

# Constrained Optimal Transport

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# Outline

- 1 Classical Optimal Transport
- 2 Martingale Optimal Transport
- 3 Supermartingale Optimal Transport

# Monge Optimal Transport

## Given:

- Probabilities  $\mu, \nu$  on  $\mathbb{R}$ .
- Reward (cost) function  $f : \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R}$ .



## Objective:

- Find a map  $T : \mathbb{R} \rightarrow \mathbb{R}$  satisfying  $\nu = \mu \circ T^{-1}$  such as to maximize the total reward,

$$\max_T \int f(x, T(x)) \mu(dx).$$

# Monge–Kantorovich Optimal Transport

## Relaxation:

- Find a probability  $P$  on  $\mathbb{R} \times \mathbb{R}$  with marginals  $\mu, \nu$  such as to maximize the reward:

$$\max_{P \in \Pi(\mu, \nu)} E^P[f(X, Y)], \quad \text{where } \Pi(\mu, \nu) := \{P : P_1 = \mu, P_2 = \nu\}$$

and  $(X, Y) = \text{Id}_{\mathbb{R} \times \mathbb{R}}$ .

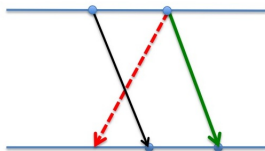
- $P \in \Pi(\mu, \nu)$  is a **Monge transport** if of the form  $P = \mu \otimes \delta_{T(x)}$ .

## Example: Hoeffding–Frechet Coupling

**Theorem:** Let  $f$  satisfy the **Spence–Mirrlees** condition  $f_{xy} > 0$ . Then the optimal  $P$  is unique and given by the **Hoeffding–Frechet Coupling**:

- $P$  is the law of  $((F_\mu)^{-1}, (F_\nu)^{-1})$  under the uniform measure on  $[0, 1]$ .
- If  $\mu$  is diffuse,  $P$  is of Monge type with  $T = (F_\nu)^{-1} \circ F_\mu$ .
- $P$  is characterized by **monotonicity**:

if  $(x, y), (x', y') \in \text{supp}(P)$  and if  $x < x'$ , then  $y \leq y'$ .



# Kantorovich Duality

- Buy  $\varphi(X)$  at price  $\mu(\varphi) := E^\mu[\varphi]$  and  $\psi(Y)$  at  $\nu(\psi)$  to **superhedge**,

$$f(X, Y) \leq \varphi(X) + \psi(Y).$$

- Then for all  $P \in \Pi(\mu, \nu)$ ,

$$E^P[f(X, Y)] \leq E^P[\varphi(X) + \psi(Y)] = \mu(\varphi) + \nu(\psi).$$

- Theorem** (Kantorovich, Kellerer): For any measurable  $f \geq 0$ ,

$$\sup_{P \in \Pi(\mu, \nu)} E^P[f(X, Y)] = \inf_{\varphi, \psi} \mu(\varphi) + \nu(\psi)$$

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## Application: Fundamental Theorem of Optimal Transport

Let  $\Gamma = \{(x, y) : \hat{\varphi}(x) + \hat{\psi}(y) = f(x, y)\}$  and  $P \in \Pi(\mu, \nu)$ . TFAE:

- (1)  $P$  is optimal.
- (2)  $P(\Gamma) = 1$ .
- (3)  $\text{supp}(P)$  is  $f$ -cyclically monotone  $P$ -a.s.; i.e.,

$$\sum_{i=1}^n f(x_i, y_i) \geq \sum_{i=1}^n f(x_i, y_{\sigma(i)}) \quad \forall (x_i, y_i) \in \text{supp}(P), \quad \sigma \in \text{Perm}(n).$$

- (1)(2) If  $P(\Gamma) < 1$ , then  $P$  charges  $\{(x, y) : \hat{\varphi}(x) + \hat{\psi}(y) > f(x, y)\}$  and thus  $\mu(\hat{\varphi}) + \nu(\hat{\psi}) > E^P[f(X, Y)]$ .
- (2)(1) If  $P(\Gamma) = 1$ , then  $\mu(\hat{\varphi}) + \nu(\hat{\psi}) = E^P[f(X, Y)]$ , hence  $P, \hat{\varphi}, \hat{\psi}$  are optimal.
- (2)(3) This argument even shows: if  $\tilde{P}(\Gamma) = 1$ , then  $\tilde{P}$  is an optimal transport between its own marginals. Apply this with discrete  $\tilde{P} \Rightarrow \Gamma$  is cyclically monotone.



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# Dynamic Hedging

- **Dynamically tradable** underlying  $S = (S_0, S_1, S_2)$ .
- Semi-static superhedge:

$$f((S_t)_t) \leq \varphi(S_1) + \psi(S_2) + H_0(S_1 - S_0) + H_1(S_2 - S_1).$$

- With  $S_0 = 0$ ,  $S_1 = X \sim \mu$ ,  $S_2 = Y \sim \nu$  and normalization  $H_0 = 0$ :

$$f(X, Y) \leq \varphi(X) + \psi(Y) + h(X)(Y - X).$$

- Formally, duality with  $P \in \Pi(\mu, \nu)$  satisfying the constraint that

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# Martingale Transport

- Set of **martingale transports**:

$$\mathcal{M}(\mu, \nu) = \{P \in \Pi(\mu, \nu) : E^P[Y|X] = X\}.$$

- **Theorem** (Strassen):  $\mathcal{M}(\mu, \nu)$  is nonempty iff  $\mu \leq_c \nu$ ; i.e.,

$$\mu(\phi) \leq \nu(\phi) \quad \forall \phi \text{ convex.}$$

- **Martingale Optimal Transport problem**: Given  $\mu \leq_c \nu$ ,

$$\sup_{P \in \mathcal{M}(\mu, \nu)} E^P[f(X, Y)].$$

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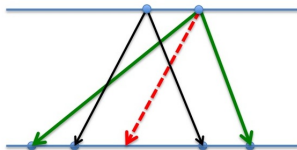
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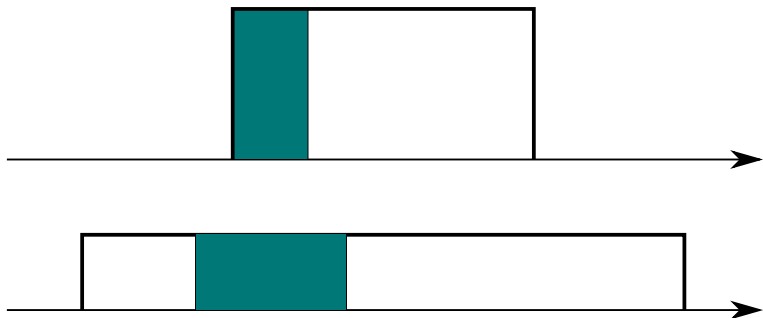


## Example: Left-Curtain Coupling

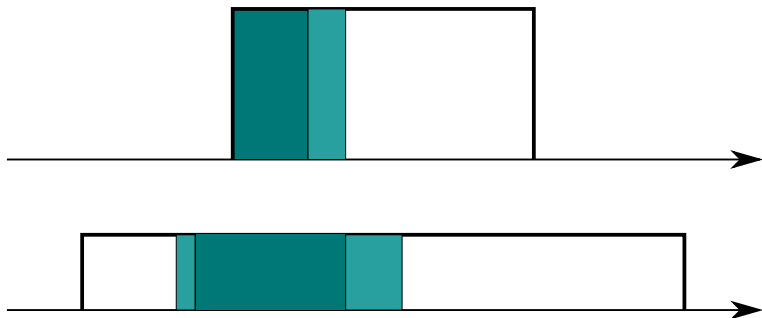
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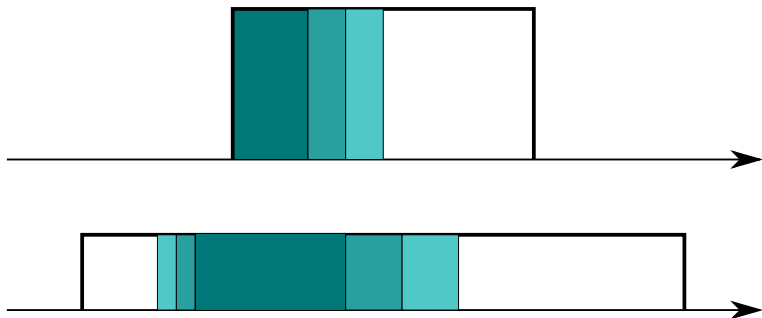
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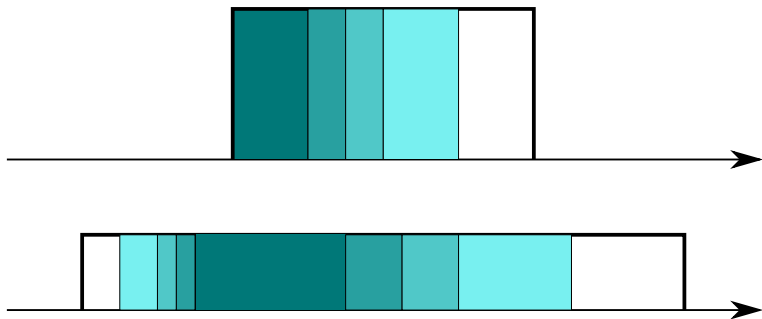
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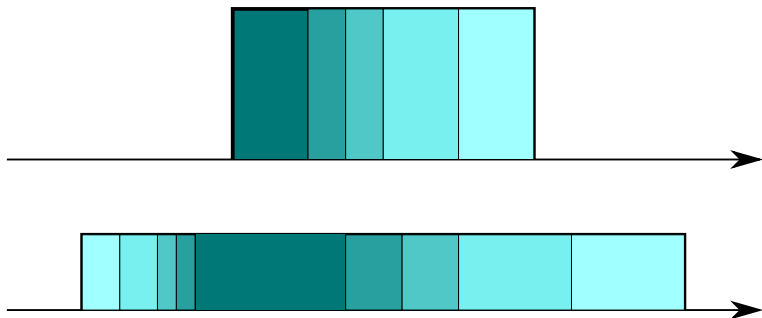
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# Duality for Martingale Optimal Transport

In analogy to Monge–Kantorovich duality we want:

(1) No duality gap:

$$\sup_{P \in \mathcal{M}(\mu, \nu)} E^P[f(X, Y)] = \inf_{\varphi, \psi, h} \mu(\varphi) + \nu(\psi).$$

(2) Dual existence:  $\hat{\varphi}, \hat{\psi}, \hat{h}$ .

Theorem (Beiglböck, Henry-Labordère, Penkner):

- For upper semicontinuous  $f \leq 0$ , there is no duality gap.
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## An Example with Duality Gap

- Let  $f$  be the bounded, **lower** semicontinuous function

$$f(x, y) = \mathbf{1}_{x \neq y} = \begin{cases} 0 & \text{on the diagonal,} \\ 1 & \text{off the diagonal.} \end{cases}$$

- Let  $\mu = \nu =$  Lebesgue measure on  $[0, 1]$ .
- There exists a **unique** martingale transport  $P$ , **concentrated on the diagonal** ( $T(x) = x$ ).
- Primal value:  $\sup_{P \in \mathcal{M}(\mu, \nu)} E^P[f(X, Y)] = 0$ .
- Dual optimizers **exist**,  $\hat{\phi} = 1$ ,  $\hat{\psi} = 0$ ,  $\hat{h} = 0$  but
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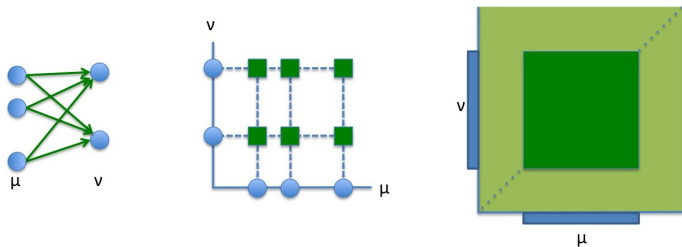
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# Ordinary and Martingale OT: What is the Difference?

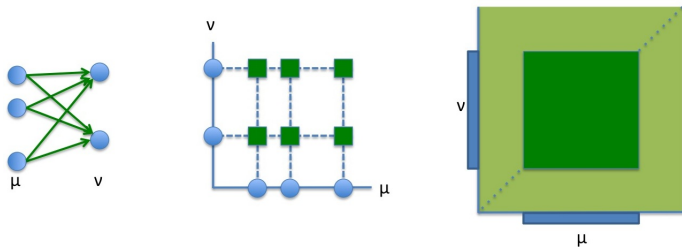
- In ordinary OT, all roads  $x \rightarrow y$  can be used.
- E.g., in the discrete case,  $\mu \times \nu$  already has full support.



- Theorem (Kellerer):  $A \subseteq \mathbb{R} \times \mathbb{R}$  is  $\Pi(\mu, \nu)$ -polar if and only if
$$A \subseteq (N_1 \times \mathbb{R}) \cup (\mathbb{R} \times N_2), \quad \text{where } \mu(N_1) = \nu(N_2) = 0.$$

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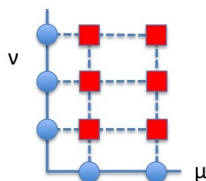
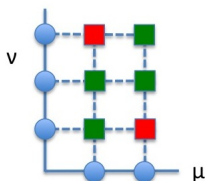
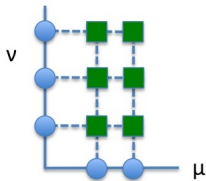
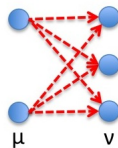
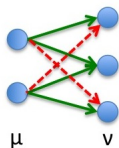
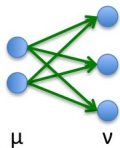


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# Obstructions for Martingale Transport

- In martingale OT, some roads  $x \rightarrow y$  can be blocked.



# Potential Functions

**Potential**  $u_\mu(x) := \int |t - x| \mu(dt) = E[|X - x|]$  under any  $P \in \mathcal{M}(\mu, \nu)$ .

- $\mu \leq_c \nu \iff u_\mu \leq u_\nu$ .

- If

$$u_\mu(x) = u_\nu(x); \quad \text{i.e.} \quad E[|X - x|] = E[|Y - x|] \quad (*),$$

then  $x$  is a **barrier** for any martingale transport:

1. Jensen:  $|X - x| = |E[Y|X] - x| = |E[Y - x|X]| \leq E[|Y - x| | X]$
2. Under (\*), it follows that  $|X - x| = E[|Y - x| | X]$  a.s. Hence,

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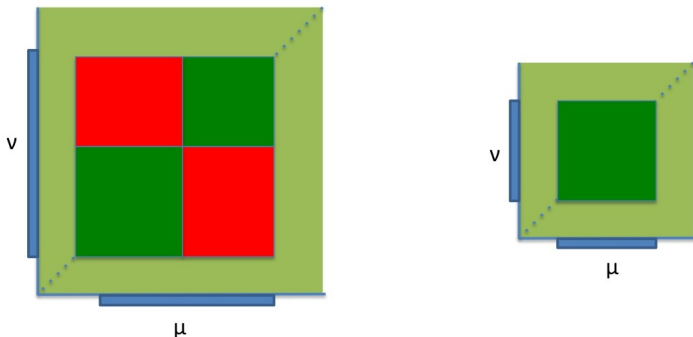
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so that  $Y \geq x$  a.s. on  $\{X \geq x\}$ .

→ **Partition**  $\mathbb{R}$  into intervals  $\{u_\mu < u_\nu\}$ .

## Structure of $\mathcal{M}(\mu, \nu)$ -polar Sets



**Theorem:** “These are precisely the  $\mathcal{M}(\mu, \nu)$ -polar sets.”



# Duality Result

## Theorem

Let  $f \geq 0$  be measurable and consider the *quasi-sure relaxation* of the dual problem:

$$f(X, Y) \leq \varphi(X) + \psi(Y) + h(X)(Y - X) \quad \mathcal{M}(\mu, \nu)\text{-q.s.}$$

Then,

- (1) *there is no duality gap,*
- (2) *dual optimizers  $\hat{\varphi}, \hat{\psi}, \hat{h}$  exist.*

- The superhedge is pointwise **on each component** (e.g.,  $\mu = \delta_{x_0}$ ).
- Dual existence in the **pointwise formulation typically fails** as soon as there is more than one component.
- Application as in the FTOT.

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# Supermartingale Optimal Transport

- Set of **supermartingale transports**:

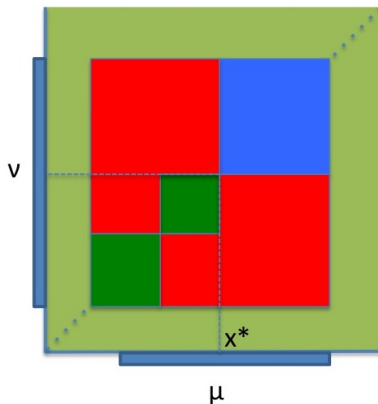
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- $\mathcal{S}(\mu, \nu)$  is nonempty iff  $\mu \leq_{cd} \nu$ ; i.e.,

$$\mu(\phi) \leq \nu(\phi) \quad \forall \phi \text{ convex decreasing.}$$

- Coincides with MOT if  $\mu, \nu$  have same mean, and with OT if supports are ordered.

## Structure of $\mathcal{S}(\mu, \nu)$ -polar Sets



**Theorem:** There exist a maximal barrier  $x^*$  such that:

- martingale transport on  $(-\infty, x^*]$ ,
- single component of strict supermartingale transport on  $[x^*, \infty)$ .

# Duality for Supermartingale Transport

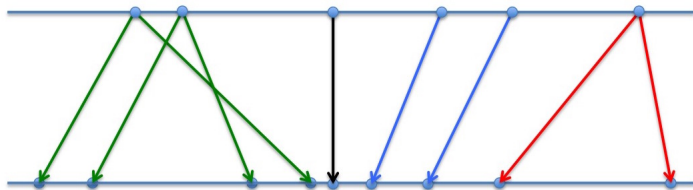
- Duality results similar to martingale case,
- with additional constraint  $h \geq 0$  (long-only hedging).
- Duality leads to a version of the Fundamental Theorem with an additional condition of complementary slackness:

$$E^P[h(X)(Y - X)] = 0.$$

# Decomposition of Optimal Supermartingale Couplings

Let  $P \in \mathcal{S}(\mu, \nu)$  be **optimal**. Then  $J_0 := \{h = 0\}$  and  $J_1 := \{h > 0\}$  yield a (non-unique) decomposition:

- $\mathbb{R} = J_0 \cup J_1$ ,  $\mu = \mu_0 + \mu_1 := \mu|_{J_0} + \mu|_{J_1}$ ,
- $P|_{J_0 \times \mathbb{R}}$  is an optimal **Monge–Kantorovich** transport from  $\mu_0$  to  $P(\mu_0)$ ,
- $P|_{J_1 \times \mathbb{R}}$  is an optimal **martingale** transport from  $\mu_1$  and  $P(\mu_1)$ .



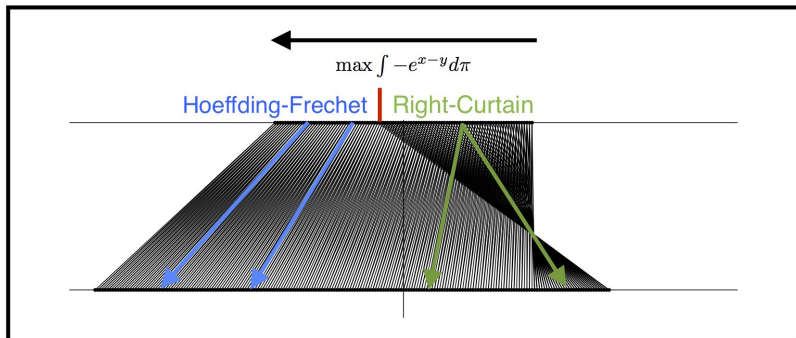
# First Canonical Coupling

**Theorem:** Let  $f$  satisfy

1)  $f_{xy} > 0$  and  $f_{xyy} < 0$  e.g.,  $f(x, y) = -\exp(x - y)$ ;

Then the optimal  $P$  exists, is **unique** and **independent** of  $f$ .

- Obtained by sending each bit of mass to the **minimal destination** relative to the convex-decreasing order.
- Here we work from **right to left**.



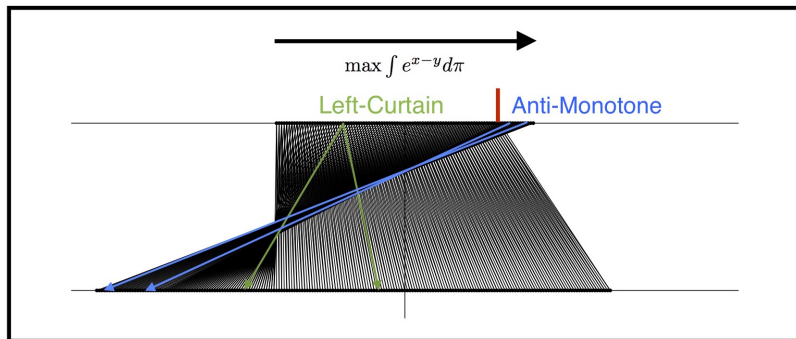
## Second Canonical Coupling

**Theorem:** Let  $f$  satisfy

2)  $f_{xy} < 0$  and  $f_{xyy} > 0$  e.g.,  $f(x, y) = \exp(x - y)$ ;

Then the optimal  $P$  is **exists**, is **unique** and **independent** of  $f$ .

- Here we work from **left to right**.
- (No) symmetry?





# Conclusion

- Interesting **new couplings** arise from problems in mathematical finance.
- Duality in a **quasi-sure** sense is useful for their analysis.
- We expect **other constraints** to be tractable as well: ongoing work with **Florian Stebegg**.

Thank you.

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Thank you.