

PDE Aspects of Mean Field Games

P. Cardaliaguet

(Paris-Dauphine)

(With the help of Yves Achdou (Paris-Diderot))

SIAM Conference
on Analysis of Partial Differential Equations
December 7-10, 2015 — Scottsdale, Arizona

Mean Field Games (MFG) study **collective behavior** of **rational agents**.

- **collective behavior** = infinitely many agents, having individually a negligible influence on the global system
- **rational agents** = each agent controls his state in order to minimize a cost which depends on the other agents' positions

Some references :

- Early work by Lasry-Lions (2006)
... and Caines-Huang-Malhamé (2006)
- Similar models in the economic literature :
heterogeneous agent models
(Aiyagari ('94), Bewley ('86),
Krusell-Smith ('98),...)



Amblematic equations

Two key equations :

- The MFG system (finite dimensional)
- The Master equation (infinite dimensional)

The MFG system :

$$(MFG) \quad \begin{cases} -\partial_t u - \nu \Delta u + H(x, Du, m) = 0 & \text{in } (0, T) \times \mathbb{R}^d \\ \partial_t m - \nu \Delta m - \operatorname{div}(m D_p H(x, Du, m)) = 0 & \text{in } (0, T) \times \mathbb{R}^d \\ u(T, x) = G(x, m(T)), \quad m(t_0, \cdot) = m_0 & \text{in } \mathbb{R}^d \end{cases}$$

where

- the unknown are $u = u(t, x)$ and $m = m(t, x)$ with $m(t, \cdot)$ a probability density for any $t \in [0, T]$,
- $H = H(x, p, m) : \mathbb{R}^d \times \mathbb{R}^d \times \mathcal{P}(\mathbb{R}^d) \rightarrow \mathbb{R}$ is a Hamiltonian (convex in p)
- $m_0 \in \mathcal{P}(\mathbb{R}^d)$ is the initial condition for m ,
- $G = G(x, m) : \mathbb{R}^d \times \mathcal{P}(\mathbb{R}^d) \rightarrow \mathbb{R}$ is a terminal condition for u
- $\nu \geq 0$ is a fixed volatility.

The Master equation :

$$\left\{ \begin{array}{l} -\partial_t U - (\nu + \beta) \Delta_x U + H(x, D_x U, m) \\ -(\nu + \beta) \int_{\mathbb{R}^d} \operatorname{div}_y [D_m U] \, dm(y) + \int_{\mathbb{R}^d} D_m U \cdot D_p H(y, D_x U, m) \, dm(y) \\ -2\beta \int_{\mathbb{R}^d} \operatorname{div}_x [D_m U] \, dm(y) - \beta \int_{\mathbb{R}^{2d}} \operatorname{Tr} [D_{mm}^2 U] \, dm \otimes dm = 0 \\ \text{in } [0, T] \times \mathbb{R}^d \times \mathcal{P}(\mathbb{R}^d) \\ U(T, x, m) = G(x, m) \quad \text{in } \mathbb{R}^d \times \mathcal{P}(\mathbb{R}^d) \end{array} \right.$$

where

- $\nu, \beta \geq 0$ are fixed parameters,
- the unknown is $U : [0, T] \times \mathbb{T}^d \times \mathcal{P}(\mathbb{R}^d) \rightarrow \mathbb{R}$,
- $\partial_t U$, $D_x U$ and $\Delta_x U$ stand for the usual derivatives with respect to the local variables (t, x) of U ,
- $D_m U$ and $D_{mm}^2 U$ are the first and second order derivatives with respect to the measure m ,
- H and G are the same as for the MFG system.

Aim of the talk

- Discuss the meaning and the well-posedness of the two equations.
- Show that the MFG system can be obtained as a “mean field limit”.
- Discuss the numerical approximation of MFG.

Missing parts : the talk **will not present** the stochastic aspects of MFG.

(Caines-Huang-Malhamé, Carmona-Delarue, Kolokoltsov, Bensoussan-Frehse-Yam,...)

- 1 Interpretation of the MFG system
- 2 The classical MFG system
 - The fixed-point approach
 - Variational aspects
- 3 The mean field limit and the master equation
 - The Master equation
 - Convergence of the Nash system
- 4 Numerical approximation and application to crowd motion
 - Numerical approximation of mean field games
 - Crowd Motion

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We discuss here the meaning of the MFG system :

$$(MFG) \quad \left\{ \begin{array}{l} (i) \quad -\partial_t u - \nu \Delta u + H(x, Du, m) = 0 \quad \text{in } (0, T) \times \mathbb{R}^d \\ (ii) \quad \partial_t m - \nu \Delta m - \operatorname{div}(m D_p H(x, Du, m)) = 0 \quad \text{in } (0, T) \times \mathbb{R}^d \\ (iii) \quad u(T, x) = G(x, m(T)), \quad m(t_0, \cdot) = m_0 \quad \text{in } \mathbb{R}^d \end{array} \right.$$

By fixed point argument : fix a family $(m = m(t))_{t \in [0, T]}$ of probability densities on \mathbb{R}^d .

An average agent controls the stochastic differential equation

$$dX_s = \alpha_s ds + \sqrt{2}\sigma dB_s, \quad X_t = x$$

where $\sigma := \sqrt{\nu}$, (α_s) is the control and (B_s) is a standard B.M. He aims at minimizing the cost

$$J(x, (\alpha_s), m) := \mathbb{E} \left[\int_t^T L(X_s, \alpha_s, m(s)) ds + G(X_T, m(T)) \right].$$

where $L(x, q, m) = \sup_{p \in \mathbb{R}^d} \{-\langle p, q \rangle - H(x, p, m)\}$.

His value function u is given by

$$u(t, x) = \inf_{(\alpha_s)} J(x, (\alpha_s), m).$$

Recall that u depends on $m!!!$

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$$u(t, x) = \inf_{(\alpha_s)} J(x, (\alpha_s), m).$$

Recall that u depends on $m!!!$

- The value function u then satisfies the Hamilton-Jacobi equation

$$\begin{cases} (i) & -\partial_t u - \nu \Delta u + H(x, Du, m) = 0 & \text{in } \mathbb{R}^d \times (0, T) \\ (iii) & u(x, T) = G(x, m(T)) & \text{in } \mathbb{R}^d \end{cases}$$

- The optimal control is given by

$$\alpha^*(t, x) = -D_p H(x, Du(t, x), m(t)) .$$

Proof by verification : If u solves (i) and (iii), we have by Itô's formula,

$$\begin{aligned} & \frac{d}{ds} \mathbf{E} \left[u(s, X_s) - \int_s^T L(X_\tau, \alpha_\tau, m(\tau)) d\tau \right] \\ &= \mathbf{E} [\partial_s u(s, X_s) + \langle Du, \alpha_s \rangle + \nu \Delta u + L(X_s, \alpha_s, m(s))] \\ &\geq \mathbf{E} [\partial_s u(s, X_s) + \nu \Delta u - H(X_s, Du, m(s))] = 0 \end{aligned}$$

with equality only for $\alpha = \alpha^*$.

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with equality only for $\alpha = \alpha^*$.

Integrating between 0 and T :

$$\mathbf{E} \left[u(T, X_T) - u(t, x) + \int_t^T L(X_\tau, \alpha_\tau, m(\tau)) d\tau \right] \geq 0$$

with equality for $\alpha = \alpha^$.*

By (iii), $u(T, X_T) = G(X_T, m(T))$, so that

$$u(t, x) \leq \mathbf{E} \left[\int_t^T L(X_\tau, \alpha_\tau, m(\tau)) d\tau + G(X_T, m(T)) \right]$$

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Therefore u is the value function.

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Therefore u is the value function.

To summarize : Given a family $(m(t))_{t \in [0, T]}$ of probability densities,

- the value function u of an average agent is the solution to the HJ eq

$$\begin{cases} (i) & -\partial_t u - \nu \Delta u + H(x, Du, m) = 0 & \text{in } \mathbb{R}^d \times (0, T) \\ (iii) & u(x, T) = G(x, m(T)) & \text{in } \mathbb{R}^d \end{cases}$$

- The optimal control is given by

$$\alpha^*(t, x) = -D_p H(x, Du(t, x), m(t)) .$$

- Therefore its optimal dynamics solves the SDE

$$dX_s = -D_p H(X_s, Du(t, X_s), m(s)) ds + \sqrt{2} \sigma dB_s, \quad X_t = x$$

- Assuming that the initial distribution of the players is the probability m_0 and that the Brownian Motions of the players are all independent, the actual distribution $(\tilde{m}(t))_{t \in [0, T]}$ of the players solves the Kolmogorov equation

$$\begin{cases} (ii) & \partial_t \tilde{m} - \nu \Delta \tilde{m} - \operatorname{div}(\tilde{m} D_p H(x, Du, m)) = 0 & \text{in } \mathbb{R}^d \times (0, T) \\ (iii) & \tilde{m}(0) = m_0 & \text{in } \mathbb{R}^d \end{cases}$$

A solution (u, m) of the MFG system is a fixed point of the map $m \rightarrow \tilde{m}$.

Comments :

- The MFG system describes a **Nash equilibrium configuration**.
—→ no agent has interest to deviate unilaterally.
- It relies on two key assumptions :
 - rationality of the agents
 - the agents are infinitesimal, indistinguishable with independent noises.



Validity of the MFG systems :

- Used in many areas :
 - Economic models (Heterogeneous agent, finance,...)
 - Engineering literature (wireless power control,...)
 - Crowd motion, vaccination strategies, etc...
- MFG models as limit of Nash equilibrium configuration for finitely many agents (C.-Delarue-Lasry-Lions)
- Learning procedures (C.-Hadikhanloo)

In terms of mathematical analysis :

- The forward-backward coupling is unusual and challenging in terms of PDE
- It is related to calculus of variation and optimal control of PDEs

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We now discuss the well-posedness of the MFG system :

$$(MFG) \quad \begin{cases} (i) & -\partial_t u - \nu \Delta u + H(x, Du, m) = 0 & \text{in } (0, T) \times \mathbb{R}^d \\ (ii) & \partial_t m - \nu \Delta m - \operatorname{div}(m D_p H(x, Du, m)) = 0 & \text{in } (0, T) \times \mathbb{R}^d \\ (iii) & u(T, x) = G(x, m(T)), m(t_0, \cdot) = m_0 & \text{in } \mathbb{R}^d \end{cases}$$

4 different regimes :

- Local/non local coupling,
 - either $(x, p) \rightarrow H(x, p, m)$ is "smooth" whatever $m \in \mathcal{P}(\mathbb{R}^d)$,
 - or $H(x, p, m) = H(x, p, m(x))$ where $m = m(x)dx$
- Uniformly parabolic/degenerate parabolic
Namely : either $\nu > 0$ or $\nu = 0$.

Here we study :

- 1 Nonlocal, uniformly parabolic regime
- 2 Nonlocal, first order regime
- 3 Local, first order regime (by variational methods)

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For simplicity, we work

- with periodic boundary conditions
i.e., in the torus $\mathbb{T}^d = \mathbb{R}^d / \mathbb{Z}^d$.
- and with separate Hamiltonian :

$$H(x, p, m) = H(x, p) - F(x, m)$$

Under these conditions, the MFG system becomes :

$$(MFG) \quad \begin{cases} (i) & -\partial_t u - \nu \Delta u + H(x, Du) = F(x, m(t)) & \text{in } (0, T) \times \mathbb{T}^d \\ (ii) & \partial_t m - \nu \Delta m - \operatorname{div}(m D_p H(x, Du)) = 0 & \text{in } (0, T) \times \mathbb{T}^d \\ (iii) & u(T, x) = G(x, m(T)), \quad m(t_0, \cdot) = m_0 & \text{in } \mathbb{T}^d \end{cases}$$

Nonlocal, uniformly parabolic regime

Existence : We assume that

- 1 $\nu > 0$,
- 2 F and G are Lipschitz continuous in $\mathbb{T}^d \times P(\mathbb{T}^d)$.
- 3 $F(\cdot, m)$ and $G(\cdot, m)$ are bounded in $C^{1+\beta}(\mathbb{T}^d)$ and $C^{2+\beta}(\mathbb{T}^d)$ (for some $\beta \in (0, 1)$) uniformly with respect to $m \in P(\mathbb{T}^d)$.
- 4 The Hamiltonian $H : \mathbb{T}^d \times \mathbb{R}^d \rightarrow \mathbb{R}$ is locally Lipschitz continuous, $D_p H$ exists and is continuous on $\mathbb{T}^d \times \mathbb{R}^d$, and H satisfies the growth condition

$$\langle D_x H(x, p), p \rangle \geq -C_0(1 + |p|^2)$$

for some constant $C_0 > 0$.

- 5 The probability measure m_0 is absolutely continuous with respect to the Lebesgue measure, has a $C^{2+\beta}$ continuous density.

Theorem (Lasry-Lions '06)

Under the above assumptions, there is at least one classical solution to the MFG system.

Proof : Let $m = (m(t)) \in C^{1/2}([0, T], \mathbb{P}(\mathbb{T}^d))$ with $m(0) = m_0$ and let u solve

$$\begin{cases} -\partial_t u - \nu \Delta u + H(x, Du) = F(x, m(t)) & \text{in } (0, T) \times \mathbb{T}^d \\ u(T, x) = G(x, m(T)), & \text{in } \mathbb{T}^d \end{cases}$$

Then $u \in C^{1+\alpha/2, 2+\alpha}$ with bounded norm.

Let now \tilde{m} be the solution to

$$\begin{cases} \partial_t \tilde{m} - \nu \Delta \tilde{m} - \operatorname{div}(\tilde{m} D_p H(x, Du)) = 0 & \text{in } (0, T) \times \mathbb{T}^d \\ \tilde{m}(t_0, \cdot) = m_0 & \text{in } \mathbb{T}^d \end{cases}$$

Then $\tilde{m} \in C^{1+\alpha/2, 2+\alpha} \cap C^{1/2}([0, T], \mathbb{P}(\mathbb{T}^d))$ with bounded norm.

Conclusion by Schauder fixed point Theorem. □

Uniqueness : Assume in addition that

- Either $T > 0$ is "small"
- Or $H = H(x, p)$ is uniformly convex in p and F and G are **monotone** :

$$\int_{\mathbb{T}^d} (F(x, m) - F(x, m'))(m - m') \geq 0, \quad \int_{\mathbb{T}^d} (G(x, m) - G(x, m'))d(m - m') \geq 0,$$

for any $m, m' \in \mathcal{P}(\mathbb{T}^d)$.

Theorem (Lasry-Lions '06)

Under the above assumptions, the solution to (MFG) is unique.

Typical example : $F(m) = (\rho \star m) \star \rho$, where ρ is smooth and symmetric.

Then

$$\int_{\mathbb{T}^d} (F(m) - F(m'))(m - m') = \int_{\mathbb{T}^d} (\rho \star (m - m'))^2 \geq 0$$

Proof : Let (u_1, m_1) and (u_2, m_2) be two solutions. Set $\bar{u} = u_1 - u_2$ and $\bar{m} = m_1 - m_2$. Then

$$\begin{aligned} \frac{d}{dt} \int_{\mathbb{T}^d} \bar{u} \bar{m} &= \int_{\mathbb{T}^d} (\partial_t \bar{u}) \bar{m} + \bar{u} (\partial_t \bar{m}) \\ &= \int_{\mathbb{T}^d} (-\Delta \bar{u} + H(x, Du_1) - H(x, Du_2) - F(x, m_1) + F(x, m_2)) \bar{m} \\ &\quad + \bar{u} (\Delta \bar{m} + \operatorname{div}(m_1 D_\rho H(x, Du_1)) - \operatorname{div}(m_2 D_\rho H(x, Du_2))) \end{aligned}$$

Note that

$$\int_{\mathbb{T}^d} -(\Delta \bar{u}) \bar{m} + \bar{u} (\Delta \bar{m}) = 0$$

and, from the monotonicity condition on F ,

$$\int_{\mathbb{T}^d} (-F(x, m_1) + F(x, m_2)) \bar{m} = \int_{\mathbb{T}^d} (-F(x, m_1) + F(x, m_2))(m_1 - m_2) \leq 0.$$

Integrating by parts the terms in H :

$$\begin{aligned} &\int_{\mathbb{T}^d} (H(x, Du_1) - H(x, Du_2)) \bar{m} - \langle D\bar{u}, m_1 D_\rho H(x, Du_1) - m_2 D_\rho H(x, Du_2) \rangle \\ &= - \int_{\mathbb{T}^d} m_1 (H(x, Du_2) - H(x, Du_1) - \langle D_\rho H(x, Du_1), Du_2 - Du_1 \rangle) \\ &\quad - \int_{\mathbb{T}^d} m_2 (H(x, Du_1) - H(x, Du_2) - \langle D_\rho H(x, Du_2), Du_1 - Du_2 \rangle) \end{aligned}$$

The uniform convexity of H then implies :

$$\begin{aligned} & \int_{\mathbb{T}^d} (H(x, Du_1) - H(x, Du_2)) \bar{m} - \langle D\bar{u}, m_1 D_p H(x, Du_1) - m_2 D_p H(x, Du_2) \rangle \\ & \leq - \int_{\mathbb{T}^d} \frac{(m_1 + m_2)}{2C} |Du_1 - Du_2|^2 \end{aligned}$$

Putting the estimates together we get

$$\frac{d}{dt} \int_{\mathbb{T}^d} \bar{u} \bar{m} \leq - \int_{\mathbb{T}^d} \frac{(m_1 + m_2)}{2C} |Du_1 - Du_2|^2.$$

Integrating on $[0, T]$ and rearranging :

$$\int_0^T \int_{\mathbb{T}^d} \frac{(m_1 + m_2)}{2C} |Du_1 - Du_2|^2 \leq - \int_{\mathbb{T}^d} \bar{u}(T) \bar{m}(T) + \int_{\mathbb{T}^d} \bar{u}(0) \bar{m}(0) \leq 0$$

because $\bar{m}(0) = m_1(0) - m_2(0) = m_0 - m_0 = 0$ and

$$\int_{\mathbb{T}^d} \bar{u}(T) \bar{m}(T) = \int_{\mathbb{T}^d} (G(x, m_1(T)) - G(x, m_2(T)))(m_1(T) - m_2(T)) \geq 0.$$

Therefore $Du_1 = Du_2$ in $\{m_1 > 0\} \cup \{m_2 > 0\}$: m_1 and m_2 solve the Kolmogorov equation, so that $m_1 = m_2$. Then, in turn, u_1 and u_2 solve the same HJ equation, and $u_1 = u_2$. □

Nonlocal, first order regime

We now consider the first order MFG system

$$(MFG) \quad \begin{cases} (i) & -\partial_t u + H(x, Du) = F(x, m(t)) & \text{in } (0, T) \times \mathbb{R}^d \\ (ii) & \partial_t m - \operatorname{div}(m D_p H(x, Du)) = 0 & \text{in } (0, T) \times \mathbb{R}^d \\ (iii) & u(T, x) = G(x, m(T)), \quad m(t_0, \cdot) = m_0 & \text{in } \mathbb{R}^d \end{cases}$$

Assumptions : Same as before, except we also assume that $H : \mathbb{T}^d \times \mathbb{R}^d \rightarrow \mathbb{R}$ is **uniformly convex in p** .

Theorem (Lasry-Lions '06)

Under the above assumptions, there is at least one solution (u, m) to the MFG system, where

- u is Lipschitz continuous and satisfies the HJ in the viscosity sense,
- $m \in L^\infty$ and satisfies the Kolmogorov equation in the sense of distribution.

If, moreover, F and G are monotone, then the solution is unique.

Proof : By viscous approximation : for $\varepsilon > 0$, let $(u^\varepsilon, m^\varepsilon)$ be the solution to

$$\left\{ \begin{array}{ll} (i) & -\partial_t u^\varepsilon - \varepsilon \Delta u^\varepsilon + H(x, Du^\varepsilon) = F(x, m^\varepsilon(t)) \quad \text{in } (0, T) \times \mathbb{R}^d \\ (ii) & \partial_t m^\varepsilon - \varepsilon \Delta m^\varepsilon - \operatorname{div} (m^\varepsilon D_\rho H(x, Du^\varepsilon)) = 0 \quad \text{in } (0, T) \times \mathbb{R}^d \\ (iii) & u^\varepsilon(T, x) = G(x, m(T)), \quad m^\varepsilon(t_0, \cdot) = m_0 \quad \text{in } \mathbb{R}^d \end{array} \right.$$

Then

- (u^ε) is uniformly Lipschitz continuous and uniformly semi-concave :

$$\|u^\varepsilon\|_\infty + \|\partial_t u^\varepsilon\|_\infty + \|Du^\varepsilon\|_\infty + D^2 u^\varepsilon \leq C$$

In particular, (Du^ε) is pre-compact in L^1 .

- Because of the semi-concavity estimate, (m^ε) is uniformly bounded in L^∞ .

Then any limit of the $(u^\varepsilon, m^\varepsilon)$ as $\varepsilon \rightarrow 0$ is a solution of the MFG system.

Uniqueness relies on Di Perna-Lions/Ambrosio theory on ODEs with discontinuous coefficients.

□

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The first order MFG system with local coupling

We now concentrate on the **first order Mean Field Game system** :

$$(MFG) \quad \begin{cases} (i) & -\partial_t u + H(x, Du) = F(x, m(t, x)) \\ & \text{in } (0, T) \times \mathbb{T}^d \\ (ii) & \partial_t m - \operatorname{div}(m D_p H(x, Du)) = 0 \\ & \text{in } (0, T) \times \mathbb{T}^d \\ (iii) & m(0, x) = m_0(x), \quad u(T, x) = u_T(x) \end{cases} \quad \text{in } \mathbb{T}^d$$

where

- $H = H(x, p)$ is convex in p , periodic in x ,
- $F = F(x, m)$ is a **local coupling**, increasing in m , periodic in x
- $u_T = u_T(x)$ is a periodic terminal cost,
- m_0 is a probability density on \mathbb{T}^d .

Specific difficulty : The fixed point argument **does not work**.

Two approaches :

- Reduction to a **quasi-linear equation** \rightsquigarrow smooth solutions for some smooth data (Lasry-Lions)

Principle : by (i),

$$m(t, x) = F^{-1}(x, -\partial_t u + H(x, Du)).$$

Replace m by u in (ii) : the equation

$$\partial_t \left(F^{-1}(x, -\partial_t u + H(x, Du)) \right) - \operatorname{div} \left(F^{-1}(x, -\partial_t u + H(x, Du)) D_p H(x, Du) \right) = 0$$

is a (singular) elliptic equation in time-space.

- MFG system as necessary conditions for two **convex optimal control problems** in duality
 - for the Hamilton-Jacobi equations
 - and for the continuity equations

—→ **Reminiscent of optimal transport** and Benamou-Brenier formulation of the Wasserstein distance.

Set :

$$\mathcal{F}(x, m) = \begin{cases} \int_1^m F(x, m') dm' & \text{if } m \geq 0 \\ +\infty & \text{otherwise} \end{cases}$$

$$\mathcal{F}^*(x, a) = \sup_{m \in \mathbb{R}} (am - \mathcal{F}(x, m)) \text{ and } H^*(x, v) = \sup_{p \in \mathbb{R}^d} p \cdot v - H(x, p).$$

- The optimal control of continuity equation.

$$(\mathbf{K} - \mathbf{Pb}) \quad \inf_{(m, w)} \left\{ \int_0^T \int_{\mathbb{T}^d} m H^*(x, -v) + \mathcal{F}(x, m) \, dx dt + \int_{\mathbb{T}^d} u_T(x) m(T, x) \, dx \right\}$$

where the infimum is taken over the pairs (m, v) such that

$$\partial_t m + \operatorname{div}(mv) = 0 \text{ in } (0, T) \times \mathbb{T}^d, \quad m(0) = m_0 \quad \text{in } \mathbb{T}^d$$

in the sense of distributions.

- The optimal control of HJ equation

$$(\mathbf{HJ} - \mathbf{Pb}) \quad \inf_{\alpha} \left\{ \int_0^T \int_{\mathbb{T}^d} \mathcal{F}^*(x, \alpha(t, x)) \, dx dt - \int_{\mathbb{T}^d} u(0, x) m_0(x) \, dx \right\}$$

where u is the solution to the HJ equation

$$-\partial_t u + H(x, Du) = \alpha \text{ in } (0, T) \times \mathbb{T}^d, \quad u(T, \cdot) = u_T \quad \text{in } \mathbb{T}^d.$$

Results :

- Both problems are in duality and have the MFG system as optimality condition.

For instance, if (u, α) is optimal for $(\mathbf{HJ} - \mathbf{Pb})$, then (u, m) solves MFG with $m := F^{-1}(x, \alpha)$.

- Existence of minimizers for both problems yields weak solutions of the MFG system. (C., Graber, C.-Graber, C.-Graber-Porretta-Tonon, C.-Porretta-Tonon).

—→ Difficulty : the optimal control of HJ eq. is very singular.

Relies on new estimates on HJ eq. with discontinuous RHS.

(C. ('09), Cannarsa-C. ('10), C.-Rainer ('11), C.-Silvestre ('12), C.-Porretta-Tonon ('14))

- Useful for numerical computations.
Works also for some non-local or second order MFG systems.

Conclusion on the MFG system

Well-understood :

- Existence/uniqueness of solutions in the 4 regimes
- The solution can often be obtained by variational methods
- Many extensions :
 - Fully non-linear equations,
 - Other boundary conditions,
 - Multi-population problems, etc...
- Few explicit solutions (Linear-quadratic MFG)
- Long time behavior (convergence to the ergodic MFG system)

Several open questions :

- Uniqueness issues (is the monotonicity condition necessary ?)
- Existence of classical solution in the local regime poorly understood (Gomes and al. ; Weak solutions : Lasry-Lions and Porretta)
- Degenerate equations and state-constraints
- Existence in the congestion setting

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MFG systems pretty well-understood, but do not answer two key points :

- MFG with **common noise** or **with a major agent**
- **Mean field limit** : Convergence of Nash equilibria of N -player differential games as $N \rightarrow +\infty$.
Derive the macroscopic model (=MFG system) from the microscopic one (= N -player differential game).

These two different issues can be understood through the **master equation**.

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- Because of the symmetry, the $v^{N,i}$ can be written as

$$v^{N,i}(t, \mathbf{x}) = U^N(t, x_i, m_{\mathbf{x}}^{N,i}), \quad \text{where } m_{\mathbf{x}}^{N,i} := \frac{1}{N-1} \sum_{j \neq i} \delta_{x_j}.$$

- Following Lasry-Lions, the expected limit U of the (U^N) should formally satisfy [the master equation](#).

$$\left\{ \begin{array}{l} -\partial_t U - (1 + \beta) \Delta_x U + H(x, D_x U) \\ - (1 + \beta) \int_{\mathbb{R}^d} \operatorname{div}_y [D_m U] dm(y) + \int_{\mathbb{R}^d} D_m U \cdot D_p H(y, D_x U) dm(y) \\ - 2\beta \int_{\mathbb{R}^d} \operatorname{div}_x [D_m U] dm(y) - \beta \int_{\mathbb{R}^{2d}} \operatorname{Tr} [D_{mm}^2 U] dm \otimes dm = F(x, m) \\ \text{in } [0, T] \times \mathbb{R}^d \times \mathcal{P}(\mathbb{R}^d) \\ U(T, x, m) = G(x, m) \quad \text{in } \mathbb{R}^d \times \mathcal{P}(\mathbb{R}^d) \end{array} \right.$$

where

- the unknown is $U : [0, T] \times \mathbb{T}^d \times \mathcal{P}(\mathbb{T}^d) \rightarrow \mathbb{R}$,
- $\partial_t U$, $D_x U$ and $\Delta_x U$ stand for the usual derivatives with respect to the local variables (t, x) of U ,
- $D_m U$ and $D_{mm}^2 U$ are the first and second order derivatives with respect to the measure m .

Derivatives in the space of measures

We denote by $\mathcal{P}(\mathbb{T}^d)$ the set of Borel probability measures on \mathbb{T}^d , endowed for the Monge-Kantorovich distance

$$\mathbf{d}_1(m, m') = \sup_{\phi} \int_{\mathbb{T}^d} \phi(y) d(m - m')(y),$$

where the supremum is taken over all Lipschitz continuous maps $\phi : \mathbb{T}^d \rightarrow \mathbb{R}$ with a Lipschitz constant bounded by 1.

2 notions of derivatives :

- The directional derivative $\frac{\delta U}{\delta m}(m, y)$
(see, e.g., Mischler-Mouhot)
- The intrinsic derivative $D_m U(m, y)$
(see, e.g., Otto, Ambrosio-Gigli-Savaré, Lions)

Directional derivative

A map $U : \mathcal{P}(\mathbb{T}^d) \rightarrow \mathbb{R}$ is \mathcal{C}^1 if there exists a continuous map $\frac{\delta U}{\delta m} : \mathcal{P}(\mathbb{T}^d) \times \mathbb{T}^d \rightarrow \mathbb{R}$ such that, for any $m, m' \in \mathcal{P}(\mathbb{T}^d)$,

$$\lim_{s \rightarrow 0^+} \frac{U((1-s)m + sm') - U(m)}{s} = \int_{\mathbb{T}^d} \frac{\delta U}{\delta m}(m, y) d(m' - m)(y).$$

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A computation : Let $\phi : \mathbb{T}^d \rightarrow \mathbb{R}^d$ be a Borel measurable and bounded **vector field**. Then

$$\begin{aligned} h^{-1} (U((id + h\phi)\#m) - U(m)) &\simeq h^{-1} \int_{\mathbb{T}^d} \frac{\delta U}{\delta m}(m, y) d((id + h\phi)\#m - m)(y) \\ &\simeq h^{-1} \int_{\mathbb{T}^d} \left(\frac{\delta U}{\delta m}(m, y + h\phi(y)) - \frac{\delta U}{\delta m}(m, y) \right) dm(y) \\ &\simeq \int_{\mathbb{T}^d} D_y \frac{\delta U}{\delta m}(m, y) \cdot \phi(y) dm(y). \end{aligned}$$

This yields to the definition :

Intrinsic derivative

If $\frac{\delta U}{\delta m}$ is of class \mathcal{C}^1 with respect to the second variable, **the intrinsic derivative**
 $D_m U : \mathcal{P}(\mathbb{T}^d) \times \mathbb{T}^d \rightarrow \mathbb{R}^d$ is defined by

$$D_m U(m, y) := D_y \frac{\delta U}{\delta m}(m, y)$$

For instance, if $U(m) = \int_{\mathbb{T}^d} g(x) dm(x)$, then $\frac{\delta U}{\delta m}(m, y) = g(y) - \int_{\mathbb{T}^d} g dm$ while
 $D_m U(m, y) = Dg(y)$.

Second order derivatives are defined in a similar way.

Well-posedness of the master equation

The master equation is the backward equation

$$\left\{ \begin{array}{l} -\partial_t U - (1 + \beta) \Delta_x U + H(x, D_x U) \\ - (1 + \beta) \int_{\mathbb{R}^d} \operatorname{div}_y [D_m U] \, dm(y) + \int_{\mathbb{R}^d} D_m U \cdot D_p H(y, D_x U) \, dm(y) \\ - 2\beta \int_{\mathbb{R}^d} \operatorname{div}_x [D_m U] \, dm(y) - \beta \int_{\mathbb{R}^{2d}} \operatorname{Tr} [D_{mm}^2 U] \, dm \otimes dm = F(x, m) \\ \text{in } [0, T] \times \mathbb{R}^d \times \mathcal{P}(\mathbb{R}^d) \\ U(T, x, m) = G(x, m(T)) \quad \text{in } \mathbb{R}^d \times \mathcal{P}(\mathbb{R}^d) \end{array} \right.$$

Theorem (C.-Delarue-Lasry-Lions, '15)

Under our standing assumptions, the master equation **(M)** has a unique classical solution.

Previous results : Lions ('13), Buckdahn-Li-Peng-Rainer ('14), Gangbo-Swiech ('14), Chassagneux-Crisan-Delarue ('15), Bessi ('15).

Relies on the key idea that the master equation is a nonlinear transport equation in the space of measure.

Idea of proof ($\beta = 0$)

- When $\beta = 0$, the master equation becomes

$$\begin{cases} -\partial_t U - \Delta_x U + H(x, D_x U) - F(x, m) \\ \quad - \int_{\mathbb{R}^d} \operatorname{div}_y [D_m U] dm(y) + \int_{\mathbb{R}^d} D_m U \cdot D_p H(y, D_x U) dm(y) = 0 \\ \quad \text{in } [0, T] \times \mathbb{R}^d \times \mathcal{P}(\mathbb{R}^d) \\ U(T, x, m) = G(x, m) \quad \text{in } \mathbb{R}^d \times \mathcal{P}(\mathbb{R}^d) \end{cases}$$

- The proof relies on [the method of characteristics](#) in infinite dimension.
- Given $(t_0, m_0) \in [0, T] \times \mathcal{P}(\mathbb{T}^d)$, let $(u, m) = (u(t, x), m(t, x))$ be the solution of the [MFG system](#) :

$$(MFG) \quad \begin{cases} -\partial_t u - \Delta u + H(x, Du) = F(x, m(t)) \\ \partial_t m - \Delta m - \operatorname{div}(m D_p H(x, Du)) = 0 \\ u(T, x) = G(x, m(T)), \quad m(t_0, \cdot) = m_0 \end{cases}$$

- Under our monotonicity assumptions on F and G , the (MFG) system is well-posed. (Lasry-Lions, 2007)
- We *define* U by

$$U(t_0, \cdot, m_0) := u(t_0, \cdot)$$

Then *formally* U solves the master equation.

- Note that, for any $h \in [0, T - t_0]$,

$$u(t_0 + h, \cdot) = U(t_0 + h, \cdot, m(t_0 + h)).$$

- So

$$\begin{aligned} \partial_t u(t_0, x) &= \partial_t U(t_0, x, m_0) + \int_{\mathbb{T}^d} \frac{\delta U}{\delta m}(t_0, x, m_0, y) \partial_t m(t_0, y) dy \\ &= \partial_t U(t_0, \cdot, m_0) + \int_{\mathbb{T}^d} \frac{\delta U}{\delta m}(m_0, y) (\Delta m + \operatorname{div}(m D_p H(x, Du))) dy \\ &= \partial_t U(t_0, \cdot, m_0) + \int_{\mathbb{T}^d} \Delta_y \left[\frac{\delta U}{\delta m} \right] (m_0, y) m_0(y) dy \\ &\quad - \int_{\mathbb{T}^d} D_y \left[\frac{\delta U}{\delta m} \right] (m_0, y) \cdot D_p H(x, Du) m_0(y) dy \\ &= \partial_t U(t_0, \cdot, m_0) + \int_{\mathbb{T}^d} \operatorname{div}_y [D_m U] (m_0, y) m_0(y) dy \\ &\quad - \int_{\mathbb{T}^d} D_m U(m_0, y) \cdot D_p H(x, Du) m_0(y) dy \end{aligned}$$

- As

$$\begin{aligned} \partial_t u(t_0, x) &= -\Delta u + H(x, Du) - F(x, m_0) \\ &= -\Delta_x U(t_0, x, m_0) + H(x, D_x U(t_0, x, m_0)) - F(x, m_0), \end{aligned}$$

the map U satisfies **(M)**.

Main difficulty :

- Show that U defined by

$$U(t_0, \cdot, m_0) := u(t_0, \cdot)$$

is smooth enough to perform the computation.

- This is obtained by linearization procedure (to compute the directional derivative).
- Requires to keep track of the monotonicity condition.

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Convergence of the Nash system

We come back to the solution $(v^{N,i})$ of the N -player Nash system :

$$(Nash) \quad \begin{cases} -\partial_t v^{N,i} - \sum_j \Delta_{x_j} v^{N,i} - \beta \sum_{j,k} \text{Tr} D_{x_j, x_k}^2 v^{N,i} + H(x_i, D_{x_i} v^{N,i}) \\ \quad + \sum_{j \neq i} D_p H(x_j, D_{x_j} v^{N,j}) \cdot D_{x_j} v^{N,i} = F(x_i, m_{\mathbf{x}}^{N,i}) & \text{in } [0, T] \times \mathbb{T}^{Nd} \\ v^{N,i}(T, \mathbf{x}) = G(x_i, m_{\mathbf{x}}^{N,i}) & \text{in } \mathbb{T}^{Nd} \end{cases}$$

where we have set, for $\mathbf{x} = (x_1, \dots, x_N) \in (\mathbb{T}^d)^N$, $m_{\mathbf{x}}^{N,i} = \frac{1}{N-1} \sum_{j \neq i} \delta_{x_j}$.

Theorem (C.-Delarue-Lasry-Lions, '15)

Let $(v^{N,i})$ be the solution to the Nash system and U be the classical solution to the master equation (\mathbf{M}) . Fix $N \geq 1$ and $(t_0, m_0) \in [0, T] \times \mathcal{P}(\mathbb{T}^d)$.

(i) For any $\mathbf{x} \in (\mathbb{T}^d)^N$, let $m_{\mathbf{x}}^N := \frac{1}{N} \sum_{i=1}^N \delta_{x_i}$. Then

$$\frac{1}{N} \sum_{i=1}^N \left| v^{N,i}(t_0, \mathbf{x}) - U(t_0, x_i, m_{\mathbf{x}}^N) \right| \leq CN^{-1}.$$

(ii) For any $i \in \{1, \dots, N\}$ and $x \in \mathbb{T}^d$, let us set

$$w^{N,i}(t_0, x_i, m_0) := \int_{(\mathbb{T}^d)^{N-1}} v^{N,i}(t_0, \mathbf{x}) \prod_{j \neq i} m_0(dx_j) \quad \text{where } \mathbf{x} = (x_1, \dots, x_N).$$

Then

$$\left\| w^{N,i}(t_0, \cdot, m_0) - U(t_0, \cdot, m_0) \right\|_{L^1(m_0)} \leq \begin{cases} CN^{-1/d} & \text{if } d \geq 3 \\ CN^{-1/2} \log(N) & \text{if } d = 2 \end{cases}$$

In (i) and (ii), the constant C does not depend on i , t_0 , m_0 , i nor N .

Conclusion on the mean field problem and the master equation

- Well-posedness of the master equation : understood under the monotonicity condition ensuring its continuity.

However, the analysis of discontinuous solutions remains very challenging ...even in its finite dimensional version :

$$\frac{\partial U}{\partial t} + (F(U) \cdot \nabla) U = 0$$

- Field limit : proved in a weak sense and under strong monotonicity assumption on the system.

However

- we do not know if a stronger convergence can be expected,
- the problem is completely open without monotonicity condition.

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Slides and numerical simulations by Y. Achdou

(Thanks a lot, Yves !)

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Numerical methods :

- Used extensively by economists as early as Krussel-Smith ('98)
- For the MFG system :
 - Finite difference schemes
Achdou-Camilli-Capuzzo Dolcetta ('12, '13), Camilli-Silva ('12),...
 - Variational techniques (augmented Lagrangian methods (ALG2))
Benamou-Carlier ('14), ...
- Very little is known for the stochastic MFG system (common noise)
... and even less for the master equation.

Finite Differences

Take $d = 1$.

$$\left\{ \begin{array}{ll} \frac{\partial u}{\partial t} + \nu \Delta u - H(x, \nabla u) = -\Phi[m] & \text{in } [0, T] \times \mathbb{T} \\ \frac{\partial m}{\partial t} - \nu \Delta m - \operatorname{div} \left(m \frac{\partial H}{\partial p}(x, \nabla u) \right) = 0 & \text{in } (0, T] \times \mathbb{T} \\ u(t = T) = \Phi_0[m(t = T)] \\ m(t = 0) = m_0 \end{array} \right. \quad (*)$$

- Let \mathbb{T}_h be a uniform grid on the torus with mesh step h , and x_i be a generic point in \mathbb{T}_h
- Uniform time grid : $\Delta t = T/N_T$, $t_n = n\Delta t$
- The values of u and m at (x_i, t_n) are approximated by u_i^n and m_i^n

Notation

- The discrete Laplace operator :

$$(\Delta_h w)_i = \frac{1}{h^2}(w_{i+1} - 2w_i + w_{i-1})$$

- Right and left sided finite difference formula for $\frac{\partial w}{\partial x}(x_i)$

$$\frac{\partial w}{\partial x}(x_i) \approx \frac{w_{i+1} - w_i}{h}, \quad \frac{\partial w}{\partial x}(x_i) \approx \frac{w_i - w_{i-1}}{h}$$

- The collection of the 2 first order finite difference formulas at x_i

$$[D_h w]_i = \left\{ \frac{w_{i+1} - w_i}{h}, \frac{w_i - w_{i-1}}{h} \right\} \in \mathbb{R}^2$$

For the Bellman equation, a semi-implicit monotone scheme

$$\frac{\partial u}{\partial t} + \nu \Delta u - H(x, \nabla u) = -\Phi[m]$$

$$\downarrow$$

$$\frac{u_i^{n+1} - u_i^n}{\Delta t} + \nu(\Delta_h u^n)_i - g(x_i, [D_h u^n]_i) = -\left(\Phi_h[m^{n+1}]\right)_i$$

where $[D_h u]_i \in \mathbb{R}^2$ is the collection of the two first order finite difference formulas at x_i for $\partial_x u$.

$$g(x_i, [D_h u^n]_i) = g\left(x_i, \frac{u_{i+1}^n - u_i^n}{h}, \frac{u_i^n - u_{i-1}^n}{h}\right)$$

Assumptions on the discrete Hamiltonian $g : (q_1, q_2) \rightarrow g(x, q_1, q_2)$.

- **Monotonicity :**

- g is nonincreasing with respect to q_1
- g is nondecreasing with respect to q_2

- **Consistency :**

$$g(x, q, q) = H(x, q), \quad \forall x \in \mathbb{T}, \forall q \in \mathbb{R}$$

- **Differentiability :** g is of class C^1

- **Convexity (for uniqueness and stability) :**

$$(q_1, q_2) \rightarrow g(x, q_1, q_2) \text{ is convex}$$

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The approximation of the Fokker-Planck equation

$$\frac{\partial m}{\partial t} - \nu \Delta m - \operatorname{div} \left(m \frac{\partial H}{\partial p}(x, \nabla v) \right) = 0. \quad (\dagger)$$

It is chosen so that

- each time step leads to a linear system for m with a matrix
 - whose diagonal coefficients are positive
 - whose off-diagonal coefficients are nonpositive
 in order to hopefully get a **discrete maximum principle**
- The argument for uniqueness should hold in the discrete case, so **the discrete Hamiltonian g should be used for (\dagger) as well**

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Principle

Discretize
$$-\int_{\mathbb{T}} \operatorname{div} \left(m \frac{\partial H}{\partial p}(x, \nabla u) \right) w = \int_{\mathbb{T}} m \frac{\partial H}{\partial p}(x, \nabla u) \cdot \nabla w$$

by
$$-h \sum_{i,j} \mathcal{T}_i(u, m) w_j \equiv h \sum_i m_i \nabla_q g(x_i, [D_h u]_i) \cdot [D_h w]_i$$

Discrete version of $\operatorname{div}(m H_p(x, \nabla u))$:

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Discretize
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Semi-implicit scheme

$$\begin{cases} \frac{u_i^{n+1} - u_i^n}{\Delta t} + \nu(\Delta_h u^n)_i - g(x_i, [D_h u^n]_i) = -(\Phi_h[m^n])_i \\ \frac{m_i^{n+1} - m_i^n}{\Delta t} - \nu(\Delta_h m^{n+1})_i - \mathcal{T}_i(u^n, m^{n+1}) = 0 \end{cases}$$

The operator $m \mapsto -\nu(\Delta_h m)_i - \mathcal{T}_i(u, m)$ is the adjoint of the linearized version of $u \mapsto -\nu(\Delta_h u)_i + g(x_i, [D_h u]_i)$.

The discrete MFG system has the same structure as the continuous one.

Semi-implicit scheme

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Well known discrete Hamiltonians g can be chosen.

For example, if the Hamiltonian is of the form $H(x, \nabla u) = \psi(x, |\nabla u|)$, a possible choice is the **upwind scheme** :

$$g(x, q_1, q_2) = \psi \left(x, \sqrt{(q_1^-)^2 + (q_2^+)^2} \right).$$

Theoretical results on the finite difference scheme

- Existence and a priori bounds (Lipschitz estimate if Φ is a smoothing operator)
- Uniqueness
- Convergence as $\Delta t, h \rightarrow 0$
- Solvers (a crucial issue)

Some references :

- Achdou and Capuzzo-Dolcetta ('10)
- Camilli-Silva ('14) : first order MFG.
- Achdou-Porretta ('15) : convergence in the local case.

Outline

- 1 Interpretation of the MFG system
- 2 The classical MFG system
 - The fixed-point approach
 - Variational aspects
- 3 The mean field limit and the master equation
 - The Master equation
 - Convergence of the Nash system
- 4 Numerical approximation and application to crowd motion
 - Numerical approximation of mean field games
 - **Crowd Motion**



Main Purpose

- Many models for crowd motion are inspired by statistical mechanics
- microscopic models : pedestrians = particles with more or less complex interactions (e.g. B. Maury et al)
- macroscopic models were recently proposed by T. Hughes et al
- in all these models, rational anticipation is not taken into account
- mean field games may lead to crowd motion models including rational anticipation

A Model for Congestion

$$\begin{aligned}
 -\frac{\partial u}{\partial t} - \nu \Delta u + H(x, Du, m) &= F(m) && \text{in } (0, T) \times \Omega \\
 \frac{\partial m}{\partial t} - \nu \Delta m - \operatorname{div} \left(m \frac{\partial H}{\partial p}(\cdot, Du, m) \right) &= 0 && \text{in } (0, T) \times \Omega \\
 \frac{\partial u}{\partial n} = \nu \frac{\partial m}{\partial n} + m \frac{\partial H}{\partial p}(\cdot, Du, m) \cdot n &= 0 && \text{on walls} \\
 u = k \quad m = 0 &&& \text{at exits}
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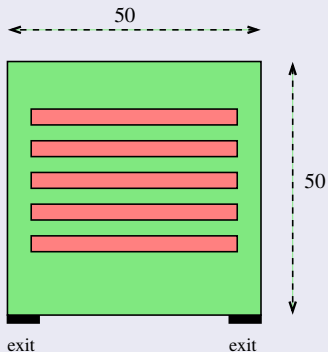
Congestion

$$H(x, p, m) = \mathcal{H}(x) + \frac{|p|^\beta}{(c_0 + c_1 m)^\alpha}$$

with $c_0 > 0$, $c_1 \geq 0$, $\beta > 1$ and $0 \leq \alpha < 4(\beta - 1)/\beta$

A Prototypical Case : Exit from a Hall with Obstacles

The geometry



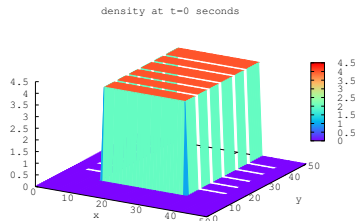
The Data

- The initial density m_0 is piecewise constant and takes two values 0 and 4 people/m². There are 3300 people in the hall.

- $\nu = 0.012$

- $H(x, p, m) = \frac{8}{(1+m)^{\frac{3}{4}}} |p|^2 - \frac{1}{3200}$

- $F(m) \sim 0$



which leads to the following HJB equation

$$-\frac{\partial u}{\partial t} - \frac{6}{500} \Delta u + \frac{8}{(1+m)^{\frac{3}{4}}} |Du|^2 = \frac{1}{3200}$$

The Results

The horizon is $T = 40$ min. The two doors stay open from $t = 0$ to $t = T$.

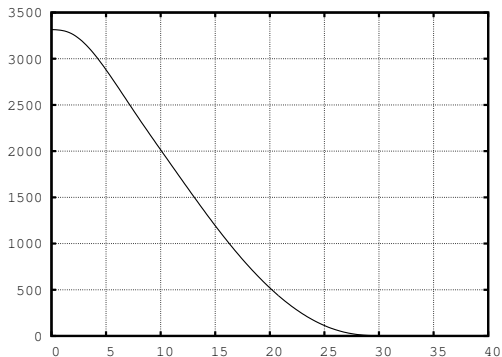
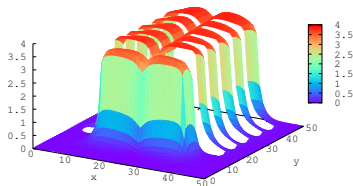
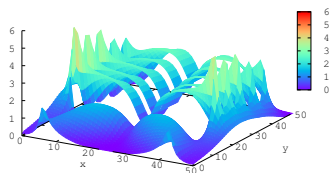
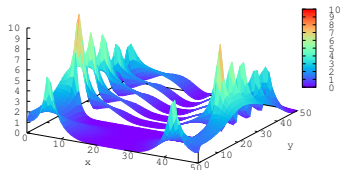
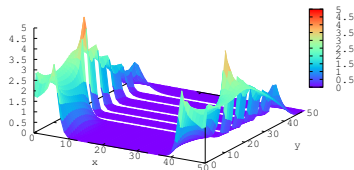


FIGURE: The number of people in the room vs. time

(Loading m2doors.mov)

FIGURE: The evolution of the density

Evolution of the Distribution

density at $t=10$ secondsdensity at $t=2$ minutesdensity at $t=5$ minutesdensity at $t=15$ minutes

(the scale varies w.r.t. t)

Exit from a Hall with a Common Uncertainty

Same geometry. The horizon is T .

- Before $t = T/2$, the two doors are closed.

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- At $T/2$, the probability that a given door be opened is $1/2$.

Hence the model involves three pairs of unknown functions

- (u^C, m^C) is defined on $(0, T/2) \times \Omega$ and corresponds to the situation when the room is closed.
- (u^L, m^L) and (u^R, m^R) are defined on $(T/2, T) \times \Omega$ and resp. correspond to the case when the left (resp. right) door is open.

The Boundary Value Problem

The systems of PDEs : for $j = C, L, R$,

$$-\frac{\partial u^j}{\partial t} - \nu \Delta u^j + H(m^j, Du^j) = F(m^j),$$

$$\frac{\partial m^j}{\partial t} - \nu \Delta m^j - \operatorname{div} \left(m^j \frac{\partial H}{\partial p}(m^j, Du^j) \right) = 0,$$

in $(0, T/2) \times \Omega$ for $j = C$ and in $(T/2, T) \times \Omega$ for $j = L, R$.

The boundary conditions

$$\frac{\partial u^C}{\partial n} = \frac{\partial m^C}{\partial n} = 0 \quad \text{on } (0, \frac{T}{2}) \times \partial\Omega,$$

and for $j = L, R$,

$$\begin{cases} \frac{\partial u^j}{\partial n} = \frac{\partial m^j}{\partial n} = 0 & \text{on } (\frac{T}{2}, T) \times \Gamma_N^j, \\ u^j = m^j = 0 & \text{on } (\frac{T}{2}, T) \times \Gamma_D^j \end{cases}$$

Transmission conditions at $t = T/2$

$$m^L\left(\frac{T}{2}, x\right) = m^R\left(\frac{T}{2}, x\right) = m^C\left(\frac{T}{2}, x\right) \quad \text{in } \Omega,$$

$$u^C\left(\frac{T}{2}, x\right) = \frac{1}{2} \left(u^L\left(\frac{T}{2}, x\right) + u^R\left(\frac{T}{2}, x\right) \right) \quad \text{in } \Omega.$$

Results

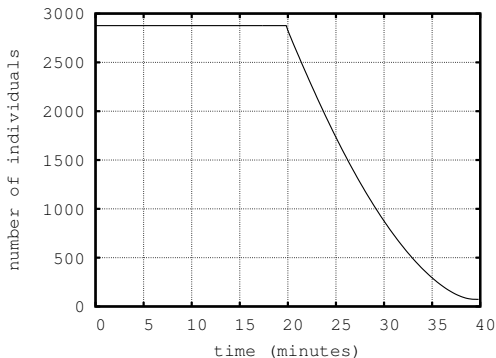
 $T = 40$ min.

FIGURE: The number of people in the room vs. time

(Loading densitynuonethird.mov)

- Such a behavior cannot be predicted by mechanical models
- Other examples with two populations (segregation, ...)

General conclusion

- MFG is a very active area in math, economics and engineering.
- Main equations :
 - The MFG system : the basic models are well-understood
... but not the more realistic ones,
... nor the stochastic MFG systems
 - The master equation remains very challenging
... as well as its finite dimensional analogue
- The mean field issue
- Still relatively little work on the numerical analysis
- Where to learn ?
 - Lasry-Lions papers, Lions' courses at the College de France (in French)
 - Few lecture notes and monographs : Achdou, C., Gomes and al., Bensoussan-Frehse-Yam...

Thank you !