Equitable and Optimal Transport with Multiple Agents

M. Scetbon*

L. Meunier*

J. Atif

M. Cuturi











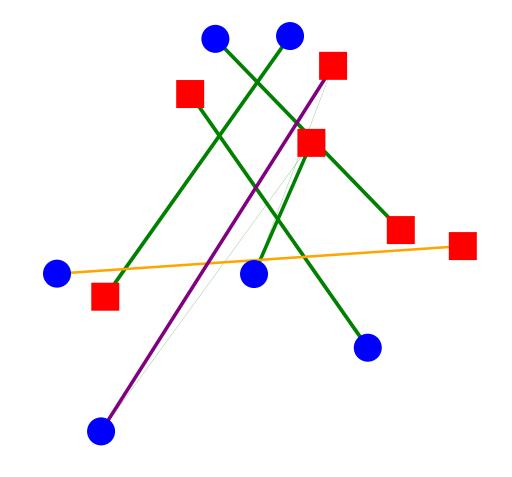
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Problem: how to split the transportation task in order to obtain an equitable and optimal transportation strategy between multiple agents?

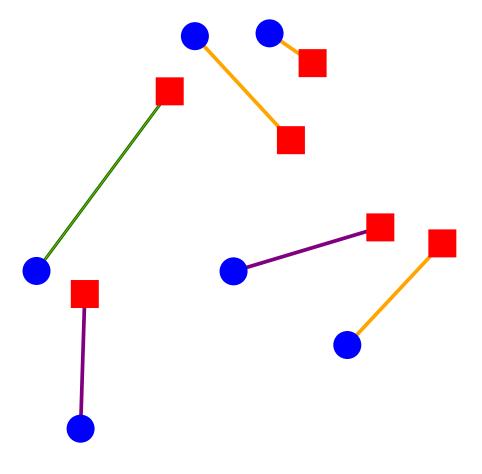
Primal Formulation

Distributions: $\mu \in \mathcal{M}_1^+(\mathcal{X})$ and $\nu \in \mathcal{M}_1^+(\mathcal{Y})$

Cost/Utility functions : $c_i: \mathcal{X} \times \mathcal{Y} \to \mathbb{R}$ for $i \in \{1,...,N\}$



Utility functions: $\forall i, c_i < 0$



Cost functions: $\forall i, c_i \geq 0$

$$\text{Couplings: } \Gamma^N_{\mu,\nu} := \left\{ \left. (\gamma_i)_{i=1}^N \text{ s.t. } \Pi_{1\sharp} \sum_{i=1}^N \gamma_i = \mu \right., \, \Pi_{2\sharp} \sum_{i=1}^N \gamma_i = \nu \right\}$$

Definition of Equitable and Optimal Transport

$$\mathsf{EOT}_{\mathbf{c}}(\mu, \nu) := \inf_{(\gamma_i)_{i=1}^N \in \Gamma_{\mu, \nu}^N} \max_{i \in \{1, \dots, N\}} \int c_i(\mathbf{x}, \mathbf{y}) d\gamma_i(\mathbf{x}, \mathbf{y}) \; .$$

• The division of the transportation task is equitable:

Proposition

If the cost/utility functions are of constant sign then we have

$$\mathsf{EOT}_{\mathbf{c}}(\mu, \nu) = \min_{(\gamma_i)_{i=1}^N \in \Gamma_{\mu, \nu}^N} \left\{ t \text{ s.t. } \forall i \in \{1, \dots, N\} \right. \left. \int c_i(\mathbf{x}, \mathbf{y}) d\gamma_i(\mathbf{x}, \mathbf{y}) = t \right\}$$

The division of the transportation task is optimal:

Proposition

If the cost/utility functions are of constant sign then for any $(\gamma_i^*)_{i=1}^N \in \Gamma_{\mu,\nu}^N$ solution of EOT, we have for all $i \in \{1,...,N\}$:

$$\gamma_i^* \in \operatorname{argmin}_{\gamma \in \Gamma^1_{\mu_i^*,\nu_i^*}} \int c_i d\gamma \text{ where } \mu_i^* := \Pi_{1\sharp} \gamma_i^* \text{ , } \nu_i^* := \Pi_{2\sharp} \gamma_i^*$$

Application: EOT solves a relaxation of the fair cake-cutting problem.

Dual Formulation

 $\text{Dual space: } \mathcal{F}_{\mathbf{c}}^{\lambda} := \{(f,g) \in \mathcal{C}^b(\mathcal{X}) \times \mathcal{C}^b(\mathcal{Y}) \text{ s.t. } \forall i \in \{1,...,N\}, \, f \oplus g \leq \lambda_i c_i\}$

Strong duality holds:

$$\mathsf{EOT}_{\mathbf{c}}(\mu, \nu) = \sup_{\lambda \in \Delta_N^+} \int f d\mu + \int g d\nu$$
$$(f, g) \in \mathscr{F}_{\mathbf{c}}^{\lambda}$$

Link with other Probability Metrics

• If N=1, EOT $_{\bf c}(\mu,\nu)=W_c(\mu,\nu)$ where $W_c(\mu,\nu)$ is the OT cost between μ and ν

$$\text{ If } c_1 = d \text{ and } c_2 = 2 \times \mathbf{1}_{x \neq y}, \text{ EOT}_{\mathbf{c}}(\mu, \nu) = \sup_{f \in B_d(\mathcal{X})} \int_{\mathcal{X}} f d\mu - \int_{\mathcal{X}} f d\nu$$
 where $B_d(\mathcal{X}) := \left\{ f \in C^b(\mathcal{X}) \colon \|f\|_{\infty} + \|f\|_{\text{lip}} \leq 1 \right\}$

Entropic Relaxation

Generalized Kullback-Leibler divergence:
$$KL(\mu \mid \mid \nu) = \int log \frac{d\mu}{d\nu} d\mu + \int d\nu - \int d\mu$$

Definition of the entropic version of EOT:

$$\mathsf{EOT}_{\mathbf{c}}^{\epsilon}(\boldsymbol{\mu}, \boldsymbol{\nu}) := \inf_{(\gamma_i)_{i=1}^N \in \Gamma_{\boldsymbol{\mu}, \boldsymbol{\nu}}^N} \max_{i \in \{1, \dots, N\}} \int c_i(\boldsymbol{x}, \boldsymbol{y}) d\gamma_i(\boldsymbol{x}, \boldsymbol{y}) + \epsilon \sum_{j=1}^N \mathsf{KL}(\gamma_j | | \boldsymbol{\mu} \otimes \boldsymbol{\nu})$$

Proposed Algorithm:

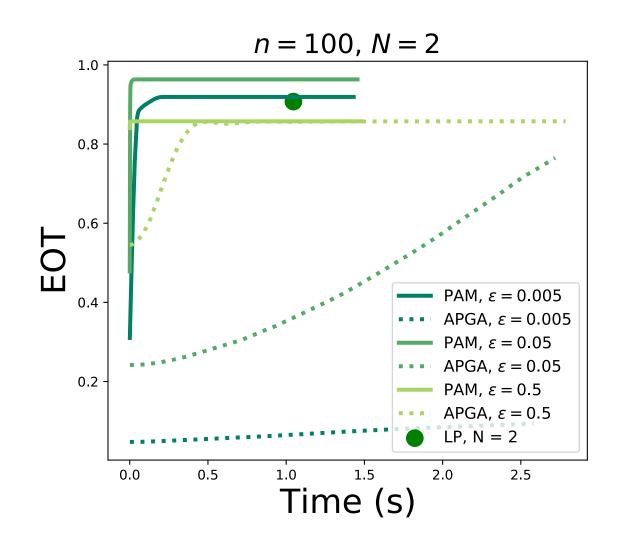
Algorithm 1 Projected Alternating Maximization Input: $\mathbf{C} = (C_i)_{1 \leq i \leq N}, \ a, \ b, \ \varepsilon, \ L_{\lambda}$ Init: $f^0 \leftarrow \mathbf{1}_n; \ g^0 \leftarrow \mathbf{1}_m; \ \lambda^0 \leftarrow (1/N, ..., 1/N) \in \mathbb{R}^N$

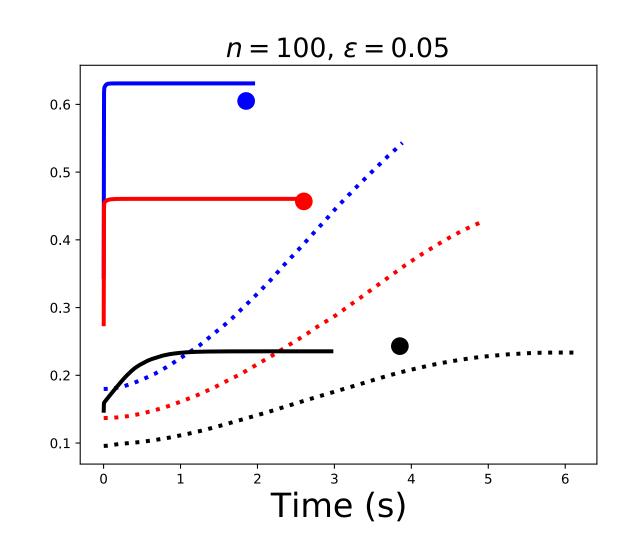
for k = 1, 2, ... do

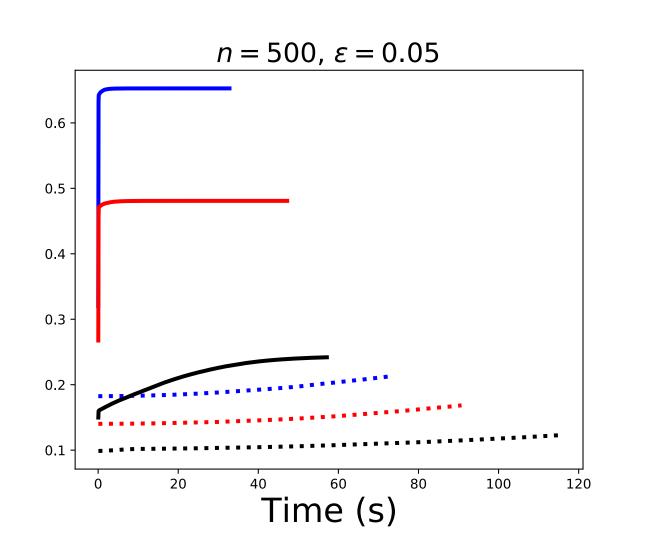
$$\begin{vmatrix} K^{k} \leftarrow \sum_{i=1}^{N} K_{i}^{\lambda_{i}^{k-1}}, \\ c_{k} \leftarrow \langle f^{k-1}, K^{k} g^{k-1} \rangle, f^{k} \leftarrow \frac{c_{k} a}{K^{k} g^{k-1}}, \\ d_{k} \leftarrow \langle f^{k}, K^{k} g^{k-1} \rangle, g^{k} \leftarrow \frac{d_{k} b}{(K^{k})^{T} f^{k}}, \\ \lambda^{k} \leftarrow \operatorname{Proj}_{\Delta_{N}^{+}} \left(\lambda^{k-1} + \frac{1}{L_{\lambda}} \nabla_{\lambda} F_{\mathbf{C}}^{\varepsilon}(\lambda^{k-1}, f^{k}, g^{k}) \right).$$

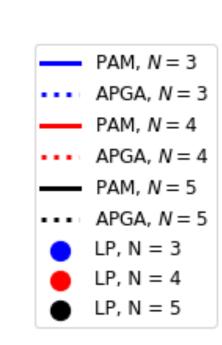
 \mathbf{end}

Result: λ, f, g









Other Applications of EOT

Minimal transportation time

Thank you

Sequential OT