closed and convex
 - $\phi : E \rightarrow E$ continuous such that $\phi(E)$ is relatively compact
 - \Rightarrow existence of a fixed point to ϕ
- In MFG \rightsquigarrow what is V , what is E , what is ϕ ?
 - recall that MFG equilibrium is a flow of measures $(\mu_t)_{0 \leq t \leq T}$
$$E \subset C([0, T], \mathcal{P}_2(\mathbb{R}^d))$$
 - need to embed into a linear structure
$$C([0, T], \mathcal{P}_2(\mathbb{R}^d)) \subset C([0, T], \mathcal{M}_1(\mathbb{R}^d))$$
 - $\mathcal{M}_1(\mathbb{R}^d)$ set of signed measures ν with $\int_{\mathbb{R}^d} |x|^d |\nu|(x) < \infty$

Compactness on the space of probability measures

- Equip $\mathcal{M}_1(\mathbb{R}^d)$ with a norm $\|\cdot\|$ and restrict to $\mathcal{P}_1(\mathbb{R}^d)$ such that
 - convergence of $(\nu_n)_{n \geq 1}$ in $\mathcal{P}_1(\mathbb{R}^d)$ **implies weak convergence**

$$\forall f \in C_b(\mathbb{R}^d, \mathbb{R}), \quad \lim_{n \rightarrow \infty} \int_{\mathbb{R}^d} f d\nu_n = \int_{\mathbb{R}^d} f d\nu$$

- if $(\nu_n)_{n \geq 1}$ has uniformly bounded moments of order $p > 2$

$$\text{Unif. square integrability} \Rightarrow W_2(\nu_n, \nu) \rightarrow 0$$

- says that the input in the coefficients varies continuously!

$$b(x, \nu_n, y, z), \sigma(x, \nu_n), \sigma^0(x, \nu_n), f(x, \nu_n, y, z), g(x, \nu_n)$$

- **Conversely**, if $(\nu_n)_{n \geq 1}$ has bounded moments of order $p > 2$
 - $(\nu_n)_{n \geq 1}$ admits a weakly convergent subsequence
 - then convergence for W_2 by unit. integrability and for $\|\cdot\|$ also

Application to MKV FBSDE

- Choose E as continuous $(\mu_t)_{0 \leq t \leq T}$ from $[0, T]$ to $\mathcal{P}_2(\mathbb{R}^d)$

$$\sup_{0 \leq t \leq T} \int_{\mathbb{R}^d} |x|^4 d\mu_t(x) \leq K \quad \text{for some } K$$

- Construct $\phi \rightsquigarrow$ fix $(\mu_t)_{0 \leq t \leq T}$ in E and solve

$$X_t = \xi + \int_0^t b(X_s, \mu_s, Y_s, Z_s) + \int_0^t \sigma(X_s, \mu_s, Y_s) dW_s$$
$$Y_t = g(X_T, \mu_T) + \int_t^T f(X_s, \mu_s, Y_s, Z_s) ds - \int_t^T Z_s dW_s$$

- let $\phi(\mu = (\mu_t)_{0 \leq t \leq T}) = (\mathcal{L}(X_t^\mu))_{0 \leq t \leq T}$

- Assume bounded coefficients and $\mathbb{E}[|\xi|^4] < \infty$

- choose K such that $\mathbb{E}[|X_t^\mu|^4] \leq K$

$\Rightarrow E$ stable by ϕ

- $W_2(\mathcal{L}(X_t^\mu), \mathcal{L}(X_s^\mu)) \leq C \mathbb{E}[|X_t^\mu - X_s^\mu|^2]^{1/2} \leq C|t - s|^{1/2}$

Conclusion

- Consider continuous $\mu = (\mu_t)_{0 \leq t \leq T}$ from $[0, T]$ to $\mathcal{P}_2(\mathbb{R}^d)$
 - for any $t \rightsquigarrow (\phi(\mu))_t$ in a compact subset of $\mathcal{P}_2(\mathbb{R}^d)$
 - $[0, T] \ni t \mapsto (\phi(\mu))_t$ is uniformly continuous in μ
 - by Arzelà-Ascoli \Rightarrow output lives in a compact subset of $E \subset C([0, T], \mathcal{P}_2(\mathbb{R}^d))$ (and thus of $C([0, T], \mathcal{M}_1(\mathbb{R}^d))$)
- Continuity of ϕ on E
 - stability of the solution of FBSDEs with respect to a continuous perturbation of the environment
 - under assumption of Chapter 1 and continuity w.r.t. environment \rightsquigarrow answer is yes
- ϕ is continuous and compact range \Rightarrow existence of a fixed point

Part II. Solving MFG without common noise

b. Statements and refinements

Non-degenerate setting

- Growth conditions

$$|b(x, \mu, \alpha)| \leq C(1 + |\alpha|), \quad |(\sigma, \sigma^{-1}, g)(x, \mu)| \leq C$$

$$|f(x, \mu, \alpha)| \leq C(1 + |\alpha|^2)$$

- Lipschitz condition

$$|(b, \sigma, \sigma^{-1}, g)(x', \mu, \alpha') - (b, \sigma, \sigma^{-1}, g)(x, \mu, \alpha)| \leq C(|x' - x| + |\alpha' - \alpha|)$$

$$|f(x', \mu, \alpha) - f(x, \mu, \alpha)| \leq C|x' - x|$$

$$|f(x, \mu, \alpha') - f(x, \mu, \alpha)| \leq C(1 + |\alpha| + |\alpha'|)|\alpha' - \alpha|$$

- b linear in α and f **strictly convex** in $\alpha \Rightarrow$ unique minimizer $\alpha^*(x, \mu, z)$ of the Hamiltonian; and regularity of the minimizer

- interpretation of the value function

- for any input $\mu = (\mu_t)_{0 \leq t \leq T} \Rightarrow$ **unique optimal path with bounded control** (comes from the fact that the gradient of HJB is bounded)

- \Rightarrow **existence of an MFG equilibrium!**

Restricted convex setting

- Use the stochastic Pontryagin principle
 - need to state the conditions for the derivative of the Hamiltonian
 - require b to be linear in $x \Rightarrow$ no a priori bound for $b \leadsto$ **need to adapt the result of Section I**
 - **simplify** \leadsto take the example when b independent of x (say $b(x, \mu, \alpha) = \alpha$)

- Backward equation ($\partial_x f = \partial_x H$)

$$Y_t = \partial_x g(X_T, \mathcal{L}(X_T)) + \int_t^T \partial_x f(X_s, \mathcal{L}(X_s), \alpha^*(X_s, \mathcal{L}(X_s), Y_s)) ds - \int_t^T Z_s dW_s$$

- require g convex in x and f convex in (x, α) but **$\partial_x g$ and $\partial_x f$ bounded** \leadsto very restrictive!
- if continuity with respect to $\mu \Rightarrow$ existence of an MFG solution

Mollification procedure

- Convex Lipschitz is not satisfactory
 - use a mollification procedure
- Approximate coefficients (f, g) by coefficients (f_n, g_n) such that
 - f_n and g_n are convex and Lipschitz
 - general procedure for approximating convex functions

$$\Phi^n(x) = \sup_{|y| \leq n} \inf_{z \in \mathbb{R}^d} [\langle y, x - z \rangle + \Phi(z)]$$

- solve MFG for $(g_n, f_n) \rightsquigarrow$ equilibrium $(\mu_t^n)_{0 \leq t \leq T}$
- Converging subsequence of $(\mu_t^n)_{0 \leq t \leq T}$?
 - new compactness problem in $C([0, T], \mathcal{P}_2(\mathbb{R}^d))$
 - analysis \rightsquigarrow boils down to control

$$\sup_{n \geq 1} \sup_{t \in [0, T]} \int_{\mathbb{R}^d} |x| d\mu_t^n(x) < \infty$$

- must prevent any blow-up of the means of the equilibria!

Solvability in the convex setting

- Convex setting
 - b linear in (x, α) , g convex in x
 - f convex in (x, α) and strictly convex in α
- Local Lipschitz continuity of the cost functionals

$$\begin{aligned} & |f(t, x', \mu', \alpha') - f(t, x, \mu, \alpha)| + |g(x', \mu') - g(x, \mu)| \\ & \leq L \left[1 + |x'| + |x| + |\alpha'| + |\alpha| + \left(\int_{\mathbb{R}^d} |y|^2 d(\mu + \mu')(y) \right)^{1/2} \right] \\ & \quad \times [|(x', \alpha') - (x, \alpha)| + W_2(\mu', \mu)], \end{aligned}$$

- f and g C^1 w.r.t. (x, α) with Lipschitz derivatives
- weak-mean reverting condition

$$\langle x, \partial_x f(t, 0, \delta_x, 0) \rangle \geq -c(1 + |x|) \quad \text{and} \quad \langle x, \partial_x g(0, \delta_x) \rangle \geq -c(1 + |x|)$$

- \Rightarrow existence of an MFG equilibrium!

Linear-quadratic in $d = 1$

- Apply **previous results** with
 - $b(t, x, \mu, \alpha) = a_t x + a'_t \mathbb{E}(\mu) + b_t \alpha_t$
 - $g(x, \mu) = \frac{1}{2} [qx + q' \mathbb{E}(\mu)]^2 \Leftrightarrow$ (mean-reverting) $qq' \geq 0$
 - $f(t, x, \mu, \alpha) = \frac{1}{2} [\alpha^2 + (m_t x + m'_t \mathbb{E}(\mu))^2] \Leftrightarrow$ (mean-rev.) $m_t m'_t \geq 0$
- Compare with **direct method** \leadsto adjoint equations

$$dX_t = [a_t X_t + a'_t \mathbb{E}(X_t) - b_t^2 Y_t] dt + \sigma dW_t$$

$$dY_t = -[a_t Y_t + m_t (m_t X_t + m'_t \mathbb{E}(X_t))] dt + Z_t dW_t$$

$$Y_T = q[qX_T + q' \mathbb{E}(X_T)]$$

- take the mean

$$d\mathbb{E}(X_t) = [(a_t + a'_t) \mathbb{E}(X_t) - b_t^2 \mathbb{E}(Y_t)] dt$$

$$d\mathbb{E}(Y_t) = -[a_t \mathbb{E}(Y_t) + m_t (m_t + m'_t) \mathbb{E}(X_t)] dt$$

$$\mathbb{E}(Y_T) = q(q + q') \mathbb{E}(X_T)$$

- existence and uniqueness if $q(q + q') \geq 0$, $m_t(m_t + m'_t) \geq 0$

Part II. Solving MFG without common noise

c. Uniqueness criterion

A counter-example to uniqueness

- Consider the MKV FBSDE

$$dX_t = b(\mathbb{E}(Y_t))dt + dW_t, \quad X_0 = x_0$$

$$dY_t = -f(\mathbb{E}(X_t))dt + Z_t dW_t, \quad Y_T = g(\mathbb{E}(X_T))$$

- take **bounded and Lipschitz coefficients** \leadsto existence of a solution
 - **uniqueness may not hold!**
 - **completely different of the system with $b(Y_t)$, $f(X_t)$ and $g(X_T)$** for which uniqueness holds true!
- Proof \leadsto take the mean

$$d\mathbb{E}(X_t) = b(\mathbb{E}(Y_t))dt, \quad \mathbb{E}(X_0) = x_0$$

$$d\mathbb{E}(Y_t) = -f(\mathbb{E}(X_t))dt, \quad \mathbb{E}(Y_T) = g(\mathbb{E}(X_T))$$

- led back to counter-example for FBSDE \leadsto choose b, f and g equal to the identity on a compact subset

Lasry Lions monotonicity condition

- Recall for an FBSDE without noise ($\sigma = \sigma^0 = 0$)
 - existence and uniqueness may hold for the Pontryagin system if convex cost functional
 - convexity \leftrightarrow monotonicity of $\partial_x g$ and $\partial_x H$
 - what is **monotonicity condition** in the direction of the measure?
- Lasry Lions monotonicity condition
 - b, σ do not depend on μ
 - $f(x, \mu, \alpha) = f_0(x, \mu) + f_1(x, \alpha)$ (μ and α are separated)
 - monotonicity property for f_0 and g w.r.t. μ

$$\int_{\mathbb{R}^d} (f_0(x, \mu) - f_0(x, \mu')) d(\mu - \mu')(x) \geq 0$$
$$\int_{\mathbb{R}^d} (g(x, \mu) - g(x, \mu')) d(\mu - \mu')(x) \geq 0$$

Monotonicity restores uniqueness

- Assume that for any input $\mu = (\mu_t)_{0 \leq t \leq T}$ unique optimal control $\alpha^{\star, \mu}$
 - + existence of an MFG for a given initial condition
- **Lasry Lions \Rightarrow uniqueness of MFG equilibrium!**
 - if two different $\leadsto \alpha^{\star, \mu} \neq \alpha^{\star, \mu'}$

$$\underbrace{J^\mu(\alpha^{\star, \mu})}_{\text{cost under } \mu} < J^\mu(\alpha^{\star, \mu'}) \quad \text{and} \quad \underbrace{J^{\mu'}(\alpha^{\star, \mu'})}_{\text{cost under } \mu'} < J^{\mu'}(\alpha^{\star, \mu})$$

so that

$$\begin{aligned} J^{\mu'}(\alpha^{\star, \mu}) - J^{\mu'}(\alpha^{\star, \mu'}) + J^\mu(\alpha^{\star, \mu'}) - J^\mu(\alpha^{\star, \mu}) &> 0 \\ J^{\mu'}(\alpha^{\star, \mu}) - J^\mu(\alpha^{\star, \mu}) - [J^{\mu'}(\alpha^{\star, \mu'}) - J^\mu(\alpha^{\star, \mu'})] &> 0 \end{aligned}$$

$$\mathbb{E} \left[\underbrace{g(X_T^{\star, \mu}, \mu'_T) - g(X_T^{\star, \mu}, \mu_T)}_{\text{cost under } \mu} - \underbrace{(g(X_T^{\star, \mu'}, \mu'_T) - g(X_T^{\star, \mu'}, \mu_T))}_{\text{cost under } \mu'} + \dots \right] > 0$$
$$\int_{\mathbb{R}^d} (g(x, \mu'_T) - g(x, \mu_T)) d\mu_T(x) \quad \int_{\mathbb{R}^d} (g(x, \mu'_T) - g(x, \mu_T)) d\mu'_T(x)$$

- same for $f_0 \Rightarrow$ LHS must be ≤ 0

Example for Lasry Lions

- Examples for $h(x, \mu)$ satisfying

$$\int_{\mathbb{R}^d} (h(x, \mu) - h(x, \mu')) d(\mu - \mu')(x) \geq 0$$

- if h is independent of x
- if h given by

$$h(x, \mu) = \langle x, \bar{\mu} \rangle, \quad \bar{\mu} = \int_{\mathbb{R}^d} y d\mu(y)$$

- if h is given by

$$h(x, \mu) = \int_{\mathbb{R}^d} f(x - y) d\mu(y) \quad \text{and } f \text{ odd}$$

- if $d = 1$ and h is independent of x

$$h(x, \mu) = \mu(-\infty, x] \quad \text{and } \mu, \mu' \text{ have no atoms}$$

Part III. Solving MFG with common noise

Part III. Solving MFG with common noise

a. Strategy of proof

General prospect

- Solve MFG with a **common noise**
 - need to solve **conditional MKV FBSDE**

$$X_t = \xi + \int_0^t b(X_s, \mathcal{L}(X_s | \mathbf{W}^0), Y_s, Z_s) ds \\ + \int_0^t \sigma(X_s, \mathcal{L}(X_s | \mathbf{W}^0), Y_s) dW_s + \int_0^t \sigma^0(X_s, \mathcal{L}(X_s | \mathbf{W}^0), Y_s) dW_s^0$$

$$Y_t = g(X_T, \mathcal{L}(X_T | \mathbf{W}^0)) + \int_t^T f(X_s, \mathcal{L}(X_s | \mathbf{W}^0), Y_s, Z_s) ds \\ - \int_t^T Z_s dW_s - \int_t^T Z_s^0 dW_s^0$$

- Again \leadsto Cauchy Lipschitz theory in small time
 - may adapt the result for MFG without common noise
- How to implement Schauder's fixed point over intervals of arbitrary length?

Need for revisiting the strategy of proof

- Try to follow the same strategy as in the case σ^0
- Fix $\mu = (\mu_t)_{0 \leq t \leq T}$ random process with values in $\mathcal{P}_2(\mathbb{R}^d)$ and adapted w.r.t. \mathbf{W}^0 on $(\Omega^0, \mathbb{F}^0, \mathbb{P}^0)$

◦ call $X^\mu = (X_t^\mu)_{0 \leq t \leq T}$ the forward component of the solution to

$$X_t = \xi + \int_0^t b(X_s, \mu_s, Y_s, Z_s) ds + \int_0^t (\sigma(X_s, \mu_s, Y_s) dW_s + \sigma^0(X_s, \mu_s, Y_s) dW_s^0)$$

$$Y_t = g(X_T, \mu_T) + \int_t^T f(X_s, \mu_s, Y_s, Z_s) ds - \int_t^T (Z_s dW_s + Z_s^0 dW_s^0)$$

- Solve $\mu_t(\omega^0) = \mathcal{L}(X_t^\mu | \mathbf{W}^0)(\omega^0)$ for any $t \in [0, T]$ and for almost every $\omega^0 \in \Omega^0 \rightsquigarrow$ fixed point in

$$\left(C([0, T], \mathcal{P}_2(\mathbb{R}^d)) \right)^{\Omega^0}$$

- much too big for nice compactness criterion!

Discretization method

- General idea \rightsquigarrow discretize the conditioning in the MKV FBSDE!
 - $\mathcal{L}(X_t|W^0) \rightsquigarrow \mathcal{L}(X_t|\text{finitely supported process})$
 - Π projection mapping onto space grid $\{x_1, \dots, x_M\} \subset \mathbb{R}^d$
 - t_1, \dots, t_N a finite time grid $\subset [0, T]$
 - $\hat{W}_{t_i}^0 = \Pi(W_{t_i}^0)$

- Solve the forward-backward system with

$$\mathcal{L}(X_t|\hat{W}_{t_1}^0, \dots, \hat{W}_{t_i}^0), \quad t_i \leq t < t_{i+1}$$

- Fixed point strategy

- input $\mu = (\mu_t)_{0 \leq t \leq T}$ adapted with respect to discrete filtration generated by $(\hat{W}_{t_1}^0, \dots, \hat{W}_{t_N}^0)$

- solve the fixed point $\mu_t(\hat{W}_{t_1}^0, \dots, \hat{W}_{t_N}^0) = \mathcal{L}(X_t^\mu|\hat{W}_{t_1}^0, \dots, \hat{W}_{t_N}^0)$

- Since $(\hat{W}_{t_1}^0, \dots, \hat{W}_{t_N}^0)$ has finite support of size $MN \rightsquigarrow$ fixed point in $(C([0, T], \mathcal{P}(\mathbb{R})))^{MN}$

Passing to the limit

- For any M and $N \rightsquigarrow \mu^{\star, M, N} = (\mu_t^{\star, M, N})_{0 \leq t \leq T}$ fixed point under the discretized conditioning

- call $(X^{\star, M, N}, Y^{\star, M, N}, Z^{\star, M, N}, Z^{0, \star, M, N})$ solution of the corresponding FBSDE

- aim at extracting converging subsequence

- Assume tightness $(\mu^{\star, M, N})_{M, N \geq 1}$ seen as processes with paths in $C([0, T], \mathcal{P}_2(d))$

$$(\mu_t^{\star, M, N})_{0 \leq t \leq T} \xrightarrow{\mathcal{L}} \mu^{\star} \quad \text{up to subsequence}$$

- $(X_t^{\star, M, N}, Y_t^{\star, M, N}, \int_0^t Z_s^{\star, M, N} ds, \int_0^t Z_s^{0, \star, M, N} ds)_{0 \leq t \leq T}$ weakly converges to solution of FBSDE in environment μ^{\star} ?

- is μ^{\star} the flow of conditional measures of the solution?

- Main issue: loose adaptability of μ^{\star} with respect to systemic noise in the limit!

Part III. Solving MFG with common noise

b. Weak and strong solutions

Need for a weak solution

- In previous slides \leadsto loose adaptability of μ^\star with respect to common noise
 - **set-up** is made of $(\Omega^0, \mathbb{F}^0, \mathbb{P}^0)$ and $(\Omega^1, \mathbb{F}^1, \mathbb{P}^1)$
 - Ω^1 carries idiosyncratic noise and Ω^0 carries both common noise and limit $\mu^\star \leadsto \mathbb{F}^0$ **larger than Brownian filtration!**
- **Loose martingale representation theorem** \leadsto FBSDE in the limit takes the form

$$X_t = \xi + \int_0^t b(X_s, \mu_s^\star, Y_s, Z_s) ds + \int_0^t (\sigma(X_s, \mu_s^\star) dW_s + \sigma^0(X_s, \mu_s^\star) dW_s^0)$$

$$Y_t = g(X_T, \mu_T) + \int_t^T f(X_s, \mu_s^\star, Y_s, Z_s) ds - \int_t^T Z_s dW_s - \underbrace{(M_T - M_t)}_{\text{mart. } \perp W}$$

- conditioning takes the form

$$\mu_t = \mathcal{L}(X_t | \mathcal{F}_t^0) \quad \left(\text{may differ from } \mathcal{L}(X_t | (W_s^0)_{0 \leq s \leq t}) \right)$$

Strong vs. weak equilibria

- **Strong sense**

- probability spaces $(\Omega^0, \mathbb{F}^0, \mathbb{P}^0)$ and $(\Omega^1, \mathbb{F}^1, \mathbb{P}^1)$ are **given**
- example \leadsto canonical spaces

$$\Omega^0 = C([0, T], \mathbb{R}^d) \quad \Omega^1 = \underbrace{\mathbb{R}^d}_{\text{initial condition}} \times C([0, T], \mathbb{R}^d)$$

- require $(\mu_t^\star)_{0 \leq t \leq T} = \mathcal{L}(X_t | \mathbb{W}^0)$

- **Weak sense:** probability space is **not** given

- \exists 2 filtered probability spaces $(\Omega^0, \mathbb{F}^0, \mathbb{P}^0)$ and $(\Omega^1, \mathbb{F}^1, \mathbb{P}^1)$
- $(W_t^0, \mu_t^\star)_{0 \leq t \leq T}$ is carried on Ω^0 , $(X_0, W_t)_{0 \leq t \leq T}$ on Ω^1
- $\mu_t^\star = \mathcal{L}(X_t | \mathcal{F}_t^0)$ (conditioning is enlarged but independent of W)

- Same type of assumptions as in Section II \Rightarrow existence of weak MFG

- **Yamada-Watanabe:** strong ! + weak $\exists \Rightarrow$ strong \exists

- reconstruct solutions on the same space

Part III. Solving MFG with common noise

c. Common noise may restore uniqueness

Smoothing effect of common noise

- Lasry Lions conditions \Rightarrow strong uniqueness
- ODEs without uniqueness \rightsquigarrow SDEs with uniqueness!
 - restoration of uniqueness with common noise

- **Simple example**

- $b(x, \mu, \alpha) = -x + b(m) + \alpha$, $m = \int x' d\mu(x')$

- $f(x, \mu, \alpha) = \frac{1}{2}[(x + f(m))^2 + \alpha^2]$

- $g(x, \mu) = \frac{1}{2}(x + g(m))^2$

- **Stochastic Pontryagin** \rightsquigarrow strong solution if $Y_t = X_t + \chi_t$

$$dm_t = (b(m_t) - 2m_t - \chi_t)dt + dW_t^0,$$

$$d\chi_t = -(f + b)(m_t)dt + \zeta_t dW_t^0, \quad \chi_T = g(m_T)$$

- $m_t = \mathbb{E}[X_t | \mathbf{W}^0]$

- b, f, g smooth bounded + noise $\Rightarrow \exists$ and !

- without noise \Rightarrow ! may fail