Mean-Field optimization problems and non-anticipative optimal transport

Beatrice Acciaio London School of Economics

based on ongoing projects with J. Backhoff, R. Carmona and P. Wang

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The story in a nutshell

Given

- a (finite or infinite) set of agents
- who need to choose their actions/strategies
- and face a cost depending on their own type, action, and on the symmetric interaction with each other:

cost(i) = fct(type(i), action(i), (empirical) distrib. actions)

Aim to

- → find/characterize equilibria
- → through connections with non-anticipative optimal transport

Outline

1 First setting: hidden/no dynamics

- Problem formulation
- Connection with non-anticipative optimal transport
- Existence and uniqueness results

2 Second setting: state dynamics

- Problem formulation
- Connection with non-anticipative optimal transport
- First results

3 Conclusions

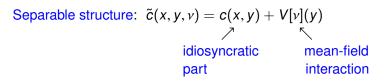
Setting

- time set: $\mathbb{T} = \{0, ..., T\}$, or $\mathbb{T} = [0, T]$
- X: agents types
 - $\mathcal{X} \subseteq \mathbb{X}^{|\mathbb{T}|}$: agents types evolutions
- Y: agents' actions

 $\boldsymbol{\mathcal{Y}} \subseteq \mathbb{Y}^{|\mathbb{T}|}$: agents' actions evolutions

- e.g. $X=Y=\mathbb{R}$, and $X=\mathcal{Y}=\mathbb{R}^{T+1}$ or $X=\mathcal{Y}=C([0, T]; \mathbb{R})$
- $\eta \in \mathcal{P}(X)$: known a priori distribution over types
- $\rightarrow \text{ cost function: } \tilde{c}(x, y, v) \quad \text{(for each agent)} \\ \nearrow \uparrow \uparrow \\ \text{type action actions' distribution} \\ x \in \mathcal{X} \quad y \in \mathcal{Y} \quad v \in \mathcal{P}(\mathcal{Y}) \\ \end{array}$

Cost function



with $c: \mathcal{X} \times \mathcal{Y} \to \mathbb{R}_+$ l.s.c., $V: \mathcal{P}(\mathcal{Y}) \to \mathcal{B}(\mathcal{Y}; \mathbb{R}_+)$

- congestion effect: $V_c[v](y) = f(y, \frac{dv}{dm}(y))$, with $m \in \mathcal{P}(\mathcal{Y})$ reference meas. w.r.t. which congestion measured, $f(y, .) \nearrow$
- attractive effect: $V_a[v](y) = \int_{\mathcal{Y}} \phi(y, z)v(dz)$, with ϕ symmetric, convex, minimal on the diagonal

Static case: Blanchet-Carlier 2015

Pure adapted strategies

pure strategy: all players of type $x \in X$ choose the same strategy $y = A(x) = (A_t(x))_{t \in \mathbb{T}}$

adapted strategy: $A_t(x) = T^t(x_{0:t})$ for some measurable T^t

Denote by \mathcal{A} the set of pure adapted strategies $A : \mathcal{X} \to \mathcal{Y}$

- type distribution: $\eta \in \mathcal{P}(X)$ (known)
- strategy distribution: ν = A_#η = T_#η ∈ P(Y), T = (T^t)_{t∈T} (will be determined in equilibrium)

Pure equilibrium

Social planner perspective: minimize average cost

For every $v \in \mathcal{P}(\mathcal{Y})$, denote

$$P(v) := \inf_{A \in \mathcal{A}} \int \left\{ c(x, A(x)) + V[v](A(x)) \right\} \eta(dx)$$

Definition

An element $A \in \mathcal{R}$ is called a pure equilibrium if

• A attains P(v),

• where
$$v = A_{\#}\eta$$
.

Cournot-Nash equilibrium

Remark. Let $\mathbb{T} = \{0, 1, ..., T\}$ (analogous in continuous time). Let $c(x, y) = \sum_{t=0}^{T} c_t(x_{0:t}, y_t)$ and $V[v](y) = \sum_{t=0}^{T} V_t[v_t](y_t)$, then pure equilibrium for social planner = Cournot-Nash equilibrium (η -a.s. each agent acts as best response to other agents' actions)

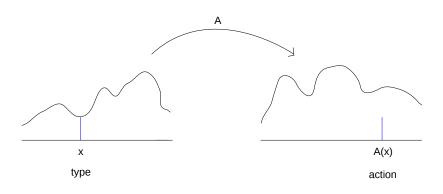
The equilibria are described by the set $\{A^{\nu}: A^{\nu}_{\#}\eta = \nu\}$, where $A^{\nu}_t(x) = T^{\nu}_t(x_{0:t}) := \arg\min_z \{c_t(x_{0:t}, z) + V_t[\nu_t](z)\}.$

- This is clearly a specific situation
- Anyway, pure equilibria rarely exists, so we shall consider the natural generalization to mixed-strategy equilibria.

State dynamics

Conclusions

From pure to mixed-strategy equilibrium

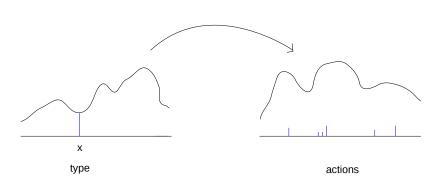


adapted pure strategy = adapted Monge transport

State dynamics

Conclusions

From pure to mixed-strategy equilibrium



non-anticipative mixed strategy = causal Kantorovich transport

Mixed non-anticipative strategy

mixed-strategy: players of same type can choose different actions non-anticipative: $A_t(x) = \text{fct}(x_{0:t}) + \text{sth indep. of } x$ \downarrow

Non-anticipative (causal) transport: $\pi \in \mathcal{P}(X \times \mathcal{Y})$ s.t. $p_{1\#}\pi = \eta$, and for all *t* and $D \in \mathcal{F}_t^{\mathcal{Y}}$, the map $X \ni x \mapsto \pi^x(D)$ is \mathcal{F}_t^X -measurable (where $(\mathcal{F}_t^X), (\mathcal{F}_t^{\mathcal{Y}})$ canonical filtr. in X, \mathcal{Y} , and π^x reg. cond. kernel)

Denote by $\Pi_c(\eta, \nu)$ the set of causal transports between η and ν , and let $\Pi_c(\eta, .) := \bigcup_{\nu \in \mathcal{P}(\mathcal{Y})} \Pi_c(\eta, \nu)$

Note that $\pi = (id, T)_{\#} \eta \in \Pi_c(\eta, .)$ are the pure adapted strategies.

Mixed-strategy equilibrium

For every $\nu \in \mathcal{P}(\mathcal{Y})$, denote

$$M(v) := \inf_{\pi \in \Pi_c(\eta,.)} \mathbb{E}^{\pi} \Big[c(x,y) + V[v](y) \Big]$$

Definition

An element $\pi \in \Pi_c(\eta, .)$ is called a mixed-strategy equilibrium if

- π attains M(v),
- where $v = p_{2\#}\pi$, i.e., $\pi \in \prod_c(\eta, v)$.

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Remark. Mixed-strategy equilibria are solutions to causal transport problems: if π^* m-s equilibrium, with $p_{2\#}\pi^* = v^*$, then it attains

$$\inf_{x\in\Pi_c(\eta,\nu^*)}\mathbb{E}^{\pi}[c(x,y)].$$

Analogously, pure equilibria = solutions to CT pbs over Monge maps

Potential games

From the remark, we always have equilibrium \implies optimal transport

For potential games, we will have ">" in some sense

Assumption

There exists $\mathcal{E} : \mathcal{P}(\mathcal{Y}) \to \mathbb{R}$ such that V is the first variation of \mathcal{E} :

$$\lim_{\epsilon \to 0^+} \frac{\mathcal{E}(\nu + \epsilon(\mu - \nu)) - \mathcal{E}(\nu)}{\epsilon} = \int_{\mathcal{Y}} V[\nu](y)(\mu - \nu)(dy), \quad \forall \nu, \mu \in \mathcal{P}(\mathcal{Y})$$

E.g. $V = V_c + V_a$ (repulsive+attractive effect) is the first variation of

$$\mathcal{E}(v) = \int_{\mathcal{Y}} F\left(y, \frac{dv}{dm}(y)\right) m(dy) + \frac{1}{2} \int_{\mathcal{Y} \times \mathcal{Y}} \phi(y, z) v(dz) v(dy),$$

where $F(y, u) = \int_0^u f(y, s) ds$.

Potential games

Consider the variational problem

(VP)
$$\inf_{\nu \in \mathcal{P}(\mathcal{Y})} \left\{ \inf_{\substack{\pi \in \Pi_{c}(\eta, \nu) \\ \mathbf{CT}(\eta, \nu)}} \mathbb{E}^{\pi}[c(x, y)] + \mathcal{E}[\nu] \right\}$$

Theorem

Let \mathcal{E} be convex, then the following are **equivalent**:

(i) π^* is a mixed-strategy equilibrium, with $p_{2\#}\pi^* = v^*$;

(ii) v^* solves (VP), and π^* solves $CT(\eta, v^*)$.

Remarks. 1. Convexity only needed for "(*i*) \Rightarrow (*ii*)"

- 2. Convexity satisfied in the congestion case ($V = V_c$)
- 3. Alternatively: displacement convexity can be used

Potential games

Corollary (uniqueness)

If \mathcal{E} strictly convex \Rightarrow all m-s equilibria have same second marginal v^* , i.e., unique optimal distribution of actions.

Indeed, $\nu \mapsto CT(\eta, \nu)$ convex, hence \mathcal{E} strictly convex implies unique solution ν^* for (VP). Then apply theorem.

Corollary (existence)

For $V = V_c$ and growth condition on $f \Rightarrow \exists m$ -s equilibrium.

Indeed, the growth condition ensures existence of a solution v^* for (VP), and $CT(\eta, v^*)$ admits a solution π^* since *c* is bounded below and l.s.c. Then apply theorem.

Example

Let
$$\mathbb{T} = \{0, 1, ..., T\}$$
, and $\mathcal{X} = \mathcal{Y} = \mathbb{R}^{T+1}$. If

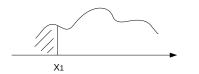
• η has independent increments, and

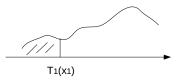
•
$$c(x, y) = c_0(x_0, y_0) + \sum_{t=1}^{T} c_t(x_t - x_{t-1}, y_t - y_{t-1})$$
, with $c_t(u, v) = k_t(u - v)$ and k_t convex,

Then:

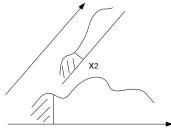
- m-s equilibria (if 3) are determined by the second marginal
- m-s equilibria are the Knothe-Rosenblatt rearrangements
- if moreover η has a density, all m-s equilibria are in fact pure

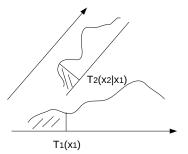
The Knothe-Rosenblatt map





The Knothe-Rosenblatt map







Actions as controls on dynamics

- The previous result describes a specific situation where optimal actions are increasing with the type.
- When these conditions not satisfied, which form of CT/equilibria?

Example. Let actions = controls on dynamics:

$$X_t = (k_t^1 X_{t-1} + k_t^2 \alpha_t) + \epsilon_t, \ t = 1, ..., T, \ X_0 = x_0,$$

with associated cost $f_t(X_t, \alpha_t, \nu_t)$ at time *t*. As $X_t = fct(\epsilon_i, \alpha_i, i \leq t)$,

$$f_t(X_t, \alpha_t, \nu_t) = c_t(\epsilon_{0:t}, \alpha_{0:t}, \nu_t),$$

hence total cost = $\mathbb{E}[\sum_{t=0}^{T} c_t(\epsilon_{0:t}, \alpha_{0:t}, \nu_t)].$

← Fits into previous framework, by reading "noises as types".

McKean-Vlasov control problem

• With the above example in mind, we will consider

McKean-Vlasov control problem:

$$\inf_{\alpha} \mathbb{E}^{\mathbb{P}}\left[\int_{0}^{T} \tilde{f}_{t}\left(X_{t}, \alpha_{t}, \mathbb{P} \circ (X_{t}, \alpha_{t})^{-1}\right) dt + \tilde{g}\left(X_{T}, \mathbb{P} \circ X_{T}^{-1}\right)\right]$$

subject to

$$dX_t = b_t \left(X_t, \alpha_t, \mathbb{P} \circ X_t^{-1}
ight) dt + dW_t$$

• Let us fist mention connections to large systems of interacting controlled state processes

N-player stochastic differential game

The private state process X^i of player *i* is given by the solution to

$$dX_t^i = b_t(X_t^i, \alpha_t^i, \bar{\mu}_t^N)dt + dW_t^i$$

• $W^1, ..., W^N$ independent Wiener processes • $\alpha^1, ..., \alpha^N$ controls of the *N* players • $\bar{\mu}_t^N = \frac{1}{N-1} \sum_{j \neq i} \delta_{X_t^j}$ empirical distrib. of states of the other players

The objective of player *i* is to choose a α^i in order to minimize

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

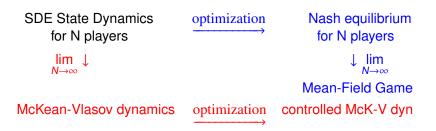
• $\bar{v}_t^N = \frac{1}{N-1} \sum_{j \neq i} \delta_{(X_t^j, \alpha_t^j)}$ empirical joint distrib. of states and controls of the other players

Statistically identical players: same functions b_t , \tilde{f}_t , \tilde{g}

From N-player game to McKean-Vlasov control problem

Approximation by asymptotic arguments:

- first optimization then limit for $N \rightarrow \infty$, or
- viceversa, first limit for $N \rightarrow \infty$ and then optimization



(Carmona-Delarue-Lachapelle 2012)

McKean-Vlasov control problem

Back to the McKean-Vlasov control problem.

For simplicity:

- no terminal cost: $\tilde{g} = 0$
- separable costs: $\tilde{f}_t(x, a, v) = f_t(x, a) + K_t(v)$

Therefore

$$\inf_{\alpha} \mathbb{E}^{\mathbb{P}} \left[\int_{0}^{T} \left\{ f_{t}(X_{t}, \alpha_{t}) + \mathcal{K}_{t} \left(\mathbb{P} \circ (X_{t}, \alpha_{t})^{-1} \right) \right\} dt \right]$$

$$dX_{t} = b_{t} \left(X_{t}, \alpha_{t}, \mathbb{P} \circ X_{t}^{-1} \right) dt + dW_{t},$$

with $f_t : \mathbb{R} \times \mathbb{R} \to \mathbb{R}, K_t : \mathcal{P}(\mathbb{R} \times \mathbb{R}) \to \mathbb{R}, b_t : \mathbb{R} \times \mathbb{R} \times \mathcal{P}(\mathbb{R}) \to \mathbb{R}$

McKean-Vlasov control problem

Definition. A weak solution to the McKean-Vlasov control problem is a tuple $(\Omega, (\mathcal{F}_t)_{t \in [0,T]}, \mathbb{P}, W, X, \alpha)$ such that:

(i) (Ω, (𝓕_t)_{t∈[0,T]}, ℙ) supports X and a BM W, α is 𝓕^X-progress. measurable and 𝔼^ℙ[∫₀^T |α_t|²] < ∞
(ii) the state equation dX_t = b_t (X_t, α_t, ℙ ∘ X_t⁻¹) dt + dW_t holds
(iii) if (Ω', (𝓕'_t)_{t∈[0,T]}, ℙ', W', X', α') is another tuple s.t. (i)-(ii) hold,
𝔼^ℙ[∫₀^T f_t(X_t, α_t)+K_t (ℙ ∘ (X_t, α_t)⁻¹)}dt] ≤ 𝔼^{ℙ'}[∫₀^T f_t(X'_t, α'_t)+K_t (ℙ' ∘ (X'_t, α'_t)⁻¹)}dt].

Assumptions

- \rightarrow We need some technical assumptions.
- \rightarrow In the case of linear drift:

$$dX_t = (c_t^1 X_t + c_t^2 \alpha_t + c_t^3 \mathbb{E}[X_t]) dt + dW_t,$$

 $c_t^i \in \mathbb{R}, c_t^2 > 0$, the assumptions reduce to:

- $f_t(x, .)$ convex (and $f_t(., y)$ at least quadratic growth)
- K_t is \prec_c -monotone

Example.

•
$$f_t(x,a) = d_t^1 x + d_t^2 a + d_t^3 x^2 + d_t^4 a^2$$
, $d_t^i \in \mathbb{R}, d_t^4 > 0$

• $K_t(\zeta) = F_t(\overline{\zeta}_1, \overline{\zeta}_2)$, any F_t , $\overline{\zeta}_i := \int y d(p_{i\#}\zeta)(y)$

Characterization via non-anticipative optimal transport

- formulate a transport problem in the path space C([0, T])
- denote by γ the Wiener measure on C([0, T])
- $(\omega, \overline{\omega})$ generic element on $C([0, T]) \times C([0, T])$
- "move noises into states"

Theorem

Under the mentioned assumptions, the weak MKV problem is equivalent to the variational problem

$$\inf_{\mu \ll \gamma} \inf_{\pi \in \Pi_{bc}(\gamma,\mu)} \left\{ \mathbb{E}^{\pi} \left[\int_{0}^{T} f_{t}(\overline{\omega}_{t}, u_{t}(\omega, \overline{\omega}, \mu)) dt \right] + \int_{0}^{T} K_{t} \left(\left(p_{2}, u_{t}(\omega, \overline{\omega}, \mu) \right)_{\#} \pi_{t} \right) dt \right\}$$

where $u_{t}(\omega, \overline{\omega}, \mu) = b_{t}^{-1}(\overline{\omega}_{t}, .., \mu_{t}) \left((\overline{\omega} - \omega)_{t} \right).$

 $\Pi_{bc}(\gamma,\mu) = \left\{ \pi \in \Pi_c(\gamma,\mu) : \ell_{\#}\pi \in \Pi_c(\mu,\gamma) \right\}, \text{ where } \ell(x,y) = (y,x)$

Characterization via non-anticipative optimal transport

Remarks.

- The optimization over Π_{bc}(γ, μ) is not a standard optimal transport problem ⇒ new analysis for existence/duality.
- When mean-field cost is K_t(ℙ ∘ X_t⁻¹) ⇒ standard causal transport problem (A.-Backhoff-Zalashko 2016)

Example.

- state dynamics: $dX_t = \alpha_t dt + dW_t$
- cost: $\mathbb{E}^{\mathbb{P}}\left[\frac{1}{2}\int_{0}^{T}\left(X_{t}^{2}+\alpha_{t}^{2}\right)dt\right]+\int_{0}^{T}K_{t}(\mathbb{P}\circ X_{t}^{-1})dt$
- ⇒ in the variational problem we have causal optimal transport w.r.t. Cameron-Martin distance:

$$\inf_{\pi\in \Pi_{bc}(\gamma,\mu)} \mathbb{E}^{\pi}[|\overline{\omega}-\omega|_{H}^{2}] = \mathcal{H}(\mu|\gamma),$$

hence we are left with

 $\inf_{\mu\ll\gamma} \{\mathcal{H}(\mu|\gamma) + \mathcal{P}(\mu)\}, \quad \mathcal{P}(\mu) \text{ penalty term}$

Conclusions

In the case with hidden/no dynamics:

- characterization of equilibrium via non-anticipative transport
- existence and uniqueness results
- characterization of causal optimal transport (\neq KR)...

In the case with state dynamics:

- characterization of weak McKean-Vlasov solutions via non-anticipative transport
- existence and uniqueness...
- characterization of causal optimal transport...



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Thank you for your attention and Buon compleanno loannis! :)