

# Uncertainty quantification for mean field games in social interactions

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## Outline

- 1 Mean Field Games**
  - Stochastic Optimal control
  - Abstract Formulation of MFG
- 2 Mean Field Sentimental Games**
- 3 Uncertainty Quantification**

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$$\begin{cases} d\mathbf{X}(t) = b(\mathbf{X}(t), \boldsymbol{\alpha}(t))dt + \sigma(\mathbf{X}(t))d\mathbf{W}_t \\ \mathbf{X}(t=0) = \mathbf{X}_0, \end{cases} \quad (1)$$

where

- the function  $b$  is the drift
- $\mathbf{W}_t$  is the standard Brownian motion
- $\boldsymbol{\alpha}$  is the control

### Remark

- If the control  $\boldsymbol{\alpha} = \boldsymbol{\alpha}(t, \mathbf{X}_0)$ ; open-loop control
- If the control  $\boldsymbol{\alpha} = \boldsymbol{\alpha}(t, \mathbf{X}(t))$ ; closed-loop control (feedback control)

## Cost functional

$$J(\mathbf{X}_0, \alpha) = \mathbb{E} \left[ \int_0^T f(\mathbf{X}, \alpha) dt + g(\mathbf{X}(T)) \right],$$

- $f(t, \alpha(t), \mathbf{X}(t)) = \underbrace{\mathcal{U}(t, \alpha(t), \mathbf{X}(t))}_{\text{utility}} - \underbrace{\mathcal{C}(t, \alpha(t), \mathbf{X}(t))}_{\text{cost}}$
- $g$  is differentiable and stands for the terminal reward.

## Control Problem

$$(\mathcal{P}) \begin{cases} \sup_{(\alpha(t))_t} J(\mathbf{X}_0, \alpha), \\ \text{subject to (1)} \end{cases} \quad (2)$$

## Pontryagin's Maximum Principle

The Hamiltonian  $H$  is defined for all  $t \in [0, T]$

$$H(t, \mathbf{p}, \mathbf{X}, \boldsymbol{\alpha}) = \mathbf{p}^{tr} \cdot b(\mathbf{X}, \boldsymbol{\alpha}) + \boldsymbol{\mu}^{tr} \cdot \sigma + f(\mathbf{X}, \boldsymbol{\alpha})$$

(1) Optimal control  $\boldsymbol{\alpha}^*$  gives  $\mathbf{X}^*$  such that

$$H(t, \mathbf{p}^*, \mathbf{X}^*, \boldsymbol{\alpha}^*) \geq H(t, \mathbf{p}^*, \mathbf{X}^*, \boldsymbol{\alpha}) \quad \forall t \in [0, T]$$

(2) Co-state equation

$$d\mathbf{p}^{tr}(t) = -\nabla_{\mathbf{X}} H(t, \mathbf{p}, \mathbf{X}, \boldsymbol{\alpha})|_{(\mathbf{X}, \boldsymbol{\alpha})=(\mathbf{X}^*, \boldsymbol{\alpha}^*)} + \boldsymbol{\mu}^{tr}(t) d\mathbf{W}_t$$

(3) Transversality condition  $\mathbf{p}^{tr}(T) = \nabla_{\mathbf{X}} g(\mathbf{X}(T))$

## Bellman Dynamic Programming

Let

$$a(t, \mathbf{x}) = \frac{1}{2} \text{Tr}(\sigma(\mathbf{x}) \cdot \sigma^{tr}(\mathbf{x})) \quad (3)$$

The generator of diffusion is

$$L\varphi(t, \mathbf{x}, \boldsymbol{\alpha}) = a(t, \mathbf{x})\Delta\varphi + b(t, \mathbf{x}, \boldsymbol{\alpha}) \cdot \nabla\varphi \quad (4)$$

The value function  $\mathbf{u} = \sup_{\boldsymbol{\alpha} \in \mathcal{A}} J(\mathbf{X}_0, \boldsymbol{\alpha})$  satisfies the HJB (Hamilton-Jacobi-Bellman equation):

$$\min_{\boldsymbol{\alpha} \in \mathcal{A}} \left\{ \frac{\partial \mathbf{u}}{\partial t} - L\mathbf{u}(t, \mathbf{x}, \boldsymbol{\alpha}) + f(t, \mathbf{x}, \boldsymbol{\alpha}) \right\} = 0$$

$$\frac{\partial \mathbf{u}}{\partial t} + a(t, \mathbf{x})\Delta \mathbf{u} + \underbrace{\max_{\boldsymbol{\alpha} \in \mathcal{A}} \{ b(t, \mathbf{x}, \boldsymbol{\alpha}) \cdot \nabla \mathbf{u} - f(t, \mathbf{x}, \boldsymbol{\alpha}) \}}_{H(t, \mathbf{x}, \nabla \mathbf{u})} = 0.$$

$\mathbf{X}$  modeled by a McKean-Vlasov process

$$\begin{cases} d\mathbf{X}(t) = b(\mathbf{X}(t), \mathbf{m}(t), \boldsymbol{\alpha}(t))dt + \sigma(\mathbf{X}(t))d\mathbf{W}_t, \\ \mathbf{X}(0) = \mathbf{X}_0, \end{cases} \quad (5)$$

where

- $\mathbf{m}(t)$  is the the probability density of the state  $\mathbf{X}$ ,
- $\boldsymbol{\alpha}(t)$  is the feedback control
- $\mathbf{X}_0$  is independent to the Wiener process  $(\mathbf{W}_t)_{t \geq 0}$ .

Hypothesis

- Infinite number of players,
- Indistinguishability of the players,
- Regularity of the drift function  $\mathbf{b}$ .

$$A\varphi(\mathbf{x}) = - \sum_{i,j} \sigma_{ij}(\mathbf{x}) \frac{\partial^2 \varphi(\mathbf{x})}{\partial x_i \partial x_j}, \quad \text{its adjoint} \quad A^* \varphi(\mathbf{x}) = - \sum_{i,j} \frac{\partial^2 (\sigma_{ij}(\mathbf{x}) \varphi(\mathbf{x}))}{\partial x_i \partial x_j}.$$



## Cost functional

$$J(\mathbf{X}_0, \mathbf{m}, \boldsymbol{\alpha}) = \mathbb{E} \left\{ \int_0^T f(\mathbf{X}(t), \mathbf{m}(t), \boldsymbol{\alpha}(t)) dt + g(\mathbf{X}(T), \mathbf{m}(T)) \right\}$$

## Value function

and formulate the optimal control problem

$$\mathbf{u}(\mathbf{X}_0, \mathbf{m}(t)) = \inf_{\boldsymbol{\alpha}(t)} J(\mathbf{X}_0, \mathbf{m}(t), \boldsymbol{\alpha}(t)).$$

## Problem

We wish to find the optimal control  $\boldsymbol{\alpha}$  and to characterize the value function  $\mathbf{u}$  (the cost functional evaluated with the optimal trajectory  $\boldsymbol{\alpha}^*$ )

Let  $H$  be the Hamiltonian:

$$H(\mathbf{x}, \mathbf{m}, \mathbf{p}) = \inf_{\alpha} (\mathbf{p}^{tr} \cdot b(\mathbf{X}(t), \mathbf{m}(t), \alpha(t)) + f(\mathbf{X}(t), \mathbf{m}(t), \alpha(t)))$$

### Basic Setup

- Best response to the mean of the field :

$$\arg \min_{\alpha} [H(\mathbf{x}, \mathbf{m}, \mathbf{p}) = \mathbf{p}^{tr} \cdot b(\mathbf{X}, \mathbf{m}, \alpha) + f(\mathbf{X}, \mathbf{m}, \alpha)]$$

- Dynamic equilibrium: No single-incentive  
Consistency of strategies (see Jovanovic' 82)

## Pontryagin's Principle

### Good points

- Gives control dynamics
- Covers nonlinear transversality condition

### Limitations

- Hard to characterize the adjoint state dynamics
- Limited;  $m = \mathbb{E}(\mathbf{X})$  works

### Existence & Uniqueness

B. Djehiche et al. 2011.

## Bellman Programming

### Good points

- Works for general form of distribution  $m$
- Theory is well developed

### Limitations

- Time inconsistency when the transversality is nonlinear
- Only average behavior of all the agents

### Existence & Uniqueness

Lasry & Lions 2006, Gueant 2009,

Huang-Caines-Malhamé 2007.

### Numerical Implementation

Gomes et al 2009, Achdou et al. 2010, LaChapelle 2010.

## Dynamic Programming for MFG

If

- the feedback control  $\alpha$  does not affect the density  $m$ ,
- the volatility function is linear on the state
- the initial distribution  $m_0$  is normalized

Then, the stochastic optimization problem is called **Mean Field Games**

$$\left\{ \begin{array}{ll} -\frac{\partial u}{\partial t} + Au = H(x, m, \nabla u) & \text{in } (0, T) \times \mathbb{R}^n, \\ \frac{\partial m}{\partial t} + A^*m + \operatorname{div}(mH_p(x, m, \nabla u)) = 0 & \text{in } (0, T) \times \mathbb{R}^n, \\ u(x, T) = g(x(T), m(T)), \quad m(x, 0) = m_0(x) & \text{in } \mathbb{R}^n. \end{array} \right.$$

## Some Remarks

- Approximate Nash equilibria may exist even when Nash equilibria do not! In this case one uses probabilistic techniques to prove that the MFG feedback gives the desired approximation.
- When the strategy of a single player affects the distribution, it is called Mean Field Type Control.

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## Optimal feedback effort I

Value function of a couple

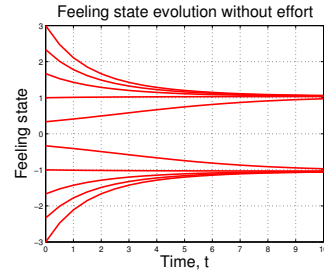
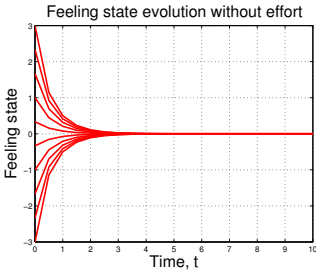
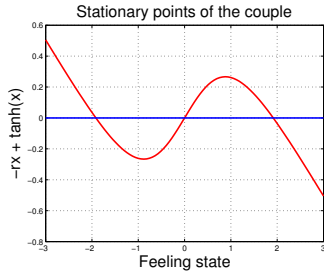
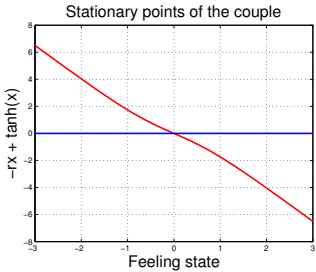
$$v(t, x) = \sup_{\mathbf{e}(t, \cdot) \geq 0} \mathbb{E} \left( g(x(T)) + \int_t^T [s(x(t')) - c(\mathbf{e}(t'))] dt' \mid x(t) = x \right),$$

where

$$\begin{cases} dx = [-h(x) + a\mathbf{e}] dt + \sigma dW(t), & \text{for } t > 0 \\ x(t=0) = x_0 \text{ such that } x_0 > \underline{x} + \varepsilon. \end{cases}$$

- $s(x)$  non-decreasing, concave and saturated at  $\infty$
- $c(\mathbf{e})$  is  $\mathcal{C}^2$  non-decreasing and strictly convex
- $a > 0$  the expected variation of the feeling in a short time
- $h(x) = rx - \tanh(x)$  (See Gottman et al. 2005)

# Optimal feedback effort II



High type society

Low type society



## Optimal feedback effort III

Dynamic programming: The Hamiltonian is

$$H(x, p) = -h(x)p + s(x) + \underbrace{\sup_e \{ap \cdot e - c(e)\}}_{\tilde{c}(ap)}.$$

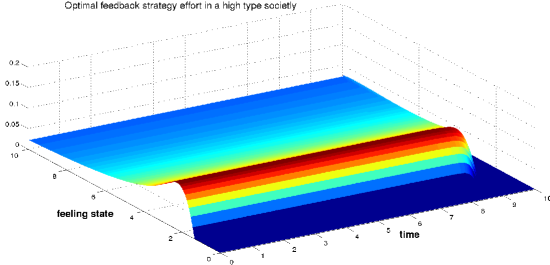
The optimal effort is

$$e^*(t, x) = \max(0, \tilde{c}'(av_x)),$$

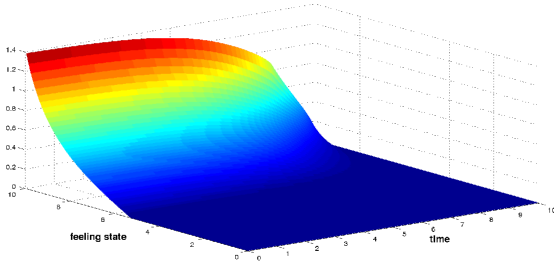
where

$$\begin{cases} v_t - h(x)v_x + s(x) + \tilde{c}(av_x) + \frac{\sigma^2}{2}v_{xx} = 0 \\ \text{with } v(T, x) = g(x), \end{cases}$$

Optimal feedback strategy effort in a high type society



Optimal feedback strategy for a couple in low type society



## Mean Field

Feeling level  $x(t)$  is modeled as a McKean-Vlasov Itô's SDE:

$$dx(t) = \left[ -\hat{h}(x(t), m(t)) + a\mathbf{e}(t) \right] dt + \sigma dW(t). \quad (6)$$

$$(\mathcal{P}_2) \begin{cases} \sup_{(\mathbf{e}(t))_t} P_{\text{field}}(x_0, m, \mathbf{e}), \\ \text{subject to the feeling state dynamics (6)}. \end{cases}$$

where

$$P_{\text{field}}(x_0, m, \mathbf{e}) = \mathbb{E} \left( g(x(T)) + \int_0^T [\hat{s}(x(t), m(t)) - c(\mathbf{e}(t))] dt \right).$$

## Mean-field equilibria

The mean-field equilibria are solution of the following backward-forward system for  $(t, x) \in [0, T] \times \mathbb{R}$  is

$$\left\{ \begin{array}{l} v_t - \hat{h}(x, m)v_x + \hat{s}(x, m) + \tilde{c}(av_x) + \frac{\sigma^2}{2}v_{xx} = 0, \\ m_t + \partial_x \left[ -m\hat{h} + am\tilde{c}'(av_x) \right] - \frac{\sigma^2}{2}m_{xx} = 0, \\ m(t=0, x) = m_0(x) \text{ for } x \in \mathbb{R}, \\ v(t=T, x) = v_T(x) = g(x) \text{ for } x \in \mathbb{R}. \end{array} \right. \quad (7)$$

### Result 1

The optimal level of effort for a long-term viability of the couple (during their lifetime) which keeps a happy relationship going is always greater than the effort level that would be chosen in a one-shot, i.e.,  $e^*(t, x) \geq \underline{e}$ , where  $c'(\underline{e}) = 0$ .

### Result 2

Even if  $x$  is below a certain threshold, Breaking Up is hard.

### Result 3

If the mean-field has a tendency to the divorce states then, there is a distributive phenomenon for divorce. Breaking Up is not seen as a negative thing in that society because the majority is Doing it Too.

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## Wiener Chaos Expansion

Wiener Chaos Space:

$$L^2(\mathbb{R}, \mu) = \left\{ f : \int_{\mathbb{R}} f^2(s) \mu(ds) < \infty \right\}$$

where  $\mu$  is the Gaussian measure

$$\mu(ds) = \rho(s) dx, \quad \rho(s) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{s^2}{2}\right).$$

- solution  $X \equiv X(t, m, dW(t))$
- $W(t)$  contains infinitely many independent Gaussian r.v.
- WCE decompose  $X(t, m, dW(t))$  by orthogonal polynomials

**Theorem (Cameron & Martin, 1947)**

Assume that the state process  $x(t)$  is in  $L^2([0, T] \times \Omega, \mathbb{R})$  and is functional of the Brownian motion  $\{W_s, 0 \leq s \leq t\}$ , then

$$x(t, \omega) = \sum_{|\beta| < \infty} x_\beta(t) T_\beta(\xi(\omega)), \quad (8)$$

where  $T_\beta$  are random Wick polynomials.

Hermite Polynomials

$$H_p(y) = y^p + \sum_{k=0}^{p-1} \alpha_{p,k} y^k$$



## Wiener Hermite Expansion

- $\{H_p\}_{p \geq 0}$  is a orthonormal basis of  $L^2(0, T)$
- $\xi_p = \int_{\mathbb{R}} H_p(s) dW(s)$  are independent Gaussian r.v. with
$$\mathbb{E}[\xi_p] = 0 \quad \text{and} \quad \text{Var}(\xi_p) = \|H_p\|_{L^2(0, T)}^2$$
- Let  $\xi = (\xi_1, \xi_2, \xi_3, \dots)$  and  $\beta = (\beta_1, \beta_2, \beta_3, \dots)$  such that  $|\beta| = \sum_{i \geq 1} \beta_i < \infty$

$$H_\beta(\xi) = \prod_{i=1}^{\infty} H_{\beta_i}(\xi_i)$$

then

$$x(t, dW) = \sum x_\beta(t) H_\beta(\xi) \quad x_\beta = \mathbb{E}[x(t, \xi) H_\beta(\xi)].$$

Moments:

$$\mathbb{E}[x](t, \xi) = x_0(t) \quad \mathbb{E}[x^2](t, \xi) = \sum_{\beta} |x_\beta|^2.$$

## Wiener Hermite Expansion

### Theorem

For each couple, given the type of the society, the best strategy:

$$\left\{ \begin{array}{l} \sup_{(\mathbf{e}_\beta(t))_t} \mathbb{E} \left( g(x(T)) + \int_0^T [\hat{S}(x(t), m^*(t)) - c(\mathbf{e}_\beta(t))] dt \right), \\ \text{subject to} \\ \dot{x}_\beta(t) = \left[ -\hat{h}(x(t), m(t)) + a\mathbf{e}_\beta(t) \right] dt + \sigma \sum_{k=1}^{\infty} \sqrt{\beta_k} H_k(t) H_{\hat{\beta}(t)}(t) \\ x_0(t) = x(0) \mathbb{1}_{\{\beta=0\}} \end{array} \right.$$

where

$$\hat{\beta}(i)(j) = \begin{cases} \beta_j & \text{if } i \neq j \\ \beta_j - 1 & \text{if } i = j \end{cases}$$

## Proof (Main Points)

- Multiply the dynamics

$$dx(t) = \left[ -\hat{h}(x(t), m(t)) + a\mathbf{e}(t) \right] dt + \sigma dW(t).$$

by  $H_\beta$  and take the expectation.

- Differentiate  $x_\beta$  using Mallavian derivative

$$dx_\beta = \sum_{k=1}^{\infty} \sqrt{\beta_k} H_k(s) H_{\hat{\beta}(t)} dW(s) \quad \text{for } \leq s \leq t.$$

- Expand the Brownian motion in Fourier series

$$W(s) = \sum_{i=1}^{\infty} \xi_i \int_0^s H_i(\tau) d\tau.$$

## References

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