

Probabilistic Approach for Mean Field Games with a Common Noise

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Common noise

- Modelling (in \mathbb{R} to simplify)

- Dynamics of player number $1 \leq i \leq N$

$$dX_t^i = b(X_t^i, \bar{\mu}_t^N, \alpha_t^i) dt + \sigma dW_t^i + \varsigma dB_t$$
$$X_0^i = x_0$$

- independent noises B, W^1, \dots, W^N

- $\bar{\mu}_t^N = \frac{1}{N} \sum_{i=1}^N \delta_{X_t^i} \quad 0 \leq t \leq T$

- α_t^i prog. meas. w.r.t. $\sigma(W^1, \dots, W^N, B)$

- Nash equilibrium w.r.t.

- $J^i = \mathbb{E} \left[g(X_T^i, \bar{\mu}_T^N) + \int_0^T f(X_t^i, \bar{\mu}_t^N, \alpha_t^i) dt \right]$

Conditional law of large numbers

- Exchangeable equilibria \rightsquigarrow conditional LLN

$$\bar{\mu}_t^N \sim_{N \uparrow +\infty} \mathcal{L}(X_t^1 | B) \quad (= \mathcal{L}(X_t^1 | (B_s)_{0 \leq s \leq t}))$$

- Scheme

- Fix the flow of random measures $(\mu_t)_{0 \leq t \leq T}$
- μ_t depends on $(B_s)_{0 \leq s \leq t}$ only!
- Optimize

$$dX_t^1 = b(X_t^1, \mu_t, \alpha_t^1) dt + \sigma W_t + \varsigma dB_t$$
$$J^1 = \mathbb{E} \left[g(X_T^1, \mu_T) + \int_0^T f(X_t^1, \mu_t, \alpha_t^1) dt \right]$$

- Solve the matching problem $\mu_t = \mathcal{L}(X_t | B)$

Strong vs. weak equilibria

- **Strong sense**

- Probability space is **given**

- **Canonical space:** $\underbrace{\mathcal{C}([0, T], \mathbb{R})}_{\text{for } B} \times \underbrace{\mathcal{C}([0, T], \mathbb{R})}_{\text{for } W}$

- $(\mu_t)_{0 \leq t \leq T}$ is prog. meas. w.r.t. $\sigma(B)$ (function of the 1st coordinate)

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

- \exists 2 filtered probability spaces $(\Omega^i, \mathcal{F}^i, \mathbb{P}^i)$, $i = 1, 2$

- $(B_t, \mu_t)_{0 \leq t \leq T}$ is carried on Ω^1 , $(W_t)_{0 \leq t \leq T}$ on Ω^2

- $\mu_t = \mathcal{L}(X_t | \mathcal{F}_t^1)$ (conditioning is enlarged but independent of W)

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

- reconstruct solutions on the same space

Stochastic maximum principle

- extended Hamiltonian

- $H(x, y, \mu, \alpha) = b(x, \mu, \alpha)y + f(x, \mu, \alpha)$

- $\hat{\alpha}(x, y, \mu) = \operatorname{argmin}_{\alpha} H(x, y, \mu, \alpha)$

- adjoint equations for a nonanticipative frozen $(\mu_t)_{0 \leq t \leq T}$

$$dX_t = b(X_t, \mu_t, \hat{\alpha}(X_t, Y_t, \mu_t)) dt + \sigma dW_t + \varsigma dB_t$$

$$dY_t = -\partial_x H(X_t, Y_t, \mu_t, \hat{\alpha}(X_t, Y_t, \mu_t)) dt + d \underbrace{\text{martingale}_t}_{\text{measurability constraint}}$$

$$Y_T = \partial_x g(X_T, \mu_T)$$

- Solve eq. with the constraint $\mu_t = \mathcal{L}(X_t|B)$: MKV FBSDE

- H and g convex w.r.t. $(x, \alpha) \Rightarrow X$ equilibrium

- numerics: discretization of the adjoint equations

Dynamics of X

- **Decoupling random field** $u : [0, T] \times \mathbb{R} \times \Omega \rightarrow \mathbb{R}$
 - $(u(t, \cdot))_{0 \leq t \leq T}$ is $\sigma(B)$ prog. meas. and $Y_t = u(t, X_t)$
- Dynamics of X at **equilibrium**

$$dX_t = \underbrace{b(X_t, \mu_t, \hat{\alpha}(X_t, u(t, X_t), \mu_t))}_{\hat{b}(t, X_t)} dt + \sigma dW_t + \varsigma dB_t$$

- Convex Hamiltonian \Rightarrow u Lipschitz in x
- **Conditional path of X** given $\mathcal{F}^1 \rightsquigarrow$ **Freeze B**
 - $\mathcal{L}(X_t | B = \beta) = \mathcal{L}(X_t^\beta)$

$$X_t^\beta = x_0 + \int_0^t \hat{b}(s, X_s^\beta) ds + \sigma W_t + \varsigma \beta t$$

PDE point of view: stochastic HJB

- **Common noise** \Rightarrow **Value function** = random field

$$U(t, x) = \inf_{\alpha, X_t=x} \mathbb{E} \left[g(X_T, \mu_T) + \int_t^T L(X_s, \mu_s, \alpha_s) ds \mid \mathcal{F}_t^B \right]$$

- U adapted \Rightarrow **Backward Stochastic HJB**

$$\begin{aligned}
 & d_t U(t, x) \\
 & + \left(\underbrace{\mathcal{L}U(t, x)}_{\text{generator}} + \underbrace{\inf_{\alpha} [b(x, \mu_t, \alpha) \partial_x U(t, x) + L(x, \mu_t, \alpha)]}_{\text{standard Hamiltonian in HJB}} \right) dt \\
 & + \underbrace{\zeta \partial_x V(t, x)}_{\text{Ito Wentzell cross term}} \underbrace{) dt - V(t, x) dB_t}_{\text{backward term}} = 0
 \end{aligned}$$

- Maximum principle $\rightsquigarrow Y_t = \partial_x U(t, X_t)$ i.e. $u = \partial_x U$

Stochastic Kolmogorov

- Dynamics of the conditional law of X given B
- Replace $(B_t)_{0 \leq t \leq T}$ by a **piecewise affine curve** $(\beta_t)_{0 \leq t \leq T}$
 - Kolmogorov equation

$$d_t \mu_t = -\operatorname{div}(b(x, \mu_t, \hat{\alpha}(x, \mu_t, u(t, x)))) dt \\ + \frac{\sigma^2}{2} \partial_{xx}^2 \mu_t dt - \operatorname{div}(\mu_t \varsigma) \dot{\beta}_t dt$$

- Use $\beta = \beta^N =$ affine **interpolation** of B with N nodes

$$d_t \mu_t = -\operatorname{div}(b(x, \mu_t, \hat{\alpha}(x, \mu_t, u(t, x)))) dt \\ + \frac{\sigma^2}{2} \partial_{xx}^2 \mu_t dt - \operatorname{div}(\mu_t \varsigma) \circ dB_t$$

- HJB + Kolmogorov \Rightarrow **forward backward SDE** in ∞ dim

Lifted value function

- Representation of the value random function

$$U(t, x, \omega) = \mathcal{U}(t, x, \mu_t(\omega)),$$

- $\mathcal{U} : [0, T] \times \mathbb{R} \times \mathcal{P}_2(\mathbb{R}) \rightarrow \mathbb{R}$
- \exists if strong uniqueness
- Write second-order (master?) PDE in infinite dimension
 - Derivatives on $\mathcal{P}_2(\mathbb{R}) \rightsquigarrow$ r.v. $\partial_\mu \mathcal{U}(t, x, \mu_t)(X_t)$
 - Connection with V in stochastic HJB equation

$$V(t, x, \omega) = \int \partial_\mu \mathcal{U}(t, x, \mu_t(\omega))(y) \zeta_{\mu_t(\omega)}(dy)$$

- Used in parametric models $\mu_t = \mu(q_t)$

$$\mathcal{U}(t, x, \mu_t) \rightsquigarrow \mathcal{U}(t, x, q_t)$$

Weak solvability conditions

- **Weakening** notion of solutions \Rightarrow same strategy
- **Convexity of the Hamiltonian** (very much demanding!)
 - $b(x, \mu, \alpha) = b_0(\mu) + b_1 x + b_2 \alpha$
 - f convex in (x, α) (and strictly convex in α)
- **Local Lipschitz bound** (linear growth) in (x, μ, α)
 - use Wasserstein W_2 for the measure
- **Mean-reverting**
 - $\langle x, \partial_x f(0, \delta_x, 0) \rangle, \langle x, \partial_x g(0, \delta_x) \rangle \geq -c(1 + |x|)$
 - example: bounded derivatives
- **Smoothness** ($\mathcal{C}^{1,1}$ in (x, α))...
- **Strong !** is welcome

Strategy of proof for solvability

- Forget strong vs. weak! Freeze the conditional measure

$$dX_t = b(X_t, \mu_t, \hat{\alpha}(X_t, Y_t, \mu_t)) dt + \sigma W_t + \varsigma dB_t$$

$$dY_t = -\partial_x H(X_t, Y_t, \mu_t, \hat{\alpha}(X_t, Y_t, \mu_t)) dt + d\text{martingale}_t$$

$$Y_T = \partial_x g(X_T, \mu_T)$$

- Find a fixed point $\Phi : (\mu_t)_{0 \leq t \leq T} \mapsto (\mathcal{L}(X_t^\mu | \mathcal{B}))_{0 \leq t \leq T}$
- If no common noise
 - Fixed point in $\mathcal{C}([0, T], \underbrace{\mathcal{P}(\mathbb{R})}_{\text{set of prob. meas.}})$
 - Use Schauder's th: Φ continuous and range of Φ compact
- If common noise
 - Fixed point in subset of $(\mathcal{C}([0, T], \mathcal{P}(\mathbb{R})))^\Omega$
 - Compactness?

Discretization of the conditioning

- Discretization: $\mathcal{L}(X_t|B) \rightsquigarrow \mathcal{L}(X_t|\text{finitely supported process})$
 - Π projection mapping onto space grid $\{x_1, \dots, x_M\} \subset \mathbb{R}$
 - t_1, \dots, t_N a finite time grid $\subset [0, T]$
 - $\hat{B}_{t_i} = \Pi(B_{t_i})$
- Forward-backward system with

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

- $(\hat{B}_{t_1}, \dots, \hat{B}_{t_N})$ has finite support of size MN
- Fixed point in $(\mathcal{C}([0, T], \mathcal{P}(\mathbb{R})))^{MN}$
- $\exists \underbrace{\hat{X}^{M,N}}_{\text{optimum}}, \underbrace{\hat{\mu}^{M,N}}_{\text{equilibrium}}, \underbrace{\hat{u}^{M,N}}_{\text{decoupling field}} \quad \text{s.t.}$

$$\hat{\mu}_t^{M,N} = \mathcal{L}(\hat{X}_t^{M,N}|\hat{B}_{t_1}, \dots, \hat{B}_{t_i}), \quad \hat{Y}_t^{M,N} = \hat{u}^{M,N}(t, \hat{X}_t^{M,N})$$

Extraction of converging subsequence

- Conditional measure $\hat{\mu}^{M,N} \sim_{M,N \uparrow \infty} \mathcal{L}(\hat{X}_t^{M,N} | B)$
- **Tightness** $\hat{X}^{M,N}$ in $\mathcal{C}([0, T] \times \mathbb{R}, \mathbb{R})$
 - Standard Kolmogorov criterion
- **Tightness** $\hat{u}^{M,N}$ in $\mathcal{C}([0, T] \times \mathbb{R}, \mathbb{R})$
 - **Convexity of Hamiltonian** \Rightarrow **regularity of $\hat{u}^{M,N}$**
- **Tightness** $\mathcal{L}(\hat{X}_t^{M,N} | B)$ in $\mathcal{C}([0, T], \mathcal{P}(\mathbb{R}))$
 - Given $B = \beta$, $\mathcal{L}(\hat{X}_t^{M,N} | B)$ is the law of

$$d\hat{X}_t^{\beta, M, N} = \hat{b}^{M, N}(t, \hat{X}_t^{\beta, M, N})dt + \sigma dW_t + \varsigma d\beta_t$$

- **Law of $\hat{X}^{\beta, M, N}$ is explicitly controlled by β**
- **Converging subsequence** in weak sense (convergence of distributions)

Uniqueness

- Standard criterion
 - b doesn't 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
- Application: **weak** \rightsquigarrow **strong**
- Other strategy: small time \rightsquigarrow long time?
 - a priori Lipschitz **estimates** of u ?
 - **degeneracy** because of ∞ dim setting

Smoothing effect

- **Example:** $dX_t = (b(\mu_t) + X_t + \alpha_t)dt + dW_t + dB_t$

$$J(\alpha) = \mathbb{E} \left[\frac{1}{2} (X_T + g(\mu_T))^2 + \int_0^T \frac{1}{2} [(X_s + f(\mu_s))^2 + \alpha_s^2] ds \right]$$

- b, f, g bounded and smooth
- Adjoint system

$$dX_t = (b(\mu_t) + X_t - Y_t)dt + dW_t + dB_t$$

$$dY_t = -(X_t + Y_t + f(\mu_t))dt + d\text{martingale}_t.$$

$$Y_T = X_T + g(\mu_T)$$

- $Y_t = \eta_t X_t + v(t, \mu_t)$
- $(\eta_t)_{0 \leq t \leq T}$ bounded
- Uniqueness related with $\partial_\mu v$?

Integration by parts

- Dynamics of X

$$dX_t = \left((1 - \eta_t)X_t + \underbrace{b(\mu_t) - v(t, \mu_t)}_{\beta(t, \mu_t)} \right) dt + dW_t + dB_t.$$

- Sensitivity w.r.t. initial condition $\nabla X = \frac{d}{d\varepsilon}|_{\varepsilon=0} X^{\xi+\varepsilon}$

$$\frac{d}{dt} \nabla X_t = (1 - \eta_t) \nabla X_t + \mathbb{E} \left[(\partial_{\mu} \beta(t, \mu_t)(X_t) \nabla X_t | \mathcal{F}_t^B] \right]$$

◦ $\nabla X_0 = 1 \Rightarrow \nabla X_t$ is \mathcal{F}_t^B -meas \Rightarrow **linear!**

- Malliavin derivative $\Rightarrow \nabla X_t = D_s X_t \nabla X_s$

$$\nabla \mathbb{E} \left[V(X_T, \mu_T) | \mathcal{F}_0 \right] = \frac{1}{T} \mathbb{E} \left[V(X_T, \mu_T) \int_0^T \nabla X_s dB_s | \mathcal{F}_0 \right]$$