

Multi-Martingale Optimal Transport

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Martingale Optimal Transport (MOT) Problem in One dimension

- ▶ $(\Omega, \mathcal{F}, \mathbb{P})$: probability space
- ▶ $X : \Omega \rightarrow \mathbb{R}, Y : \Omega \rightarrow \mathbb{R}$: random variables
- ▶ cost function $c : \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R}$
- ▶ (marginal constraint) $\text{Law}(X) = \mu, \text{Law}(Y) = \nu$
- ▶ $E(Y|X) = X$.

Study the one-step martingales (stocks) (X, Y) with prescribed marginals, which **minimize** the expected cost (option price)

$$\min_{X \sim \mu, Y \sim \nu, E(Y|X)=X} \mathbb{E}_\pi c(X, Y).$$

Motivation:

- ▶ [Model-free Finance] find the minimum price of option $c(x, y)$ given market information μ, ν , that is, given the prices of call / put options.

A structure result in dimension one

- ▶ Denote $\pi = \text{Law}(X, Y)$
- ▶ Let $(\pi_x)_x$ be a disintegration (=conditional probability) of π w.r.t. μ
- ▶ $\pi(dx \cdot dy) = \pi_x(dy) \cdot \mu(dx)$

Theorem [Hobson-Neuberger-Klimmek, Beiglböck-Juillet '13]

Assume:

- ▶ $c(x, y) = \pm|x - y|$
- ▶ $\mu \ll \mathcal{L}^1$

Then: for μ - a.e. x ,

- ▶ π_x is concentrated at two boundary points of an interval, i.e. $\pi_x = \lambda\delta_{y-(x)} + (1 - \lambda)\delta_{y+(x)}$.

Question: What is a right generalization of this theorem in higher dimension?

Multi-Martingale Optimal Transport (MMOT) Problem [L. '16]

- ▶ $(\Omega, \mathcal{F}, \mathbb{P})$: probability space
- ▶ $X_i : \Omega \rightarrow \mathbb{R}, Y_i : \Omega \rightarrow \mathbb{R}$: random variables, $i = 1, 2, \dots, d$
- ▶ cost function $c : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}$
- ▶ (marginal constraint) $\text{Law}(X_i) = \mu_i, \text{Law}(Y_i) = \nu_i$
- ▶ $E(Y|X) = X$, where $X = (X_1, \dots, X_d), Y = (Y_1, \dots, Y_d)$

Study the one-step martingales (stocks) (X, Y) with prescribed marginals, which **minimize** the expected cost (option price)

$$\min_{X_i \sim \mu_i, Y_i \sim \nu_i, E(Y|X)=X} \mathbb{E}_\pi c(X, Y).$$

Motivation:

- ▶ [Finance] find the minimum price of the option whose value depends on **many** stocks $(X_i, Y_i), i = 1, \dots, d$, given the information that can be observed from the market.

Extremal structure of MMOT in general dimension

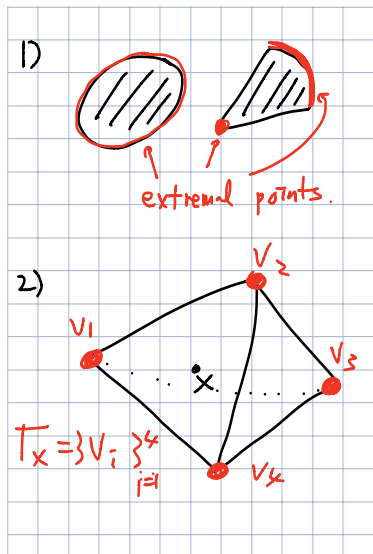
Theorem [L. '16]

Assume:

- ▶ $\mu_i \leq_c \nu_i$ (convex order)
- ▶ $\mu_i \ll \mathcal{L}^1$
- ▶ $c(x, y) = \pm \|x - y\|$ where $\|\cdot\|$ is any strictly convex norm on \mathbb{R}^d
- ▶ $\pi = \text{Law}(X, Y) \in P(\mathbb{R}^{2d})$ is any minimizer of MMOT
- ▶ $\pi(dx \cdot dy) = \pi_X(dy) \cdot \pi^1(dx)$, where $\pi^1 := \text{Law}(X) \in P(\mathbb{R}^d)$.

Then: support of π_X consists of the extreme points of a convex set:

$$\text{supp } \pi_X = \text{Ext}(\text{conv}(\text{supp } \pi_X)), \quad \pi^1 - \text{a.e. } x.$$



How to obtain such structure result? Study the Dual Optimizer of MOT

- ▶ We say that a triple of functions (ϕ, ψ, h) is a dual maximizer of the MOT problem, if for every minimizer π of MOT we have

$$\phi(x) + \psi(y) + h(x) \cdot (y - x) \leq c(x, y) \quad \forall x \in \mathbb{R}, \forall y \in \mathbb{R}, \quad (1)$$

$$\phi(x) + \psi(y) + h(x) \cdot (y - x) = c(x, y) \quad \pi - a.e. (x, y). \quad (2)$$

- ▶ $\phi(x) + \psi(y) + h(x) \cdot (y - x)$ can be interpreted as an optimal subhedging strategy for the option $c(x, y)$.

Irreducibility of (μ, ν) is essential to achieve duality in MOT

- ▶ Beiglböck-Juillet, Beiglböck-Nutz-Touzi showed that in dimension one ($d = 1$), duality is attained if the marginals (μ, ν) are **irreducible**.
- ▶ The irreducibility of (μ, ν) is characterized by their *potential functions*

$$u_\mu(x) := \int |x - y| d\mu(y), \quad u_\nu(x) := \int |x - y| d\nu(y).$$

- ▶ This is also where the OT and MOT are divergent: in OT theory essentially no relation between μ, ν is required for duality.
- ▶ The seemingly harmless linear term $h(x) \cdot (y - x)$ drastically changes the picture.

Duality in MMOT (is also attained!)

Theorem [L. '16] Assume:

- ▶ (μ_i, ν_i) is **irreducible**, $\forall i = 1, \dots, d$
- ▶ π is any minimizer of MMOT

Then: there exist a bunch of functions $\phi_i, \psi_i : \mathbb{R} \rightarrow \mathbb{R}$, $i=1, \dots, d$, $h : \mathbb{R}^d \rightarrow \mathbb{R}^d$ which is a **dual maximizer**:

$$\sum_{i=1}^d \phi_i(x_i) + \sum_{i=1}^d \psi_i(y_i) + h(x) \cdot (y - x) \leq c(x, y) \quad \forall x \in \mathbb{R}^d, \forall y \in \mathbb{R}^d,$$

$$\sum_{i=1}^d \phi_i(x_i) + \sum_{i=1}^d \psi_i(y_i) + h(x) \cdot (y - x) = c(x, y) \quad \pi - \text{a.e. } (x, y).$$

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- ▶ But not only this, we find that $\text{Law}(X)$ and $\text{Law}(Y)$ also solve a classical dual optimal transport problem:

$\text{Law}(X)$, $\text{Law}(Y)$ are also optimizers for OT

Theorem [L. '16] Assume:

- ▶ $(\phi_i, \psi_i, h_i)_{i \leq d}$ is a dual maximizer
- ▶ $\pi = \text{Law}(X, Y)$ is any minimizer of MMOT

Then: its induced **d -copulas** π^1, π^2 (i.e. $\pi^1 = \text{Law}(X)$, $\pi^2 = \text{Law}(Y)$) solve the dual optimal transport problem with respect to the **costs** α, β respectively:

$$\sum_i \phi_i(x_i) \leq \alpha(x) \quad \mu_i - \text{a.e. } x_i, \text{ and } \sum_i \phi_i(x_i) = \alpha(x) \quad \pi^1 - \text{a.e. } x,$$
$$\sum_i \psi_i(y_i) \geq \beta(y) \quad \nu_i - \text{a.e. } y_i, \text{ and } \sum_i \psi_i(y_i) = \beta(y) \quad \pi^2 - \text{a.e. } y.$$

Law(X), Law(Y) are also optimizers for OT

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$$\sum_i \psi_i(y_i) \geq \beta(y) \quad \nu_i - \text{a.e. } y_i, \text{ and } \sum_i \psi_i(y_i) = \beta(y) \quad \pi^2 - \text{a.e. } y.$$

- ▶ Here the functions $\alpha : \mathbb{R}^d \rightarrow \mathbb{R}$, $\beta : \mathbb{R}^d \rightarrow \mathbb{R}$ are naturally defined in terms of the function $y \mapsto \sum_{i=1}^d \psi_i(y_i)$ and are called the **martingale Legendre transform**.

(Ghossoub-Kim-L. '15)

- ▶ OT theory can enter for the study of the structure of π^1, π^2 .

Extremal structure of MMOT: norm-type option

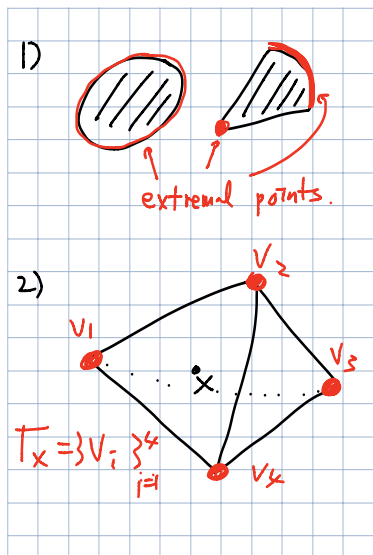
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Then: support of π_X consists of the extreme points of a convex set:

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Extremal structure of MMOT: maximum covariance

Example [L. '16] Assume:

- ▶ $d = 2$ & dual maximizer exists (e.g. (μ_i, ν_i) is irreducible)
- ▶ $c(x, y) = -y_1 y_2$ or equivalently $c(x, y) = \frac{1}{2}|y_1 - y_2|^2$
- ▶ $\pi = \text{Law}(X, Y) \in P(\mathbb{R}^4)$ is any minimizer of MMOT
- ▶ $\pi(dx \cdot dy) = \pi_x(dy) \cdot \pi^1(dx)$, where $\pi^1 := \text{Law}(X) \in P(\mathbb{R}^2)$.

Then: there exists an increasing function $\psi : \mathbb{R} \rightarrow \mathbb{R}$ and a function $h : \mathbb{R}^2 \rightarrow \mathbb{R}$ such that $Y_2 = \psi(Y_1) + h(X)$.

And: $\pi^1 = \text{Law}(X)$ is the **quantile coupling** of μ_1, μ_2 (that is, π^1 must be supported on the graph of an increasing function).

Conclusion:

- ▶ **The duality attainment results presented so far shall serve as the cornerstones for further development of the MOT / MMOT theory, as it did so in the classical OT theory.**
- ▶ **As the classical optimal transport theory (in higher dimensions) has made important contributions to many areas of mathematics and economics, I believe that this new development of probabilistic optimal embedding theory in higher dimensions will have far-reaching consequences as well.**

Thank You Very Much!