

Non-anticipative optimal transport: a powerful tool in stochastic optimization

Beatrice Acciaio

London School of Economics

based on several projects with
J. Backhoff, R. Carmona, A. Zalashko

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Outline

- 1 Classical and Causal Optimal Transport
- 2 Semimartingale preservation in enlargement of filtrations
- 3 MkKean-Vlasov optimal control
- 4 Dynamic Cournot-Nash equilibria
- 5 Value of information in stochastic optimization problems
- 6 Concluding remarks

OT and COT
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Semim. preservation
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MkKean-Vlasov
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CN-equilibria
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Value of information
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Conclusions

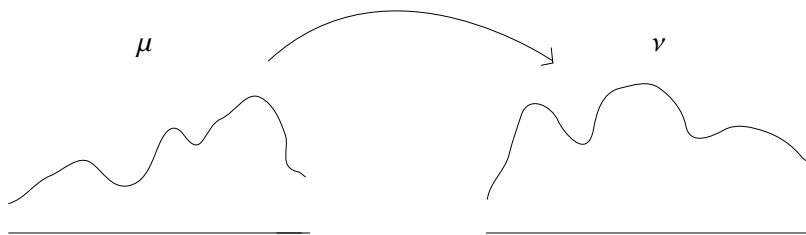
Classical and Causal Optimal Transport

Classical Monge-Kantorovich optimal transport

Given two Polish probability spaces (\mathcal{X}, μ) , (\mathcal{Y}, ν) , move the mass from μ to ν minimizing the cost of transportation $c : \mathcal{X} \times \mathcal{Y} \rightarrow [0, \infty]$:

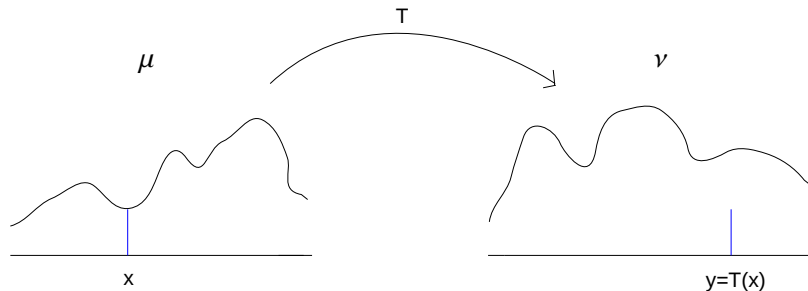
$$\text{OT}(\mu, \nu, c) := \inf \{ \mathbb{E}^\pi [c(x, y)] : \pi \in \Pi(\mu, \nu) \},$$

$\Pi(\mu, \nu)$: probability measures on $\mathcal{X} \times \mathcal{Y}$ with marginals μ and ν .



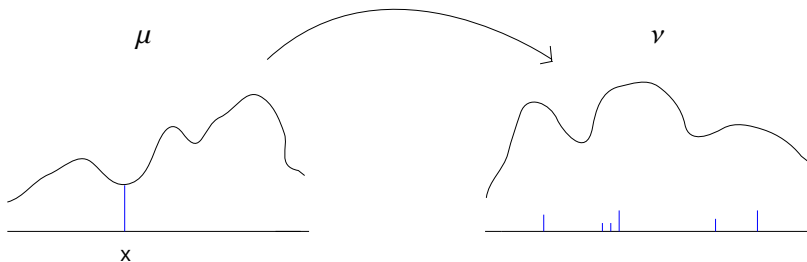
Classical Monge-Kantorovich optimal transport

Monge transport: all mass sitting on x is transported into $y=T(x)$.



Classical Monge-Kantorovich optimal transport

Kantorovich transport: mass can split.



From Monge-Kantorovich to causal optimal transport

Some literature on OT:

- G. Monge (1781)
- L.V. Kantorovich (1942, '48)
- L. Ambrosio, Y. Brenier, L. Caffarelli, A. Figalli, N. Gigli, R. McCann, F. Otto, F. Santambrogio, K.T. Sturm, C. Villani ...

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→ We consider a **dynamic setting**: we have the **time component** (mathematically: spaces \mathcal{X} and \mathcal{Y} endowed with filtrations)

→ **Idea**: move the mass in a **non-anticipative** way: what is transported into the 2^{nd} coordinate at time t , depends on the 1^{st} coordinate only up to t (+ possibly on sth independent)

⇒ **causal (non-anticipative) transport**

Causal optimal transport

Let $\mathcal{F}^X = (\mathcal{F}_t^X)_t$ on \mathcal{X} , $\mathcal{F}^Y = (\mathcal{F}_t^Y)_t$ on \mathcal{Y} be right-cont. filtrations.

Definition (Causal transport plans $\Pi^{\mathcal{F}^X, \mathcal{F}^Y}(\mu, \nu)$)

A **transport plan** $\pi \in \Pi(\mu, \nu)$ is called **causal** between $(\mathcal{X}, \mathcal{F}^X, \mu)$ and $(\mathcal{Y}, \mathcal{F}^Y, \nu)$ if, for all t and $D \in \mathcal{F}_t^Y$, the map $\mathcal{X} \ni x \mapsto \pi^x(D)$ is measurable w.t.to \mathcal{F}_t^X (π^x regular conditional kernel w.r.to \mathcal{X}).

The concept goes back to T. Yamada and S. Watanabe (1971); see also R. Lassalle (2013), J. Backhoff et al. (2016)

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Causal optimal transport problem:

$$\text{COT}(\mu, \nu, c) := \inf \{ \mathbb{E}^\pi [c(X, Y)] : \pi \in \Pi_c(\mu, \nu) \},$$

where $\Pi_c(\mu, \nu) =$ set of causal transports with marginals μ and ν

Example: weak-solutions of SDEs

- $\mathcal{X} = \mathcal{Y} = C_0[0, \infty)$
- \mathcal{F} right-continuous canonical filtration

Example (Yamada-Watanabe'71)

Assume weak-existence of the solution to the SDE:

$$dY_t = \sigma(Y_t)dB_t + b(Y_t)dt, \quad b, \sigma \text{ Borel measurable.}$$

Then $\mathcal{L}(B, Y)$ is a causal transport plan between the spaces $(C_0[0, \infty), \mathcal{F}, \gamma)$ and $(C_0[0, \infty), \mathcal{F}, \mathcal{L}(Y))$, $\gamma =$ Wiener measure.

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- **Transport perspective:** from an observed trajectory of B , the mass can be split at each moment of time into Y only based on the information available up to that time.

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- **Transport perspective:** from an observed trajectory of B , the mass can be split at each moment of time into Y only based on the information available up to that time.
- **No splitting of mass:**

Monge transport \iff **strong solution** $Y = F(B)$.

Semimartingale preservation in enlargement of filtrations

Semimartingale preservation

Problem formulation:

- given two filtrations $\mathcal{F} \subset \mathcal{G}$ on a space of events Ω
 - and X semimartingale in $(\Omega, \mathcal{F}, \mathbb{P})$
- when is X going to **remain a semimartingale** in $(\Omega, \mathcal{G}, \mathbb{P})$?

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- Semimartingales are the processes for which classical stochastic integration works: $\int HdX$ (e.g. asset price proc.)
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Today: $X = B$ Brownian motion in its own filtration $\mathcal{F}^B \subset \mathcal{G}^B$:

- when is B semimartingale w.r.t. \mathcal{G}^B ? $B_t = \tilde{B}_t + A_t$
- in particular, when is FV \ll Leb? $B_t = \tilde{B}_t + \int_0^t a_s ds$

Filtration enlargement

→ Two most studied types of filtration enlargement:

- **initial enlargement:** $\mathcal{G}_t = \mathcal{F}_t \vee \sigma(L)$
- **progressive enlargement** with a random time:

$$\mathcal{G}_t = \mathcal{F}_t \vee \sigma(\tau \wedge t)$$

Some literature:

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→ We consider a **general enlargement** of a (right cont.) filtration $(\mathcal{F}_t)_{t \in [0, T]}$ to a (right cont.) filtration $(\mathcal{G}_t)_{t \in [0, T]}$:

$$\mathcal{F}_t \subseteq \mathcal{G}_t \quad \forall t \in [0, T], \quad \mathcal{F}_T = \mathcal{G}_T$$

and characterize semim. preservation via **causal transport**: $\tilde{B} \rightarrow B$

Filtration enlargement

- $\mathcal{X} = \mathcal{Y} = C_0[0, \infty)$, W coordinate process: $W_t(\omega) = \omega_t$
- $\mathcal{F}^{\mathcal{X}} = \mathcal{F}$ filtration generated by W
- $\mathcal{F}^{\mathcal{Y}} = \mathcal{G} \supset \mathcal{F}$
- $\mathcal{F}^B = B^{-1}(\mathcal{F})$, $\mathcal{G}^B = B^{-1}(\mathcal{G})$

Example

Let B be a Brownian motion on $(\Omega, \mathcal{F}^B, \mathbb{P})$, which remains a semimartingale w.r.to the enlarged filtration \mathcal{G}^B , with decomposition

$$dB_t = d\tilde{B}_t + dA_t.$$

Then $\mathcal{L}(\tilde{B}, B)$ is a causal transport plan between the spaces $(C_0[0, \infty), \mathcal{F}, \gamma)$ and $(C_0[0, \infty), \mathcal{G}, \gamma)$.

Semimartingale preservation: characterization via COT

Theorem

For any fixed anticipation \mathcal{G} , **TFAE**:

- i. any process B which is a *Brownian motion* on some (Ω, \mathbb{P}) , *remains a semimartingale* in the enlarged filtration \mathcal{G}^B ;
- ii. for some $\nu \sim \gamma$, the following *causal transport problem is finite*

$$\inf_{\pi \in \Pi^{\mathcal{F}, \mathcal{G}}(\gamma, \nu)} \mathbb{E}^{\pi}[V_T(\bar{\omega} - \omega)].$$

Optimal $\hat{\pi} := (\xi, id)_{\#}\nu$, where $\xi_t(\bar{\omega}) := \bar{\omega}_t - A_t(\bar{\omega})$, with A dual pred. proj. of $(\bar{\omega} - \omega)$ w.r.t. $(\pi, \{\emptyset, C_0[0, T]\} \times \mathcal{G})$, $\forall \pi$ with finite cost.

Notation. $(\omega, \bar{\omega})$: generic element in $C[0, T] \times C[0, T]$

V_T : total variation up to T

The absolutely continuous case

We have given a characterization of BM remaining semimartingale in a bigger filtration ($B_t = \tilde{B}_t + A_t$). Now we want to answer:

- When does it have an **absolutely continuous** finite variation part? ($B_t = \tilde{B}_t + \int_0^t \alpha_s ds$ **information drift**)

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- Brownian bridge: $dB_t = d\tilde{B}_t + \frac{B_T - B_t}{T-t} dt$
- Initial enlargement under Jacod's condition
- Progressive enlargement with a random τ (Jeulin-Yor formula)
- Enlargement with $J_t := \inf_{s \geq t} R_s$, where $dR_t = \frac{1}{R_t} dt + dB_t$:
$$dB_t = d\tilde{B}_t + 2dJ_t - \frac{1}{R_t} dt$$

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→ This question can be **answered in an analogous way**.
[see slides at the end]

Extensions

Our results have natural extensions in two directions:

- **Multidimensional processes.**
- **General continuous semimartingales:** for non-Brownian processes, **generalization of the definition of causality:**

$$\mathbb{E}^\pi[(\omega_t - \omega_s)f_s(\bar{\omega})] = 0, \quad 0 \leq s < t \leq T, f_s \in L^\infty(\mathcal{C}, \mathcal{G}_s, \nu),$$

which leads to analogous results.

In particular, if X continuous semimartingale which remains a semimartingale in the enlarged filtration \mathcal{G}^X , with $X = \tilde{X} + N \Rightarrow$ the transport plan $\mathcal{L}(\tilde{X}, X)$ satisfies the condition above.

OT and COT
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MkKean-Vlasov
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CN-equilibria
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Value of information
○○○○○

Conclusions

MkKean-Vlasov optimal control

N-player stochastic differential game

→ N players with **private state processes** evolving as

$$dX_t^{N,i} = b_t(X_t^{N,i}, \alpha_t^{N,i}, \bar{v}_t^{N,-i})dt + dW_t^i, \quad i = 1, \dots, N$$

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

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→ **Objective** of player i : to choose a control $\alpha^{N,i}$ that minimizes

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

- $\bar{\eta}_t^{N,-i} = \frac{1}{N-1} \sum_{j \neq i} \delta_{(X_t^{N,j}, \alpha_t^{N,j})}$ empirical distrib. of states & controls

→ Statistically identical players: same functions b_t, f_t, g

N-player stochastic differential game

Problems:

- search for equilibria: very difficult
- even when they exist, difficult to characterize

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Idea:

- for large symmetric games, some averaging is expected when the number of players tends to infinity
- resort to approximation by **asymptotic arguments:**

N-player game - - - - - > $N \rightarrow \infty$

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N-player game - - - - - > $N \rightarrow \infty$

Nash equilibrium (non-coop) - - - - > Mean Field Game

Social planner (cooperative) - - - - > **McKean Vlasov**

McKean-Vlasov control problem

→ Asymptotic formulation in the case of cooperative equilibria, as well as for non-cooperative equilibria in the potential case:

McKean-Vlasov control problem:

$$\inf_{\alpha} \mathbb{E} \left[\int_0^T f_t(X_t, \alpha_t, \mathcal{L}(X_t, \alpha_t)) dt + g(X_T, \mathcal{L}(X_T)) \right]$$

$$\text{subject to } dX_t = b_t(X_t, \alpha_t, \mathcal{L}(X_t)) dt + dW_t, \quad X_0 = 0$$

Some literature on MFG and MKV:

- J.M. Lasry and P.L. Lions (2006, '07)
- M. Huang, P.E. Caines, and R.P. Malhamé (2006, '07)
- P. Cardaliaguet, R. Carmona, F. Delarue, M. Fischer, J.P. Fouque, A. Lachapelle, D. Lacker, C.A. Lehalle, H. Pham, X. Wei ...

McKean-Vlasov control problem

Classical approaches for MFG/MKV:

- **analytic** (Lasry-Lions): HJB, forward-backward system of PDEs
- **probabilistic**: Pontryagin maximum principle, FBSDEs

McKean-Vlasov control problem

Classical approaches for MFG/MKV:

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Our approach: use **causal transport**: $W \rightarrow X$, with the aim of:

- ↪ providing different existence results
- ↪ finding explicit solutions

McKean-Vlasov control problem and Causal Transport

→ McKean-Vlasov control problem:

$$\inf_{\alpha} \mathbb{E} \left[\int_0^T f_t(X_t, \alpha_t, \mathcal{L}(X_t, \alpha_t)) dt + g(X_T, \mathcal{L}(X_T)) \right]$$

subject to

$$dX_t = b_t(X_t, \alpha_t, \mathcal{L}(X_t)) dt + dW_t, \quad X_0 = 0$$

→ The joint distribution $\mathcal{L}(W, X)$ is a causal transport plan between $(C_0[0, T], \mathcal{F}, \gamma)$ and $(C_0[0, T], \mathcal{F}, \mathcal{L}(X))$:

$\gamma \rightarrow ? =$ distribution of the state

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) $(\Omega, (\mathcal{F}_t)_{t \in [0, T]}, \mathbb{P})$ supports X , BM W , α is \mathcal{F} -progress. meas.
- (ii) the state equation $dX_t = b_t(X_t, \alpha_t, \mathcal{L}(X_t)) dt + dW_t$ holds
- (iii) if $(\Omega', (\mathcal{F}'_t)_{t \in [0, T]}, \mathbb{P}', W', X', \alpha')$ is another tuple s.t. (i)-(ii) hold,

$$\begin{aligned} & \mathbb{E}^{\mathbb{P}} \left[\int_0^T f_t(X_t, \alpha_t, \mathcal{L}_{\mathbb{P}}(X_t, \alpha_t)) dt + g(X_T, \mathcal{L}_{\mathbb{P}}(X_T)) \right] \\ & \leq \mathbb{E}^{\mathbb{P}'} \left[\int_0^T f_t(X'_t, \alpha'_t, \mathcal{L}_{\mathbb{P}'}(X'_t, \alpha'_t)) dt + g(X'_T, \mathcal{L}_{\mathbb{P}'}(X'_T)) \right] \end{aligned}$$

Assumptions

→ We need some **convexity assumptions**.

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→ In the **case of linear drift**:

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

$c_t^i \in \mathbb{R}, c_t^2 > 0$, our assumptions reduce to: for all x, a, η ,

- f_t is bounded from below uniformly in t
- $f_t(x, \cdot, \eta)$ is convex
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E.g. satisfied by the inter-bank borrowing & lending model of Carmona-Fouque-Sun [see slides at the end]

Characterization of weak MKV solutions via COT

Here $\mathcal{X} = \mathcal{Y} = C_0[0, T]$, and for simplicity control = drift, sq. integr.

Theorem

The *weak MKV* problem is **equivalent** to the *variational problem*

$$\inf_{v \ll \gamma} \inf_{\pi \in \Pi_c(\gamma, v)} \mathbb{E}^\pi \left[\int_0^T f_t(\bar{\omega}_t, (\widehat{\bar{\omega} - \omega})_t, p_t((\bar{\omega}, \widehat{\bar{\omega} - \omega})_{\#} \pi)) dt + g(\bar{\omega}_T, v_T) \right]$$

$$\left(= \inf_{\pi \in \Pi_c(\gamma, \cdot)} \mathbb{E}^\pi [\dots] \right)$$

Notation: $(\widehat{\bar{\omega} - \omega})_t = \beta_t$ when $\bar{\omega} - \omega = \int_0^t \beta_s ds$, and $+\infty$ else

[for the general case: see slides at the end]

Characterization of weak MKV solutions via COT

'**Equivalence**' means that the above variational problem and

$$\inf \mathbb{E}^{\mathbb{P}} \left[\int_0^T f_t(X_t, \alpha_t, \mathcal{L}(X_t, \alpha_t)) dt + g(X_T, \mathcal{L}(X_T)) \right]$$

have the **same value**, where the infimum is taken over tuples $(\Omega, (\mathcal{F}_t), \mathbb{P}, W, X, \alpha)$ s.t. $dX_t = b_t(X_t, \alpha_t, \mathcal{L}(X_t)) dt + dW_t$, and that moreover the optimizers are related via:

- $v^* = \mathcal{L}(X^*)$
- $\pi^* \longleftrightarrow \alpha^*$, with $\pi^* = \mathcal{L}(W^*, X^*)$

Characterization of weak MKV solutions via COT

Corollary (Weak closed loop)

- 1 The infimum can be taken over tuples s.t. α is \mathcal{F}^X -measurable (*weak closed loop*).
- 2 If the infimum is *attained*, then the optimal control α is in weak closed loop form.

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Corollary (Existence)

Minimizations in the variational problem done over *compact sets*, hence *lower-semicontinuity* \Rightarrow existence.

Note: in classical the approaches, strong regularity is required

Special case: separable costs [see slides at the end]

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Conclusions

Dynamic Cournot-Nash equilibria

Problem formulation

Given: a population of Agents whose **type evolves in time**. Each of them:

- selects its own actions/strategies
- faces a cost depending on its own type, action, and on the symmetric interaction with the rest of the population:

$$\text{cost}(i) = \text{fcn}(\text{type}(i), \text{action}(i), \text{actions distribution})$$

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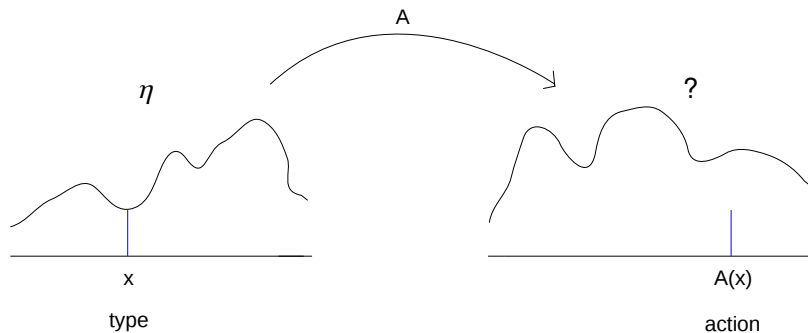
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Crucial: the actions of a player should not anticipate its type!

Our aim is to:

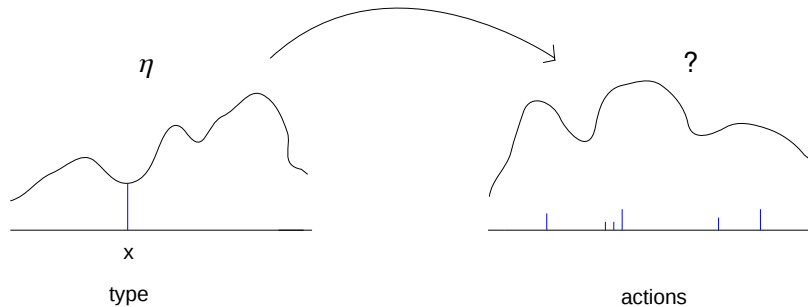
- find/characterize **equilibria** for games in this setting
- develop/exploit connection with **causal optimal transport**

Pure strategies



adapted **pure** strategy = adapted **Monge** transport

Mixed strategies



non-anticipative **mixed** strategy = causal **Kantorovich** transport

Main results

- mixed strategy equilibria are solutions to COT problems
- pure strategy equilibria are solutions to COT problems over Monge maps
- for potential games, we characterize Cournot-Nash equilibria as solutions to a variational problem involving COT problems:
 - ↪ new existence results
 - ↪ new uniqueness results
 - ↪ results on first structure of equilibria

[for precise setting and results see slides at the end]

Value of information in stochastic optimization problems

Value of information

- **Aim:** use causal transport framework to give an **estimate of the value of the additional information**, for some classical stochastic optimization problems (difference of optimal value of these problems with or without additional information).
 - **Idea:** take **projection w.r.to causal couplings** of the optimizers in the problem with the larger filtration (additional information), so building a feasible element in the problem with the smaller filtration and making a comparison possible.
 - Pflug (2009) uses this idea in discrete-time, to gauge the dependence of multistage stochastic programming problems w.r.to different reference probability measures.
- Here we see utility maximisation [for optimal stopping: see slides at the end]

Utility maximisation

- B d -dimensional Brownian motion on (Ω, \mathbb{P}) .
- Financial market: riskless asset $\equiv 1$, and $m \leq d$ risky assets:

$$dS_t^i = S_t^i \left(b_t^i dt + \sum_{j=1}^d \sigma_t^{ij} dB_t^j \right), \quad i = 1, \dots, m.$$

- $|b_t^i(\omega) - b_t^i(\tilde{\omega})| \leq L \sum_{k=1}^d \sup_{s \leq t} |\omega_s^k - \tilde{\omega}_s^k|$, same for σ^{ij} , σ bdd

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- $|b_t^i(\omega) - b_t^i(\tilde{\omega})| \leq L \sum_{k=1}^d \sup_{s \leq t} |\omega_s^k - \tilde{\omega}_s^k|$, same for σ^{ij} , σ bdd
- λ_t^i : proportion of an agent's wealth invested in the i^{th} stock at time t : assume $\lambda_t^i \in [0, 1]$ (no short-selling)
- $\mathcal{A}(\mathcal{F}^B)$: set of admissible portfolios for the agent without anticipative information (\mathcal{F}^B -progressively measurable λ)
- $\mathcal{A}(\mathcal{G}^B)$: set of admissible portfolios for the agent with anticipative information (\mathcal{G}^B -progressively measurable λ)

Utility maximisation

→ We want to compare the utility maximization problems:

$$v^{\mathcal{F}} = \sup_{\lambda \in \mathcal{A}(\mathcal{F}^B)} \mathbb{E}[U(X_T^\lambda)], \quad v^{\mathcal{G}} = \sup_{\lambda \in \mathcal{A}(\mathcal{G}^B)} \mathbb{E}[U(X_T^\lambda)].$$

- $(X_t^\lambda)_t$: wealth process corresponding to λ , $X_0^\lambda = 1$.
- utility function $U : \mathbb{R}_+ \rightarrow \mathbb{R}$ concave, increasing, and s.t.

$F := U \circ \exp$ is C -Lipschitz, concave and increasing.

e.g. $U(x) = \frac{x^a}{a}$, $a \leq 0$; $U(x) = \ln(x)$; $U(x) = -\frac{1}{a}e^{-ax}$, $a \geq 1$

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Proposition

The following bound holds, for a specific constant K :

$$0 \leq v^{\mathcal{G}} - v^{\mathcal{F}} \leq K \inf_{\pi \in \Pi^{\mathcal{F}, \mathcal{G}}(\gamma, \gamma)} \mathbb{E}^\pi[V_T(\bar{\omega} - \omega)].$$

Causal transports on $C_0[0, T] \times C_0[0, T]$

Utility maximisation

Remark. If complete market, log utility, and initial enlargement, then $v^{\mathcal{G}} - v^{\mathcal{F}}$ is known explicitly (Pikovsky-Karatzas 1996).

Utility maximisation

Remark. If complete market, log utility, and initial enlargement, then $v^{\mathcal{G}} - v^{\mathcal{F}}$ is known explicitly (Pikovsky-Karatzas 1996).

Steps of the proof:

- fix a causal transport $\pi \in \Pi^{\mathcal{F}, \mathcal{G}}(\gamma, \gamma)$
- consider $v^{\mathcal{F}}$ to be solved in the ω variable and $v^{\mathcal{G}}$ in $\bar{\omega}$
- take (ϵ -)optimizer $\hat{\lambda} = \hat{\lambda}(\bar{\omega})$ for $v^{\mathcal{G}}$
- $(\pi, \mathcal{F} \otimes \{\emptyset, C\})$ -optional projection: $\tilde{\lambda} \in \mathcal{A}(\mathcal{F}^B)$
- in particular $\tilde{\lambda}_t(\omega) = \tilde{\lambda}_t(\omega, \bar{\omega}) = \mathbb{E}^{\pi}[\hat{\lambda}_t | \mathcal{F}_t] = \mathbb{E}^{\pi}[\hat{\lambda}_t | \mathcal{F}_T]$
- substitute in $v^{\mathcal{F}}$

Conclusions

We have exploited **causal transport** to study several problems:

- semimartingale preservation:

$$\mathcal{G} - \text{BM} \longrightarrow \mathcal{F} - \text{BM}$$

- weak solutions to MKV:

$$\text{noise} \longrightarrow \text{state dynamics}$$

- Cournot-Nash equilibria:

$$\text{types} \longrightarrow \text{actions}$$

- value of information:

$$\mathcal{G} - \text{BM} \longrightarrow \mathcal{F} - \text{BM}$$

THANK YOU FOR YOUR ATTENTION!

Addendum to the Semimartingale preservation section

The absolutely continuous case

- Semimartingale preservation \iff finite causal transport problem for the **total variation cost**
- In the **A.C. case**, the cost functions of interest are

$$c_\rho(\omega, \bar{\omega}) := \int_0^T \rho(\widehat{(\bar{\omega} - \omega)}_t) dt,$$

where $\rho : \mathbb{R} \rightarrow \mathbb{R}_+$ is convex, even, $\rho(0) = 0$, $\rho(+\infty) = +\infty$, and $\widehat{(\bar{\omega} - \omega)}_t = \beta_t$ when $\bar{\omega} - \omega = \int_0^\cdot \beta_s ds$, and $+\infty$ else. E.g. $\rho(x) = x^2/2 \Rightarrow$ Cameron-Martin cost $c_\rho(\omega, \bar{\omega}) = \frac{1}{2} |\bar{\omega} - \omega|_H^2$.

\rightarrow In the A.C. case we get a characterization of the semim. preservation via COT over π 's under which $\bar{\omega} - \omega \ll \text{Leb}$.

The absolutely continuous case

Theorem

For any fixed anticipation \mathcal{G} , **TFAE**:

- i. any process B which is a *Brownian motion* on some (Ω, \mathbb{P}) , *remains a semimartingale* in the enlarged filtration \mathcal{G}^B , with *absolutely continuous* FV part, i.e.

$$dB_t = d\tilde{B}_t + \alpha_t(B)dt;$$

- ii. for some $\nu \sim \gamma$, and some ρ as above (eqv., for $\rho = | \cdot |$) the following *causal transport problem is finite*

$$\inf_{\pi \in \Pi^{\mathcal{F}, \mathcal{G}}(\gamma, \nu)} \mathbb{E}^{\pi} [c_{\rho}(\omega, \bar{\omega})].$$

Optimal transport $\hat{\pi} := (\xi, id)_{\#} \nu$, where $\xi_t(\bar{\omega}) := \bar{\omega}_t - \int_0^t a_s(\bar{\omega}) ds$, a pred.pr. of $\widehat{\bar{\omega} - \omega}$ w.r.t. $(\pi, \{\emptyset, C\} \times \mathcal{G})$, $\forall \pi$ with finite cost.

Cameron-Martin cost

Let $c_\rho(\omega, \bar{\omega}) = \frac{1}{2}|\bar{\omega} - \omega|_H^2$. If $\inf_{\pi \in \Pi^{\mathcal{F}, \mathcal{G}}(\gamma, \gamma)} \mathbb{E}^\pi[c_\rho] < \infty$, then:

- $dB_t = d\tilde{B}_t + \alpha_t(B)dt$, with α **square integrable**;
- by Girsanov, B BM w.r.t. \mathcal{G}^B under a new measure \mathbb{Q} , and

$$\text{COT} = \frac{1}{2} \mathbb{E}^\gamma \left[\int_0^T \alpha_t^2 dt \right] = H(\mathbb{P}|\mathbb{Q});$$

- by martingale representation, **\mathcal{H} -hypothesis** holds for \mathcal{F}^B , \mathcal{G}^B , i.e. all \mathcal{F}^B -semimartingales are \mathcal{G}^B -semimartingales;
- in case of initial enlargement with r.v. $L = L(B)$ with law ℓ :

$$\text{COT} = \int H(\gamma^{L=x}|\gamma)\ell(dx) = I(B, L(B)) := H(P_{B, L(B)}|P_B \otimes P_{L(B)}),$$
mutual information between B and $L(B)$;
- if L is discrete, COT = **entropy of the partition** $\{L = x_n\}_n$:

$$\text{COT} = - \sum_n p_n \ln(p_n), \quad p_n = \mathbb{P}(L = x_n).$$

OT and COT
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Semim. preservation
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McKean-Vlasov
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CN-equilibria
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Value of information
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Conclusions

Addendum to the McKean-Vlasov section

Example: Inter-bank borrowing & lending

Carmona-Fouque-Sun (2013)

- Consider a network of N banks, with **log-monetary reserve**

$$\begin{aligned} dX_t^i &= \left[\frac{k}{N-1} \sum_{j \neq i} (X_t^j - X_t^i) + \alpha_t^i \right] dt + dW_t^i, \\ &= \left[k(\bar{X}_t^{N,-i} - X_t^i) + \alpha_t^i \right] dt + dW_t^i, \quad i = 1, \dots, N \end{aligned}$$

- $k \geq 0$ rate of m-r in the interaction from b&l between banks
- α^i control of bank i , b&l outside of the N bank network
- Bank i tries to **minimize the cost**

$$\mathbb{E} \left[\int_0^T \left(\frac{1}{2} (\alpha_t^i)^2 - q \alpha_t^i (\bar{X}_t^{N,-i} - X_t^i) + \frac{c}{2} (\bar{X}_t^{N,-i} - X_t^i)^2 \right) dt + \frac{d}{2} (\bar{X}_T^{N,-i} - X_T^i)^2 \right]$$

- $q > 0$ incentive to borrowing ($\alpha_t > 0$) or lending ($\alpha_t < 0$)
- $c, d > 0$ penalize departure from average

Example: Inter-bank borrowing & lending

In the previous example:

- The log-monetary reserve of each bank, asymptotically, is governed by the MKV equation

$$dX_t = [k(\mathbb{E}[X_t] - X_t) + \alpha_t]dt + dW_t$$

(all banks control their rate of b&l with the same policy α)

- Need to minimize the cost

$$\mathbb{E} \left[\int_0^T \left(\frac{1}{2} \alpha_t^2 - q \alpha_t (\mathbb{E}[X_t] - X_t) + \frac{c}{2} (\mathbb{E}[X_t] - X_t)^2 \right) dt + \frac{d}{2} (\mathbb{E}[X_T] - X_T)^2 \right]$$

Separable cost

Special case: separable running cost = $f_t^1(x, a) + f_t^2(v_t, x)$:

$$\inf_{v \ll \gamma} \left\{ \text{COT}(\gamma, v, c_{f^1}) + F_{f^2, g}(v) \right\}$$

\uparrow \uparrow
 standard COT penalty
 (A. et al. 2016)

- For COT easy to get existence (& uniqueness) of $\pi^* \in \Pi_c(\gamma, \nu)$
- $\nu \mapsto \text{COT}(\gamma, \nu, c_{f^1})$ convex
- Need conditions on F to have existence/uniqueness, e.g.
 - F lsc \Rightarrow exist ν^*
 - F strictly convex \Rightarrow unique ν^*

Separable cost

Example: take $k = q = 0$ in the example above, then

- state dynamics: $dX_t = \alpha_t dt + dW_t$
- cost: $\mathbb{E} \left[\int_0^T \left(\frac{1}{2} \alpha_t^2 + \frac{c}{2} (\mathbb{E}[X_t] - X_t)^2 \right) dt + \frac{d}{2} (\mathbb{E}[X_T] - X_T)^2 \right]$

⇒ COT w.r.t. Cameron-Martin distance (Lassalle 2015):

$$\frac{1}{2} \inf_{\pi \in \Pi_c(\gamma, \nu)} \mathbb{E}^\pi [|\bar{\omega} - \omega|_H^2] = H(\nu|\gamma), \quad \text{thus}$$

$$\inf_{\nu \ll \gamma} \left\{ H(\nu|\gamma) + \frac{c}{2} \int_0^T \text{Var}(\nu_t) dt + \frac{d}{2} \text{Var}(\nu_T) \right\}$$

More generally: for cost $\frac{1}{2} \alpha_t^2 + h_t(X_t, \mathcal{L}(X_t))$, by Sanov theorem:

$$\inf_{\nu \ll \gamma} \left\{ H(\nu|\gamma) + F(\nu) \right\} = \lim_{n \rightarrow \infty} -\frac{1}{n} \ln \mathbb{E} e^{nF(\frac{1}{n} \sum_{i=1}^n \delta_{W_i})}, \quad \{W_i\} \text{ ind. BMs.}$$

And this does not seem to be limited to the entropic case ($\frac{1}{2} \alpha_t^2$).

Characterization: the general case

Assumptions. For all $x, a \in \mathbb{R}, m \in \mathcal{P}(\mathbb{R}), \eta \in \mathcal{P}(\mathbb{R} \times \mathbb{R})$:

- (A1) $b_t(x, \cdot, m)$ injective and convex
- (A2) f_t bdd below unif. in t , and $f_t(x, b_t^{-1}(x, \cdot, m)(y), \eta)$ convex in y
- (A3) $f_t(x, a, \cdot)$ is $<_{cm}$ -monotone (resp. $<_{conv}$ -monotone if b is linear)
($<_{cm}$ (resp. $<_{conv}$) denotes the conv/monotone (resp. conv) order)

Pathwise quadratic variation. For $\omega \in C := C_0[0, T], n \in \mathbb{N}$, let
 $\sigma_0^n(\omega) := 0, \sigma_{k+1}^n(\omega) := \inf\{t > \sigma_k^n(\omega) : |\omega(t) - \omega(\sigma_k^n)| \geq 2^{-n}\}, k \in \mathbb{N}$

We say that ω has **quadratic variation** if

$$V_n(\omega)(t) := \sum_{k=0}^{\infty} (\omega(\sigma_{k+1}^n \wedge t) - \omega(\sigma_k^n \wedge t))^2 \xrightarrow{u} =: \langle \omega \rangle_t \in C$$

Notation. $\tilde{\mathcal{P}} = \{\nu \in \mathcal{P}(C) : \langle \omega \rangle \exists \nu\text{-a.s.}, \text{ with } \langle \omega \rangle_t = t \text{ for all } t\}$

Characterization: the general case

Under the above assumptions, the following characterization of weak McKean-Vlasov solutions via causal transport holds.

Theorem

The *weak MKV problem* is **equivalent** to the following problem

$$\inf_{\nu \in \tilde{\mathcal{P}}} \inf_{\pi \in \Pi_c(\gamma, \nu)} \mathbb{E}^\pi \left[\int_0^T f_t(\bar{\omega}_t, u_t^\nu(\omega, \bar{\omega}), p_t((\bar{\omega}, u^\nu)_\# \pi)) dt + g(\bar{\omega}_T, \nu_T) \right]$$

where $u_t^\nu(\omega, \bar{\omega}) = b_t^{-1}(\bar{\omega}_t, \cdot, \nu_t)(\widehat{(\bar{\omega} - \omega)_t})$ and $p_t(\eta) = \eta_t$.

OT and COT
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Semim. preservation
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MkKean-Vlasov
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CN-equilibria
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Value of information
○○○○○

Conclusions

Addendum to the CN-equilibria section

Setting

- Discrete time $\mathbb{T} = \{1, \dots, N\}$.
- \mathcal{X} = path-space of types, and \mathcal{Y} = path-space of actions, e.g.

$$\mathcal{X} = \mathcal{Y} = \mathbb{R}^N.$$
- $\eta \in \mathcal{P}(\mathcal{X})$: types' distribution (of public knowledge).

$$\begin{array}{ccccc}
 \text{Cost function: } k(x, y, \nu) & = & c(x, y) + V[\nu](y) \\
 \begin{array}{ccc} \nearrow & \uparrow & \nwarrow \\ \text{type} & \text{action} & \text{actions} \\ x \in \mathcal{X} & y \in \mathcal{Y} & \text{distribution} \\ & & \nu \in \mathcal{P}(\mathcal{Y}) \end{array} & & \begin{array}{cc} \nearrow & \nwarrow \\ \text{idiosyncratic} & \text{mean-field} \\ \text{part} & \text{interaction} \end{array}
 \end{array}$$

Usually,

$$c(x, y) = \sum_{t=1}^N c_t(x_{1:t}, y_{1:t}), \quad V[\nu](y) = \sum_{t=1}^N V_t[\nu_{1:t}](y_{1:t})$$

Setting

The mean-field interaction term may capture repulsive/attractive effects. For example:

- **Congestion effect:** $V^c[\nu](y) = f\left(y, \frac{d\nu}{dm}(y)\right)$, with $m \in \mathcal{P}(\mathcal{Y})$ reference measure wrt which congestion measured, $f(y, \cdot) \nearrow$
- **Attractive effect:** $V^a[\nu](y) = \int_{\mathcal{Y}} \phi(y, z) d\nu(z)$, with ϕ cont, symmetric, convex, minimal on the diagonal

Non-cooperative equilibrium with a continuum of agents.

Static case:

- Schmeidler (1973)
- Mas-Colell (1984)
- . . .
- Blanchet and Carlier (2015)

A motivating example: n-player game

- $\mathbb{T} = \{1, 2\}$ meaning *this week* or *next week*.
- $\mathcal{X} = \{(s, s), (s, h), (h, s), (h, h)\}$, with
 $s = \textit{sick}$ and $h = \textit{healthy}$.
- $\mathcal{Y} = \{(v, v), (v, w), (w, v), (w, w)\}$ with
 $v = \textit{vacation}$ and $w = \textit{work}$.
- $\eta^{x_1}(x_2) = \mathbb{P}(\text{time-2 type} = x_2 \mid \text{time-1 type} = x_1)$.

We denote (x_1^i, x_2^i) and (y_1^i, y_2^i) for Agent i 's types and actions.

The Game: Agents must decide “now” how they will distribute *work* and *vacation* for *this* and *next week*, taking into account:

- current types $x_1^i \in \{s, h\}$, and priors $\eta^{x_1^i} \in \mathcal{P}(\{s, h\})$ (known)
- the fact that taking holidays gets more expensive if many people are thinking likewise

A motivating example: n-player game

Agent i selects $y_1^i \in \{v, w\}$ for current week, and guesses a time-2 action $y_2^i(x_2^i) \in \{v, w\}$ depending on its unknown time-2 type.

The cost of such arrangement, seen from now, is

$$J^i \left(\{y_1^i, y_2^i(\cdot)\}, \{y_1^k, y_2^k(\cdot)\}_{k \neq i} \right) := c_1(x_1^i, y_1^i) + V_1 \left[\frac{1}{n-1} \sum_{k \neq i} \delta_{y_1^k} \right] (y_1^i) \\ + \int \left\{ c_2(x_1^i, x_2^i, y_1^i, y_2^i(x_2^i)) + V_2 \left[\frac{1}{n-1} \sum_{k \neq i} \delta_{(y_1^k, y_2^k(x_2^k))} \right] (y_1^i, y_2^i(x_2^i)) \right\} \otimes_k \eta^{x_1^k} (dx_2^k).$$

Definition (Dynamic Nash equilibrium)

$\{y_1^i, y_2^i(\cdot)\}_{i=1}^n$ is a dynamic Nash equilibrium if, for all i ,

$$(y_1^i, y_2^i(\cdot)) \in \operatorname{argmin}_{(a, A(\cdot))} J^i \left(\{a, A(\cdot)\}, \{y_1^k, y_2^k(\cdot)\}_{k \neq i} \right)$$

A motivating example: n-player game

Problems:

- search for equilibria: very difficult
- even when they exist, difficult to characterize

Idea:

- If size n of population is big, one tries to **approximate** this difficult equilibrium problem by a hopefully simpler one
- For this we need that, as $n \rightarrow \infty$, the empirical distributions of the **n-player game equilibria** converge to distributions that corresponds to **equilibria for infinitely many players** (dynamic **Nash** equilibria \rightarrow dynamic **Cournot-Nash** equilibria)

\rightarrow From now on we think of the limiting case (**infinitesimal agents**)

Pure adapted strategies

Pure strategy: all players of type-path $x \in \mathcal{X}$ choose same strategy

$$\mathcal{Y} \ni y = A(x) = (A_t(x))_{t \in \mathbb{T}}$$

Adapted strategy: $A_t(x) = A_t(x_{1:t})$ for all $t \in \mathbb{T}$

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

- types' distribution: $\eta \in \mathcal{P}(\mathcal{X})$ (of public knowledge)
- strategies' distribution: $\nu = A(\eta) \in \mathcal{P}(\mathcal{Y})$ (to be determined in equilibrium)

Pure equilibrium

Definition ((Pure) dynamic Cournot-Nash equilibrium)

$(A^*, \nu^*) \in \mathcal{A} \times \mathcal{P}(\mathcal{Y})$ is called dynamic Cournot-Nash equilibrium if

- A^* attains

$$P(\nu^*) := \inf_{A \in \mathcal{A}} \int_{\mathcal{X}} \{c(x, A(x)) + V[\nu^*](A(x))\} d\eta(x)$$

- and $A^*(\eta) = \nu^*$

→ “minimization of an average cost + fixed point condition”

→ Pure equilibria known to rarely exist, so we shall consider:
generalization to mixed-strategy (i.e. randomized) equilibria

Mixed non-anticipative strategy

mixed-strategy: players of same type can choose different actions

non-anticipative: $A_t(x) = \text{fcn}(x_{1:t}) + \text{sth independent of } x$

- Non-anticipative mixed-strategy = causal (Kantorovic) transport
- The causal Monge transports $\pi = (id, A)(\eta) \in \Pi_c(\eta, \cdot)$ are the pure adapted strategies with prior η on types.
- The set of pure adapted strategies with prior η is dense in (and equals the extreme point of) the set $\Pi_c(\eta, \cdot)$.

Mixed-strategy equilibrium

For $\nu \in \mathcal{P}(\mathcal{Y})$, denote $M(\nu) := \inf_{\pi \in \Pi_c(\eta, \cdot)} \mathbb{E}^\pi [c(x, y) + V[\nu](y)]$.

Definition (Mixed-strategy dynamic Cournot-Nash equilibrium)

$(\pi^*, \nu^*) \in \Pi_c(\eta, \cdot) \times \mathcal{P}(\mathcal{Y})$ is called a mixed-strategy equilibrium if

- π^* attains $M(\nu^*)$,
- with $\nu^* = p_2(\pi^*)$, i.e., $\pi^* \in \Pi_c(\eta, \nu^*)$.

→ Mixed-strategy equilibria are solutions to causal transport problems, i.e. π^* as above does also attain

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

→ Analogously, pure equilibria are solutions to causal transport problems over Monge maps.

Potential games

We have seen that **equilibrium** \implies **optimal transport**

For **potential games**, we will have “ \iff ” in a precise sense

Definition (Potential Game)

V is the **first variation** of an energy functional $\mathcal{E} : \mathcal{P}(\mathcal{Y}) \rightarrow \mathbb{R}$:

$$\lim_{\epsilon \rightarrow 0^+} \frac{\mathcal{E}(v + \epsilon(\mu - v)) - \mathcal{E}(v)}{\epsilon} = \int_{\mathcal{Y}} V[v] d(\mu - v), \quad \forall v, \mu \in \mathcal{P}(\mathcal{Y})$$

E.g. for congestion and attractive costs V^c and V^a , we have

$$\mathcal{E}^c(v) = \int_{\mathcal{Y}} F\left(y, \frac{dv}{dm}(y)\right) dm(y), \quad \mathcal{E}^a(v) = \frac{1}{2} \int_{\mathcal{Y} \times \mathcal{Y}} \phi(y, z) dv(z) dv(y),$$

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

Potential games

Consider the **variational problem**

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

Theorem

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

- (i) (π^*, ν^*) is a **mixed-strategy equilibrium**;
- (ii) ν^* solves (VP), and π^* solves $CT(\eta, \nu^*)$.

Convexity of \mathcal{E} only needed for “(i) \Rightarrow (ii)”.

Remark. Note:

$$(VP) = \inf_{\pi \in \Pi_c(\eta, \cdot)} \{ \mathbb{E}^\pi [c] + \mathcal{E}[p_2(\pi)] \}.$$

Thus if \mathcal{E} concave and \exists equilibrium $\Rightarrow \exists$ pure equilibrium.

Potential games

Corollary (existence)

Let c be l.s.c. and bounded below. Then

- $V = V^c$ and growth condition on $f \Rightarrow \exists$ *m-s equilibrium*;
- $V = V^a$ and growth condition on $c \Rightarrow \exists$ *m-s equilibrium*.

Growth conditions ensure existence of a solution v^* to (VP), and $\text{CT}(\eta, v^*)$ admits a solution π^* easily. Now apply previous theorem.

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

Addendum to the Value of information section

Optimal stopping

- With the same method used above, we can estimate the value of information wrt other optimization problems, e.g.

$$v^{\mathcal{F}} := \inf_{\mathcal{F}^{W-st.t.}} \mathbb{E}^{\mathbb{P}} [\ell(W, \tau)], \quad v^{\mathcal{G}} := \inf_{\mathcal{G}^{W-st.t.}} \mathbb{E}^{\mathbb{P}} [\ell(W, \tau)],$$

where $\ell : C[0, T] \times \mathbb{R}_+$ cost function, W BM

Proposition

Let ℓ be \mathcal{F} -optional, and K -Lipschitz in its first argument wrt a metric d on $C \times C$, uniformly in time. Then

$$0 \leq v^{\mathcal{F}} - v^{\mathcal{G}} \leq K \inf_{\pi \in \Pi^{\mathcal{F}, \mathcal{G}}(\gamma, \gamma)} \mathbb{E}^{\pi} [d(\omega, \bar{\omega})].$$

E.g. $\ell(x, t) = f(x_t)$ and $\ell(x, t) = f(\sup_{s \leq t} x_s)$ satisfy the above conditions, with $d(\omega, \tilde{\omega}) = \|\omega - \tilde{\omega}\|_{\infty}$, if f is Lipschitz. In this case

$$0 \leq v^{\mathcal{F}} - v^{\mathcal{G}} \leq K \inf_{\pi \in \Pi^{\mathcal{F}, \mathcal{G}}(\gamma, \gamma)} \mathbb{E}^{\pi} [V_T(\bar{\omega} - \omega)].$$

Optimal stopping

Steps of the proof:

- Fix a causal transport $\pi \in \Pi^{\mathcal{F}, \mathcal{G}}(\gamma, \gamma)$.
- Similar idea, but “projecting stopping times” less obvious.
- **Randomized stopping time:** $\Sigma \in RST(\mathcal{F}, \mu)$ is increasing, right-cont., \mathcal{F} -adapted, with $\Sigma_0 = 0$ and $\Sigma_T = 1$, μ -a.s.
- For $\Sigma \in RST(\mathcal{G}, \gamma)$, let $\tilde{\Sigma}$ be its $(\pi, \mathcal{F} \otimes \{\emptyset, C\})$ -opt. proj.
- By causality: **opt. proj.** is π -ind. from **dual opt. proj.**
- Then $\tilde{\Sigma} \in RST(\mathcal{F}, \gamma)$ and

$$\mathbb{E}^{\pi} \left[\int_0^T \ell(\omega, t) d\Sigma_t(\bar{\omega}) \right] = \mathbb{E}^{\gamma} \left[\int_0^T \ell(\omega, t) d\tilde{\Sigma}_t(\omega) \right]$$

- Conclude by using $\inf_{\mathcal{F}^W\text{-st.t.}} \mathbb{E}^{\mathbb{P}} [\ell(W, \tau)] = \inf_{\tilde{\Sigma} \in RST(\mathcal{F}, \gamma)} \mathbb{E}^{\gamma} \left[\int \ell_t d\tilde{\Sigma}_t \right]$
(analogous in the enlarged filtration)