

Numerical resolution of semi-discrete generated Jacobian equation and application to non-imaging optics

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Joint work with Boris Thibert and Quentin Mérigot

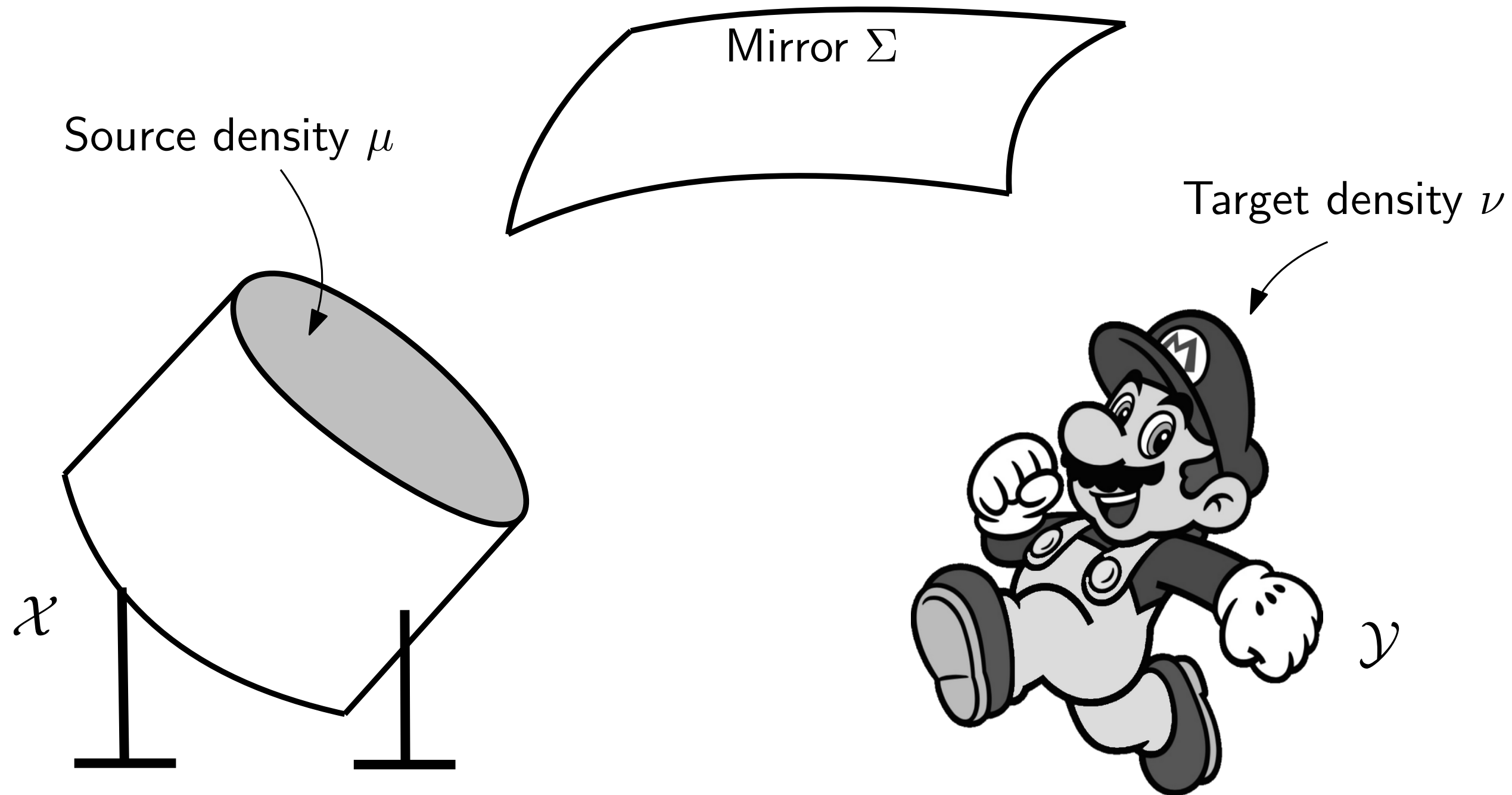
Optimal Transport Cargese Workshop - April 8-12, 2024

Non-imaging optics



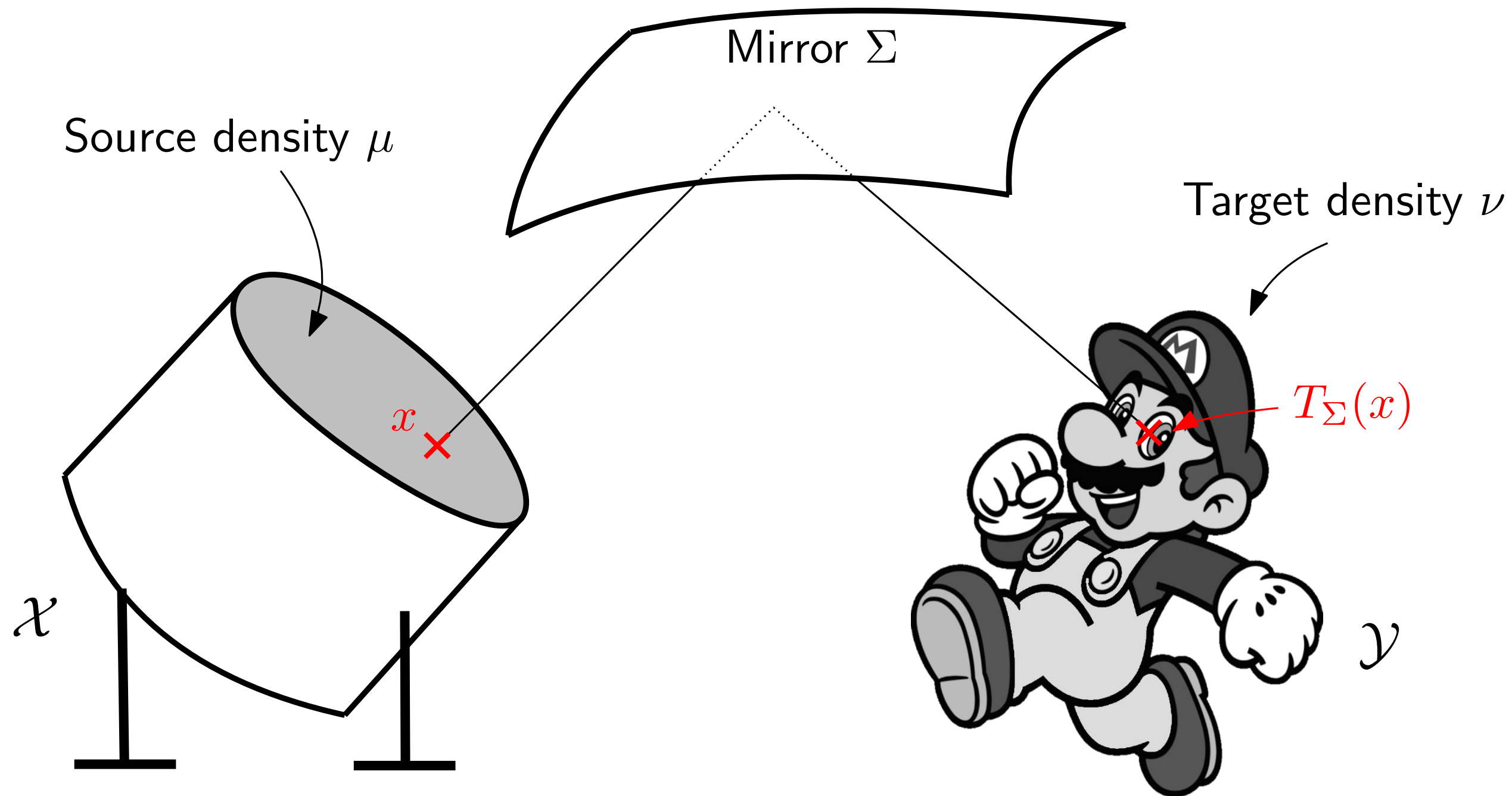
Goal: Construct a mirror that reflects a given light source toward a prescribed target.

Non-imaging optics: transport of measure



Input: Light source \mathcal{X} with intensity $\mu \in \mathcal{P}(\mathcal{X})$.
Target distribution \mathcal{Y} with intensity $\nu \in \mathcal{P}(\mathcal{Y})$.

Non-imaging optics: transport of measure



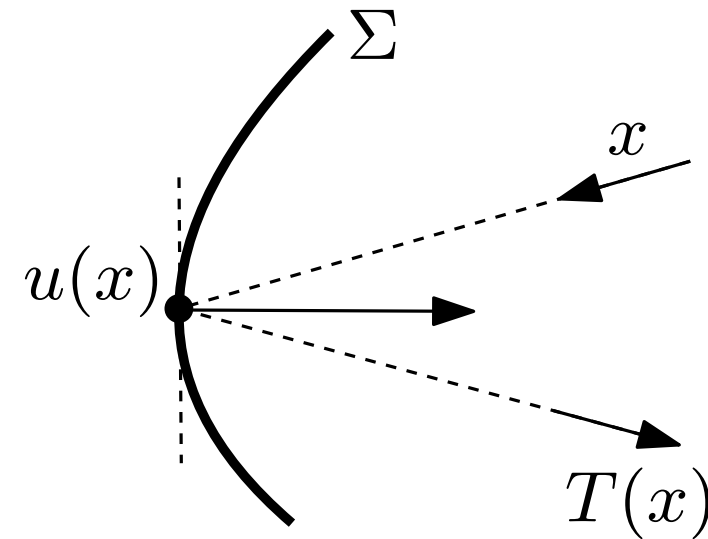
Input: Light source \mathcal{X} with intensity $\mu \in \mathcal{P}(\mathcal{X})$.
Target distribution \mathcal{Y} with intensity $\nu \in \mathcal{P}(\mathcal{Y})$.

Output: A surface Σ such that $T_{\Sigma\#}\mu = \nu$ with $T_{\Sigma\#}\mu(B) = \mu(T_\Sigma^{-1}(B))$

Optimal transport & Generated Jacobian eq.

- Assume $\mu(x) = \rho(x) \, dx$ and $\nu(y) = \sigma(y) \, dy$
then $T_{\#}\mu = \nu$ amounts to: $\forall x \in \mathcal{X}, \sigma(T(x)) \det(DT(x)) = \rho(x)$

- From Snell's law if Σ is parametrized by a function $u : \mathcal{X} \rightarrow \mathbb{R}$ then T is a function of x , $u(x)$ and $\nabla u(x)$.



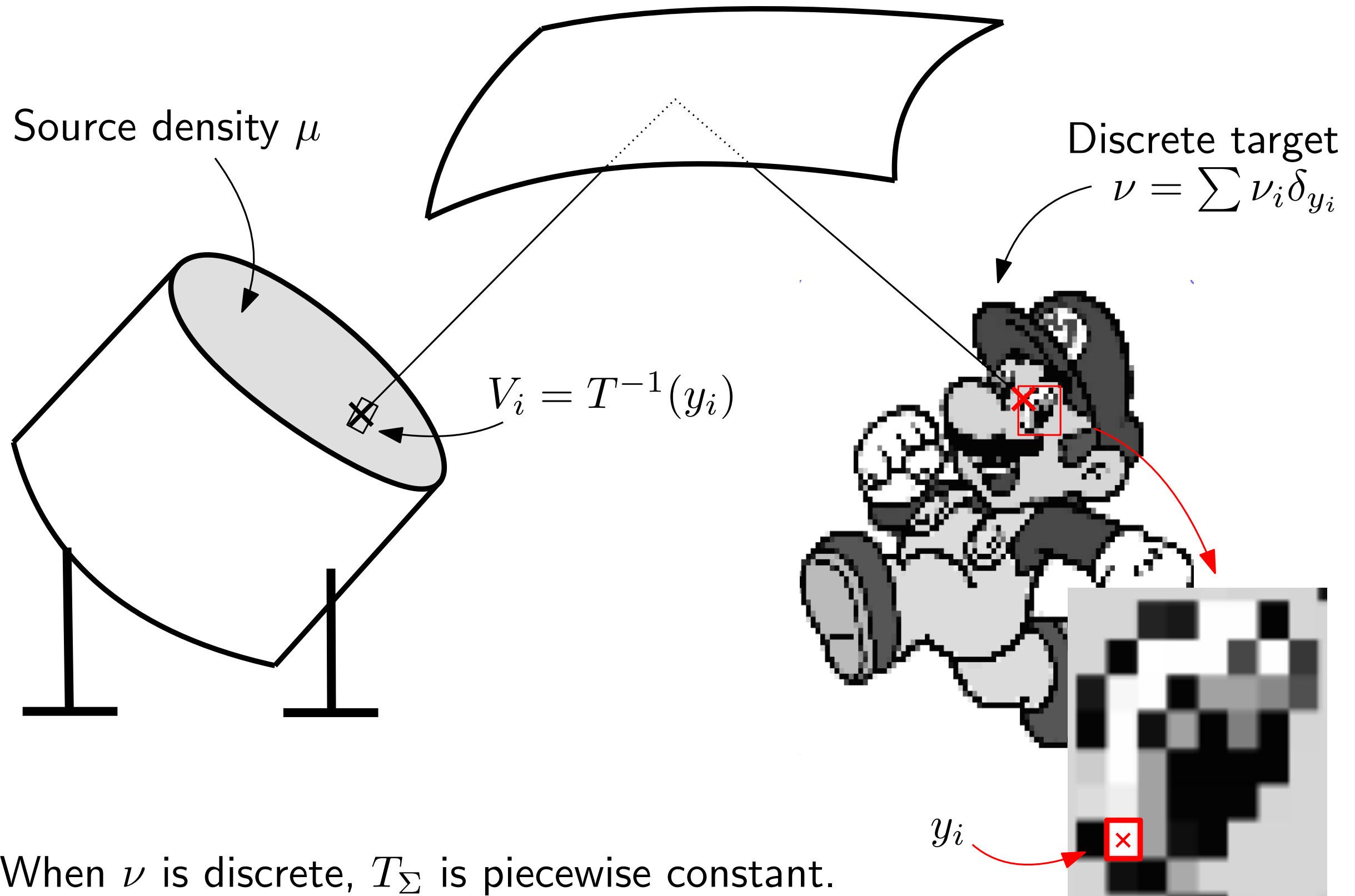
A Monge-Ampère type equation:

$$\forall x \in \mathcal{X}, \det(DT(x)) = \frac{\rho(x)}{\sigma(T(x))} \text{ with } T(x) = f(x, u(x), \nabla u(x)).$$

- In some particular cases this equation is OT, otherwise it is a GJE.

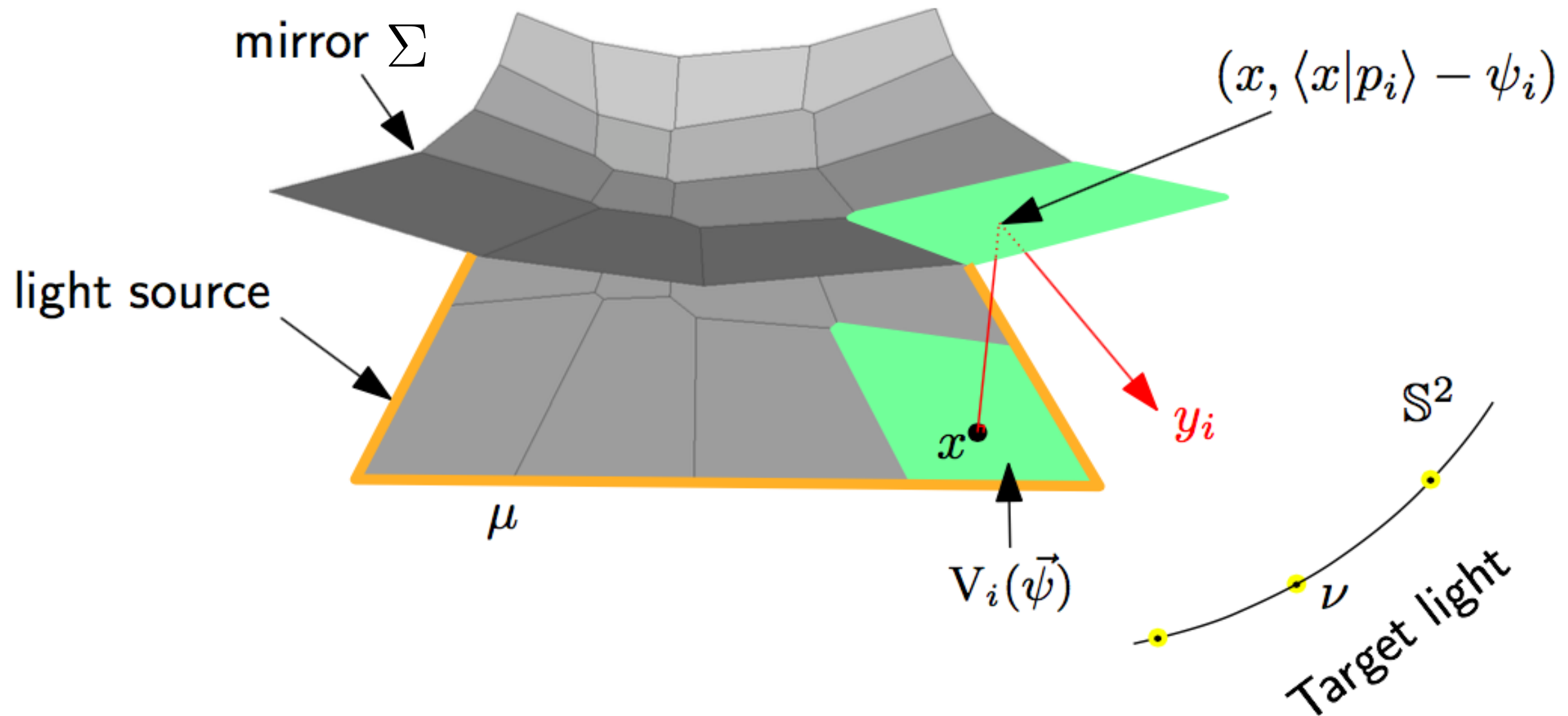
[Trudinger '14]

Discretization for numerical purposes



- When ν is discrete, T_Σ is piecewise constant.
- $T_{\Sigma\#}\mu = \nu$ becomes $\forall i, \mu(V_i) = \nu_i$ ← Prescribe the mass of each cell

The far-field reflector problem

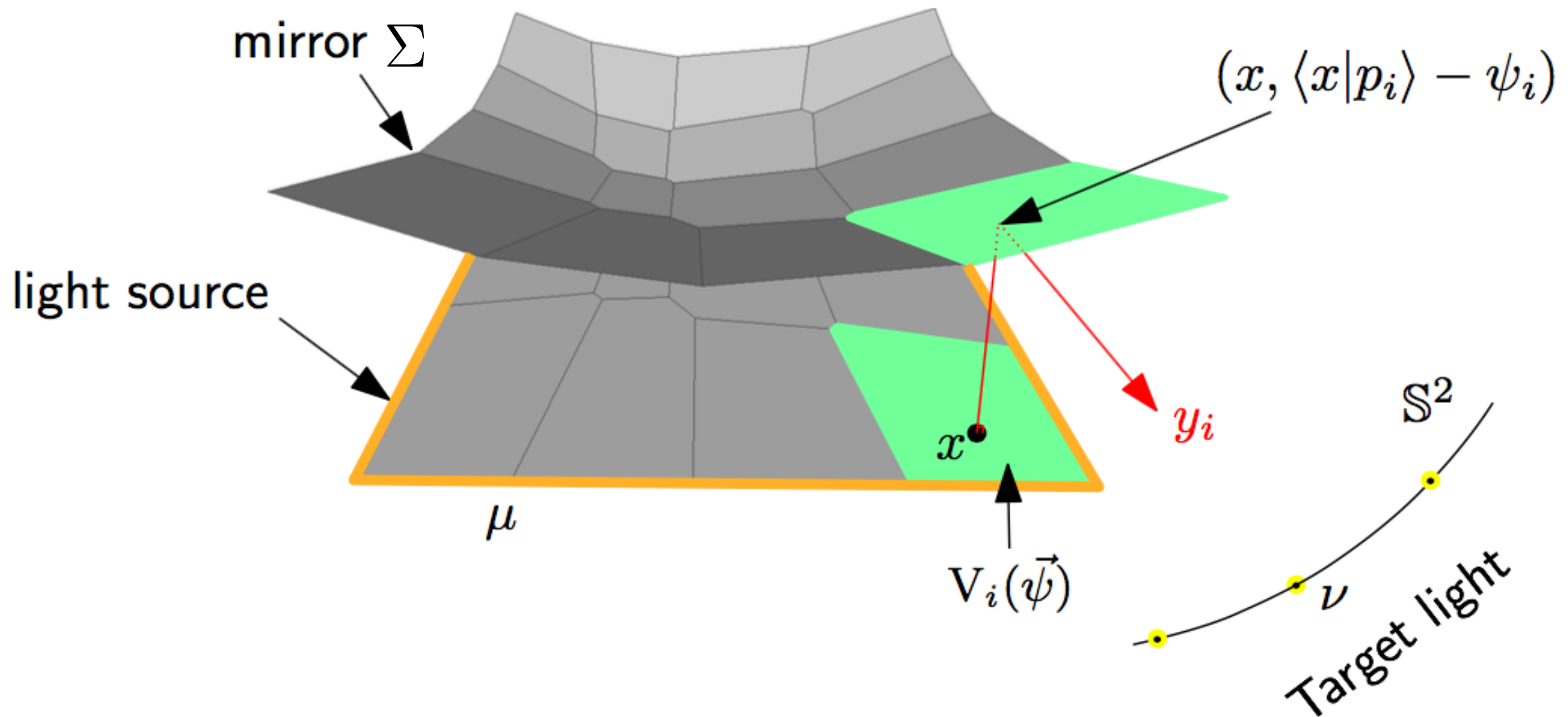


■ Collimated light source $\mu \in \mathcal{P}^{\text{ac}}(\mathcal{X})$.

■ Far field target $\nu = \sum_{1 \leq i \leq N} \nu_i \delta_{y_i}$ with $y_i \in \mathbb{S}^2$.

Target "at infinity"

The far-field reflector problem



- Impose Σ to be the graph of $u(x) = \max_{1 \leq i \leq N} \langle x|p_i\rangle - \psi_i$
- $V_i(\psi) = T^{-1}(y_i) = \{x \in \mathcal{X} \mid \forall j, \langle x|p_i\rangle - \psi_i \geq \langle x|p_j\rangle - \psi_j\}$

Problem: Find $\psi \in \mathbb{R}^N$ such that for all $i \in \{1, \dots, N\}$, $\mu(V_i(\psi)) = \nu_i$

↳ Semi-discrete Optimal Transport with $c(x, y) = -\langle x|y\rangle$

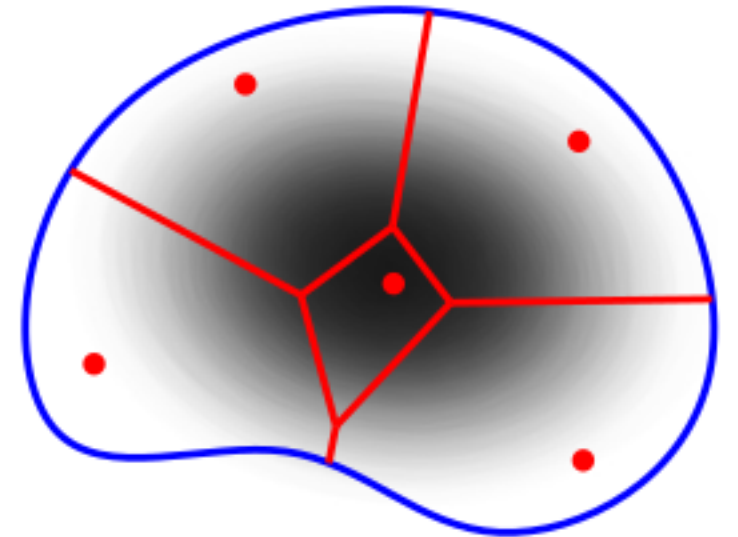
Semi-discrete optimal transport

Definition: (Laguerre diagram) Let $c : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$ be a twisted cost. For $\mathcal{Y} = (y_i)_{1 \leq i \leq N}$, and $\psi \in \mathbb{R}^{\mathcal{Y}}$, the Laguerre diagrams partitions \mathcal{X} in N cells by

$$\text{Lag}_y(\psi) = \{x \in \mathcal{X} \mid \forall z \neq y, c(x, y) + \psi(y) \leq c(x, z) + \psi(z)\}$$

Let T_ψ defined by $T_\psi(x) = y \iff x \in \text{Lag}_y(\psi)$

Let $\mu \in \mathcal{P}(X)$ and $\nu = T_{\psi\#}\mu \in \mathcal{P}(\mathcal{Y})$



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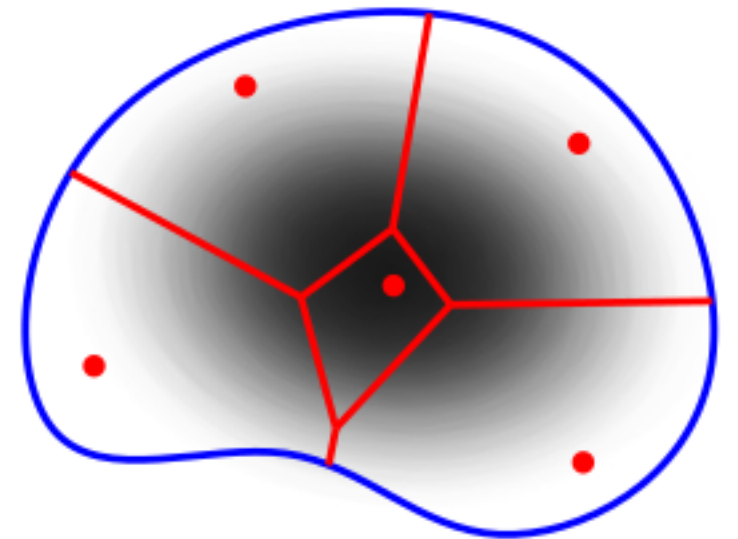
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Let $\mu \in \mathcal{P}(X)$ and $\nu = T_{\psi\#}\mu \in \mathcal{P}(\mathcal{Y})$

Then $\forall (x, y) \in \mathcal{X} \times \mathcal{Y}$

$$c(x, T_\psi(x)) + \psi(T_\psi(x)) \leq c(x, y) + \psi(y)$$

So for any $\gamma \in \Pi(\mu, \nu)$, $\int c(x, T_\psi(x)) + \psi(T_\psi(x)) \, d\mu \leq \int c(x, y) + \psi(y) \, d\gamma$



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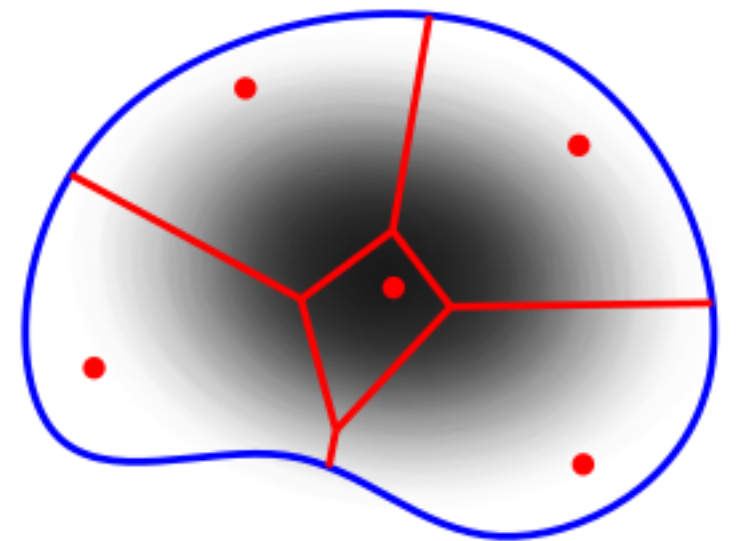
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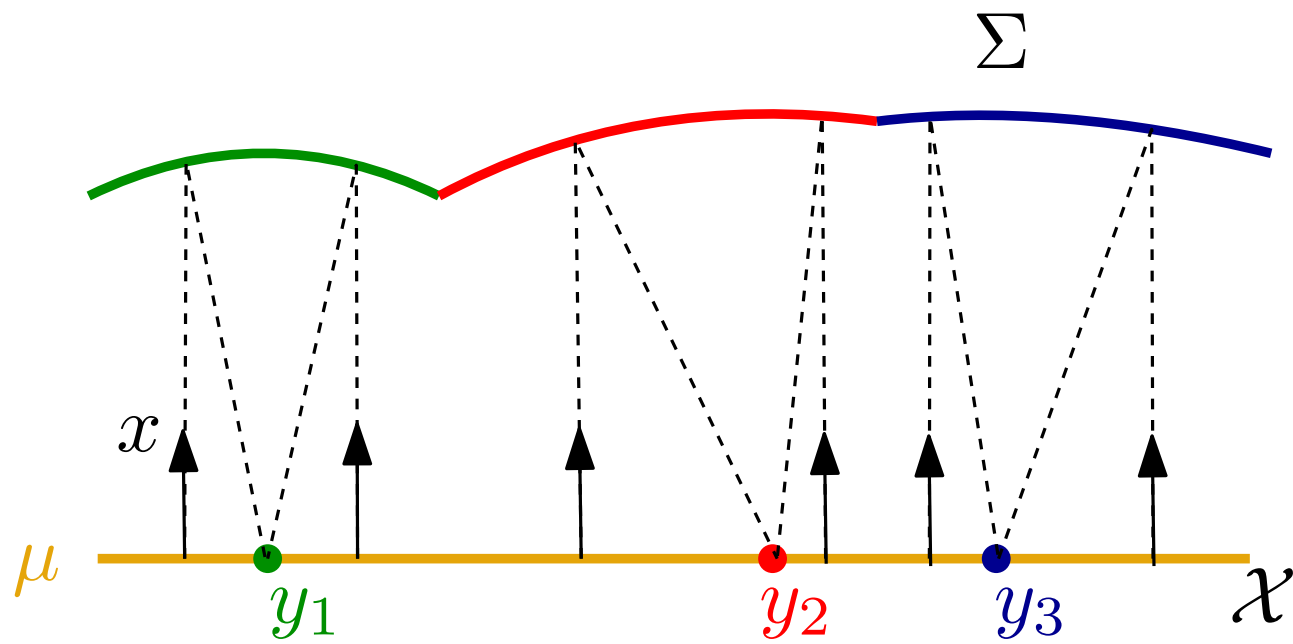
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T_ψ is optimal between μ and $\nu = T_{\psi\#}\mu$ for the cost c



The Near-Field Parallel reflector

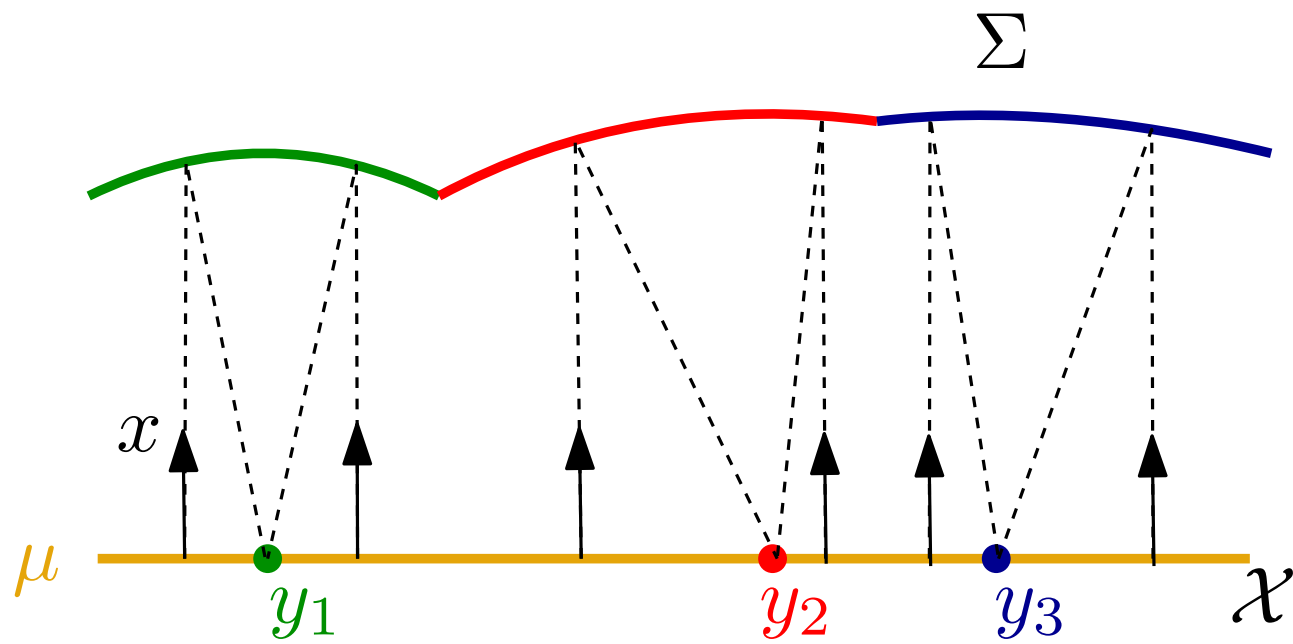


- Collimated light source:
 $\mu \in \mathcal{P}(\mathcal{X})$ abs. cont.

- Near field target:

$$\nu = \sum_{1 \leq i \leq N} \nu_i \delta_{y_i} \text{ with } y_i \in \mathbb{R}^2.$$

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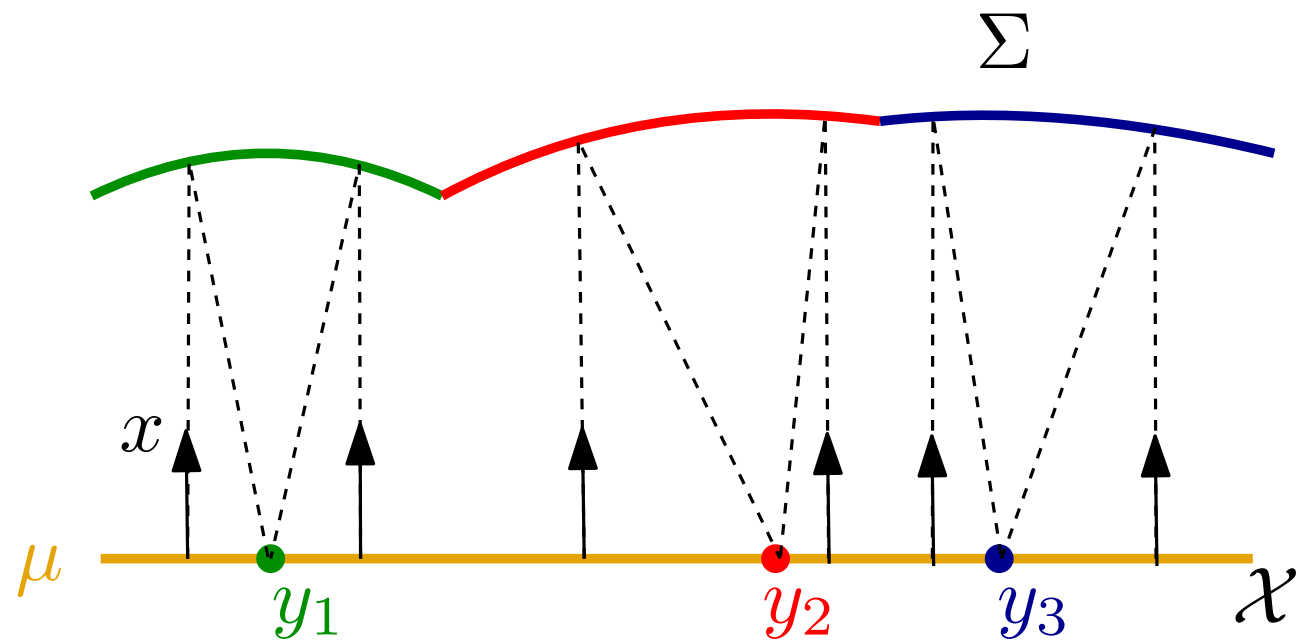
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- Mirror Σ is a maximum of paraboloids of focus (y_i) .

- Parametrization of Σ : $u(x) = \max_{1 \leq i \leq N} \frac{1}{2\psi_i} - \frac{\psi_i}{2} \|x - y_i\|^2$

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$$\text{Lag}_i(\psi) = \left\{ x \in \mathcal{X} \mid \forall j, \frac{1}{2\psi_i} - \frac{\psi_i}{2} \|x - y_i\|^2 \geq \frac{1}{2\psi_j} - \frac{\psi_j}{2} \|x - y_j\|^2 \right\}$$

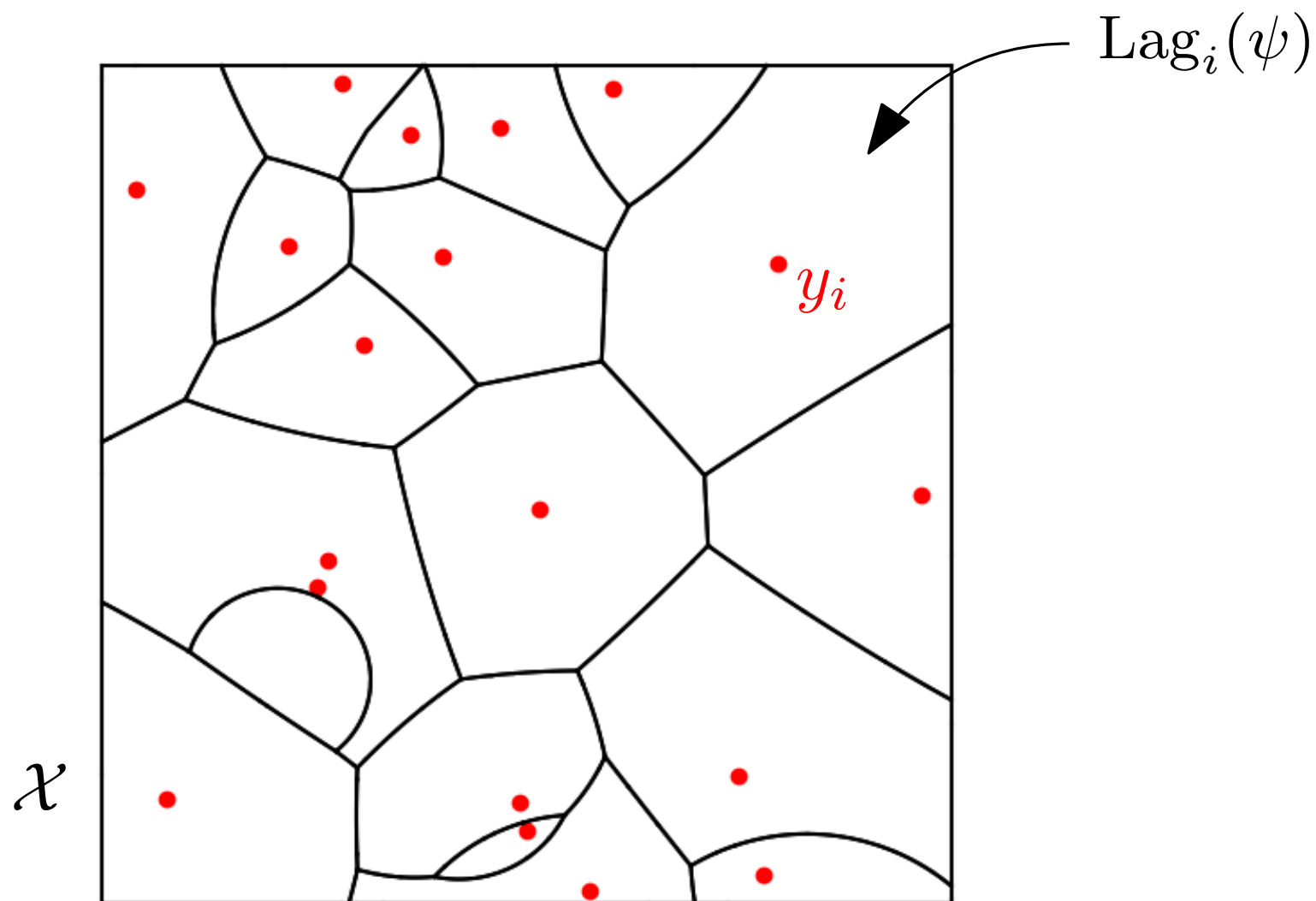
Problem: Find $\psi \in \mathbb{R}^N$ such that for all $i \in \{1, \dots, N\}$, $\mu(\text{Lag}_i(\psi)) = \nu_i$

Not linear in $\psi \rightarrow$ not optimal transport.

Semi-discrete generated Jacobian eq.

Definition: (Generating function & generalized Laguerre cells)

- **Generating function** $G : \mathcal{X} \times \mathcal{Y} \times \mathbb{R} \rightarrow \mathbb{R}$ satisfies (Reg), (Twist), (UC) and (Mono).
- **Generalized Laguerre diagram** for $\psi \in \mathbb{R}^N$
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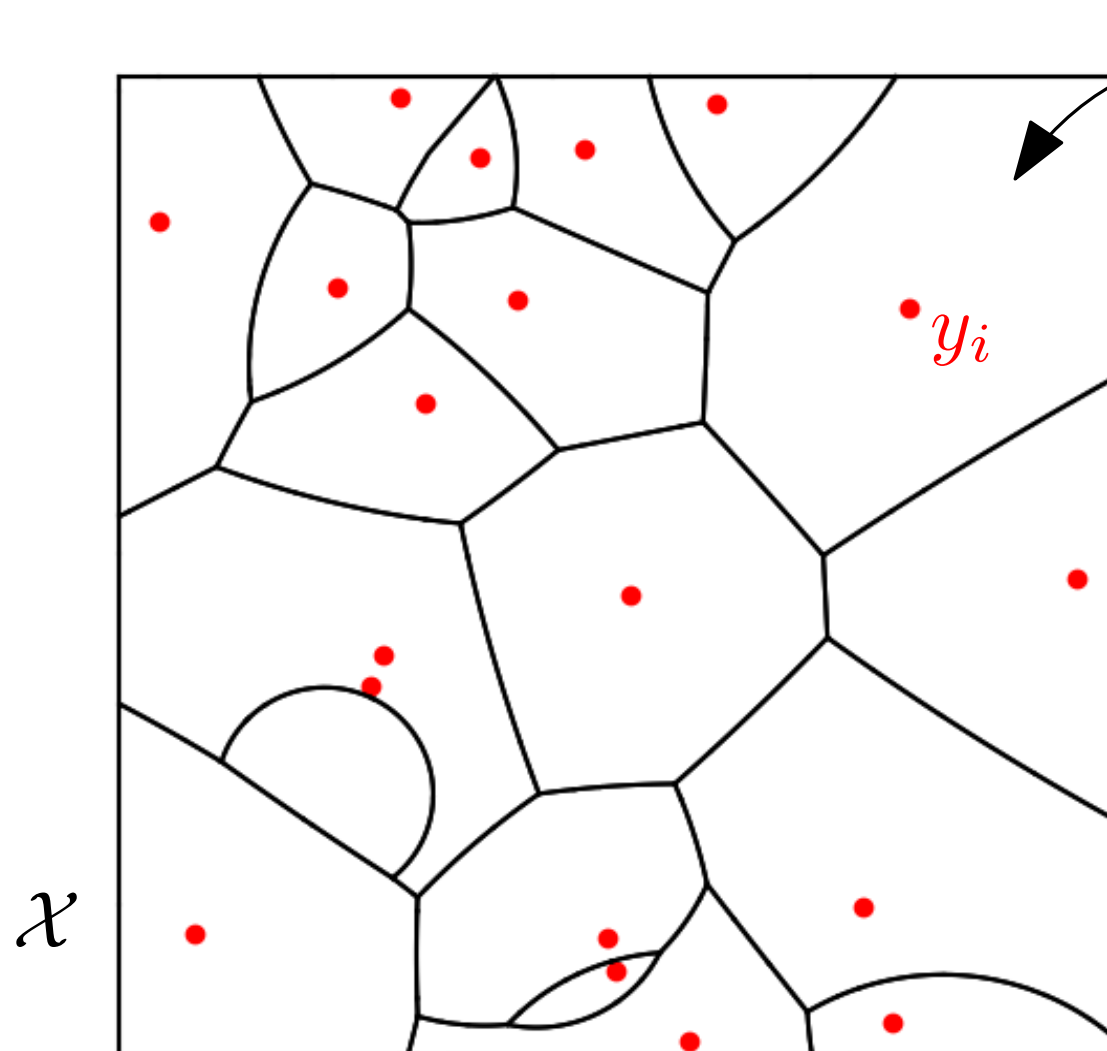


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- **Mass function:**

$$H : \mathbb{R}^N \rightarrow \mathbb{R}^N$$

$$\psi \mapsto (\mu(\text{Lag}_i(\psi)))_{1 \leq i \leq N}$$

Generated Jacobian eq: (*Trudinger '14*)

Find $\psi \in \mathbb{R}^N$ such that

$$H(\psi) = \nu$$

Examples:

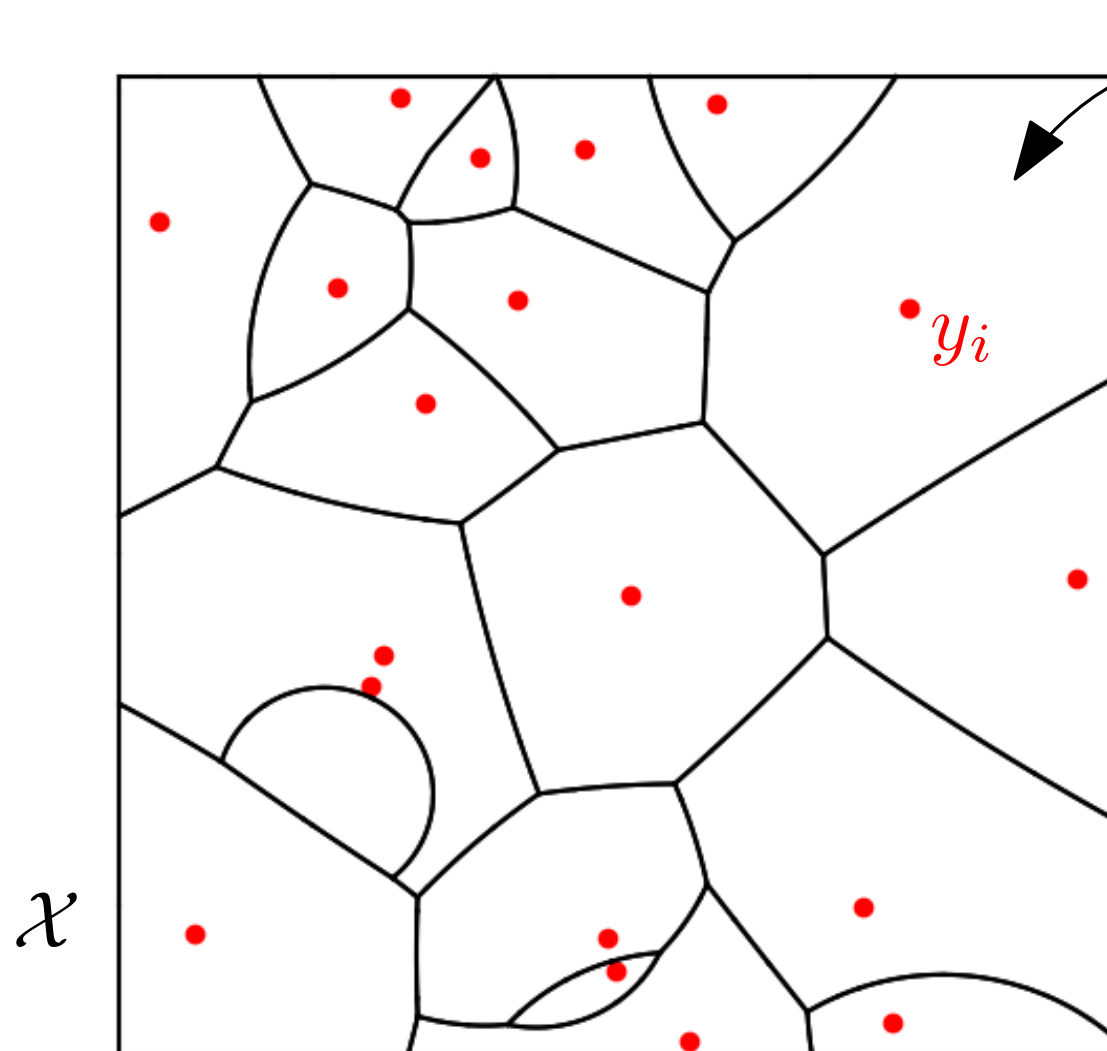
- $G(x, y, v) = -c(x, y) - v \quad (OT)$

- $G(x, y, v) = \frac{1}{2v} - \frac{v}{2} \|x - y\|^2 \quad (NFPar)$

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Solve using
Newton alg.

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The optimal transport case

Dual formulation of Optimal Transport:

$$\max_{\psi \in \mathbb{R}^{\mathcal{Y}}} \int_{\mathcal{X}} \psi^c \, d\mu - \sum_{y \in \mathcal{Y}} \psi(y) \nu(y) := \mathcal{K}(\psi)$$

where $\psi^c(x) = \min_i c(x, y_i) + \psi_i$

- \mathcal{K} is concave and invariant by addition of a constant.
- $\text{Lag}_i(\psi) = \{x \mid \forall j, c(x, y_i) + \psi_i \leq c(x, y_j) + \psi_j\}$
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Theorem: [Mérigot-Thibert '16] If the cost is \mathcal{C}^2 and twisted, and $\text{spt}(\mu)$ is connected and compact, then \mathcal{K} is \mathcal{C}^2 and **locally strongly concave** on $\mathcal{S}^+ \cap \mathbf{1}^\perp$, where $\mathcal{S}^+ = \{x \mid \forall i, H_i(\psi) > 0\}$.

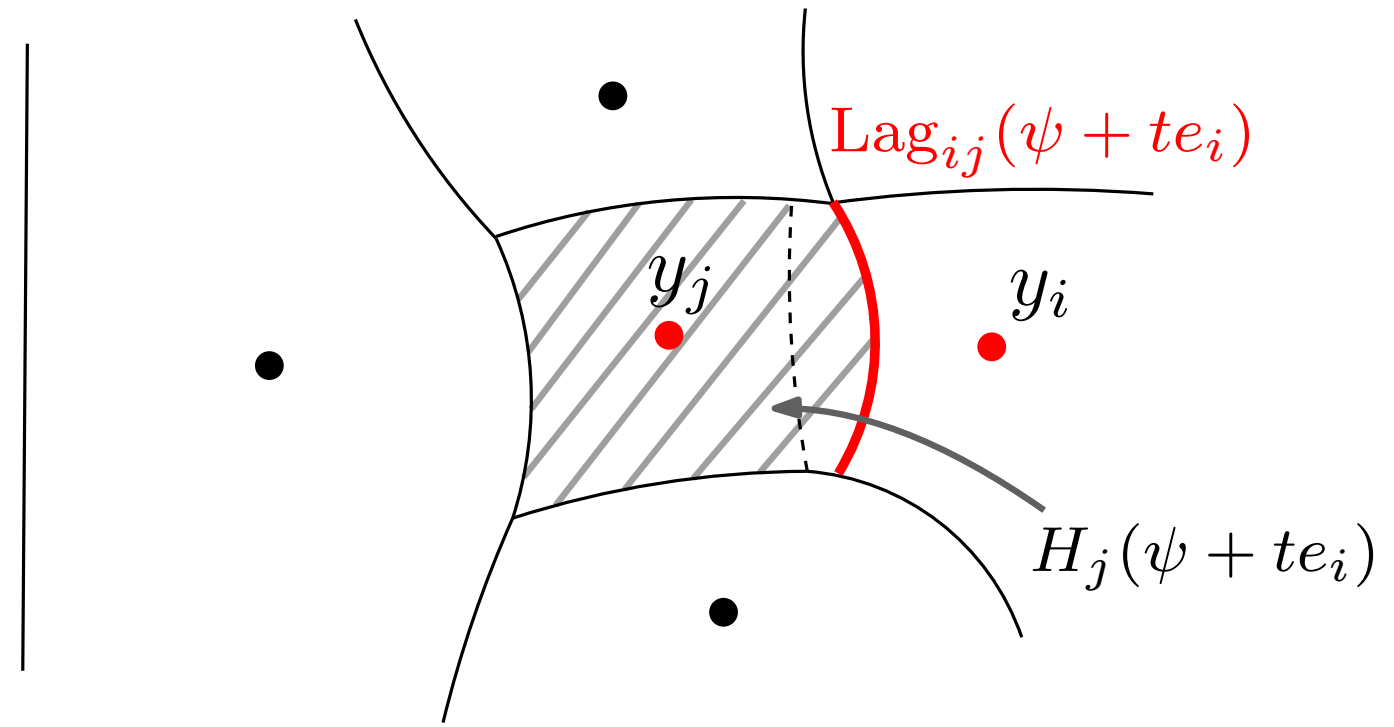
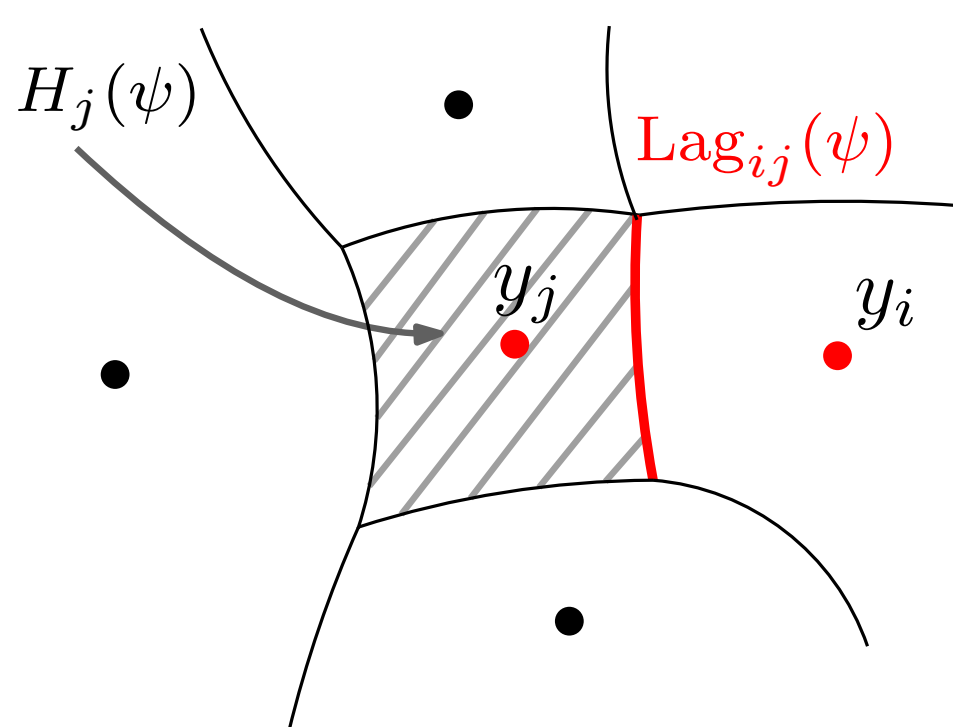
- In particular DH is symmetric non-positive definite
- Solving $H(\psi) = \nu$ amounts to maximize a (strongly) concave function.

Differential of the mass function H

Proposition 1:[G-M-T '21](Formula for DH) Assume that G is \mathcal{C}^2 and $\text{spt}(\mu)$ is compact, then for any $i \neq j$ we have:

- $$\frac{\partial H_j}{\partial \psi_i}(\psi) = \int_{\text{Lag}_{ij}(\psi)} \rho(x) \frac{|\partial_3 G(x, y_i, \psi_i)|}{\|\nabla_x G(x, y_j, \psi_j) - \nabla_x G(x, y_i, \psi_i)\|} d\mathcal{H}^{d-1}(x) \geq 0$$
- $$\sum_i H_i(\psi) = 1 \implies \frac{\partial H_i}{\partial \psi_i}(\psi) = - \sum_{j \neq i} \frac{\partial H_j}{\partial \psi_i}(\psi)$$

$\text{Lag}_{ij} = \text{Lag}_i \cap \text{Lag}_j$



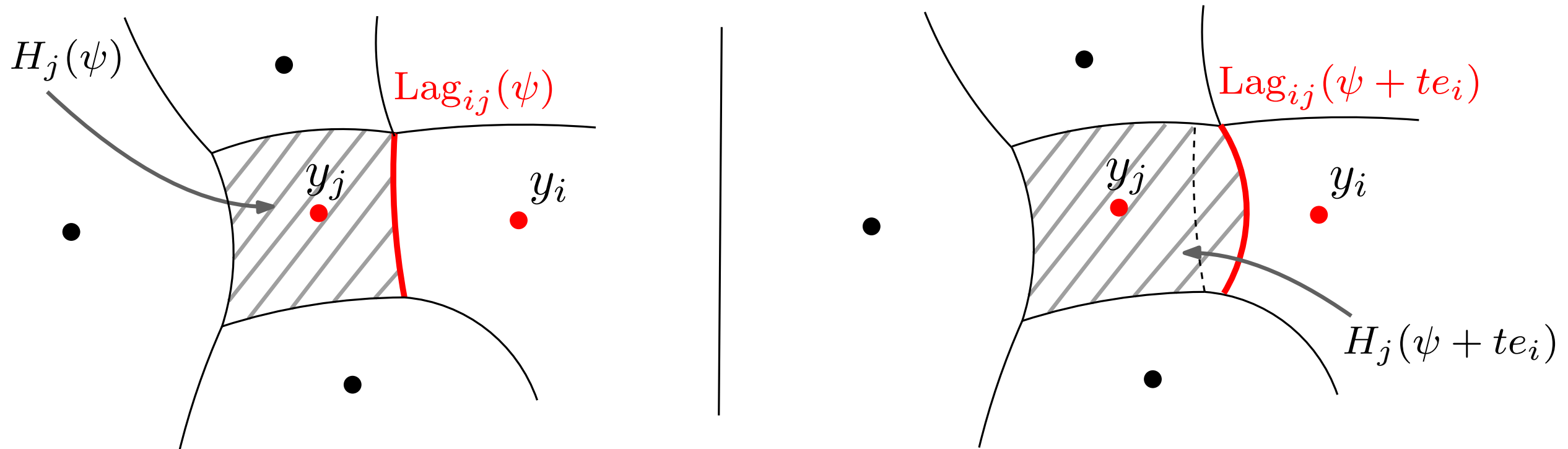
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$\text{Lag}_{ij} = \text{Lag}_i \cap \text{Lag}_j$
 > 0 by (Mono)
 $\neq 0$ by (Twist)

$$\blacksquare \quad \sum_i H_i(\psi) = 1 \implies \frac{\partial H_i}{\partial \psi_i}(\psi) = - \sum_{j \neq i} \frac{\partial H_j}{\partial \psi_i}(\psi) < 0 \text{ if } H_i(\psi) > 0$$



Descent direction for Newton

Proposition 2:[G-M-T '21] Let $\psi \in \mathcal{S}^+ = \{\psi \in \mathbb{R}^N \mid \forall i, H_i(\psi) > 0\}$, then

- The differential $DH(\psi)$ is of rank $N - 1$.
 - Its image is $\text{Im}(DH(\psi)) = \mathbf{1}^\perp$ where $\mathbf{1} = (1, \dots, 1) \in \mathbb{R}^N$.
 - Its kernel is $\ker(DH(\psi)) = \text{span}(w)$ with $w_i > 0$ for $1 \leq i \leq N$.
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- Consequence of Perron-Frobenius for irreducible matrices
 - The differential DH has no reason to be symmetric

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- The differential DH has no reason to be symmetric

Corollary: (Descent direction) Let $\psi \in \mathcal{S}^+$, the system

$$\begin{cases} DH(\psi)u = H(\psi) - \nu \\ u_1 = 0 \end{cases}$$

has a unique solution $u \in \mathbb{R}^N$.

Idea of proof:

- We have $H(\psi) - \nu \in \mathbf{1}^\perp = \text{Im}(DH(\psi))$.
- Fixing $u_1 = 0$ is possible because of the structure of $\ker(DH(\psi))$.
- Uniqueness comes from the rank of $DH(\psi)$.

Damped Newton algorithm

Newton algorithm for solving $H(\psi) = \nu$

Initialize $\psi^0 \in \mathcal{S}^\delta = \{\psi \in \mathbb{R}^N \mid \forall i, H_i(\psi) > \delta\}$ and $\varepsilon > 0$.

While $\|H(\psi) - \nu\| \geq \varepsilon$:

→ Compute u^k solution of $\begin{cases} DH(\psi)u^k = H(\psi) - \nu \\ u_1^k = 0 \end{cases}$

ψ_1^k is fixed

→ Define for $\tau \in [0, 1]$, $\psi^{k,\tau} = \psi^k - \tau u^k$.

Damping Parameter → Compute $\tau^k = \sup \left\{ \tau \in [0, 1] \mid \|H(\psi^{k,\tau}) - \nu\| \leq (1 - \frac{\tau}{2}) \|H(\psi^k) - \nu\| \right. \\ \left. \text{and } \psi^{k,\tau} \in \mathcal{S}^\delta \right\}$

→ Put $\psi^{k+1} \leftarrow \psi^{k,\tau^k}$ and $k \leftarrow k + 1$

Return ψ^k .

Iterate stays
in admissible set

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Linear convergence

Damping
Parameter

→ Compute $\tau^k = \sup \left\{ \tau \in [0, 1] \mid \|H(\psi^{k,\tau}) - \nu\| \leq \left(1 - \frac{\tau}{2}\right) \|H(\psi^k) - \nu\| \right. \\ \left. \text{and } \psi^{k,\tau} \in \mathcal{S}^\delta \right\}$

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Iterate stays
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Return ψ^k .

Theorem : [G-M-T '21] (Convergence) Assume that the support of μ is connected and compact and that the set \mathcal{Y} is generic. Then $\exists \tau^* > 0$ s.t

$$\|H(\psi^k) - \nu\| \leq \left(1 - \frac{\tau^*}{2}\right)^k \|H(\psi^0) - \nu\|$$

Proof: Bound τ^k below for any k by compactness of the set

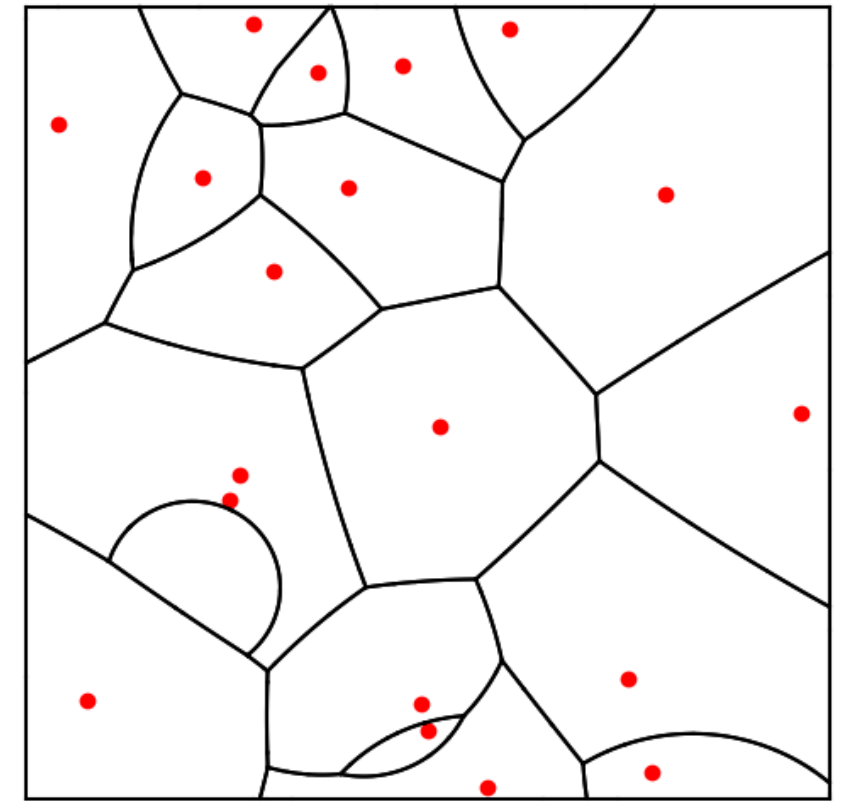
$$K = \{\psi \in \mathcal{S}^\delta \mid \psi_1 = \psi_1^0 \text{ and } \|H(\psi) - \nu\| \leq \|H(\psi^0) - \nu\|\}.$$

Implementation for the Near field reflector

- Laguerre diagram for (NF-par):

$$\text{Lag}_i(\psi) = \left\{ x \in \mathbb{S}^2 \mid \forall j, \frac{1}{2\psi_i} - \frac{\psi_i}{2} \|x - y\|^2 \geq \frac{1}{2\psi_j} - \frac{\psi_j}{2} \|x - y\|^2 \right\}$$

- Particular case of Möbius diagram



Definition: (Power and Möbius diagram)

- Power diagram : $\text{Pow}_i(c, r) = \{x \mid \forall j, \|x - c_i\|^2 + r_i \leq \|x - c_j\|^2 + r_j\}$
- Möbius diagram : $\text{Mob}_i(y, \lambda, \mu) = \{x \mid \forall j, \lambda_i \|x - y_i\|^2 + \mu_i \leq \lambda_j \|x - y_j\|^2 + \mu_j\}$

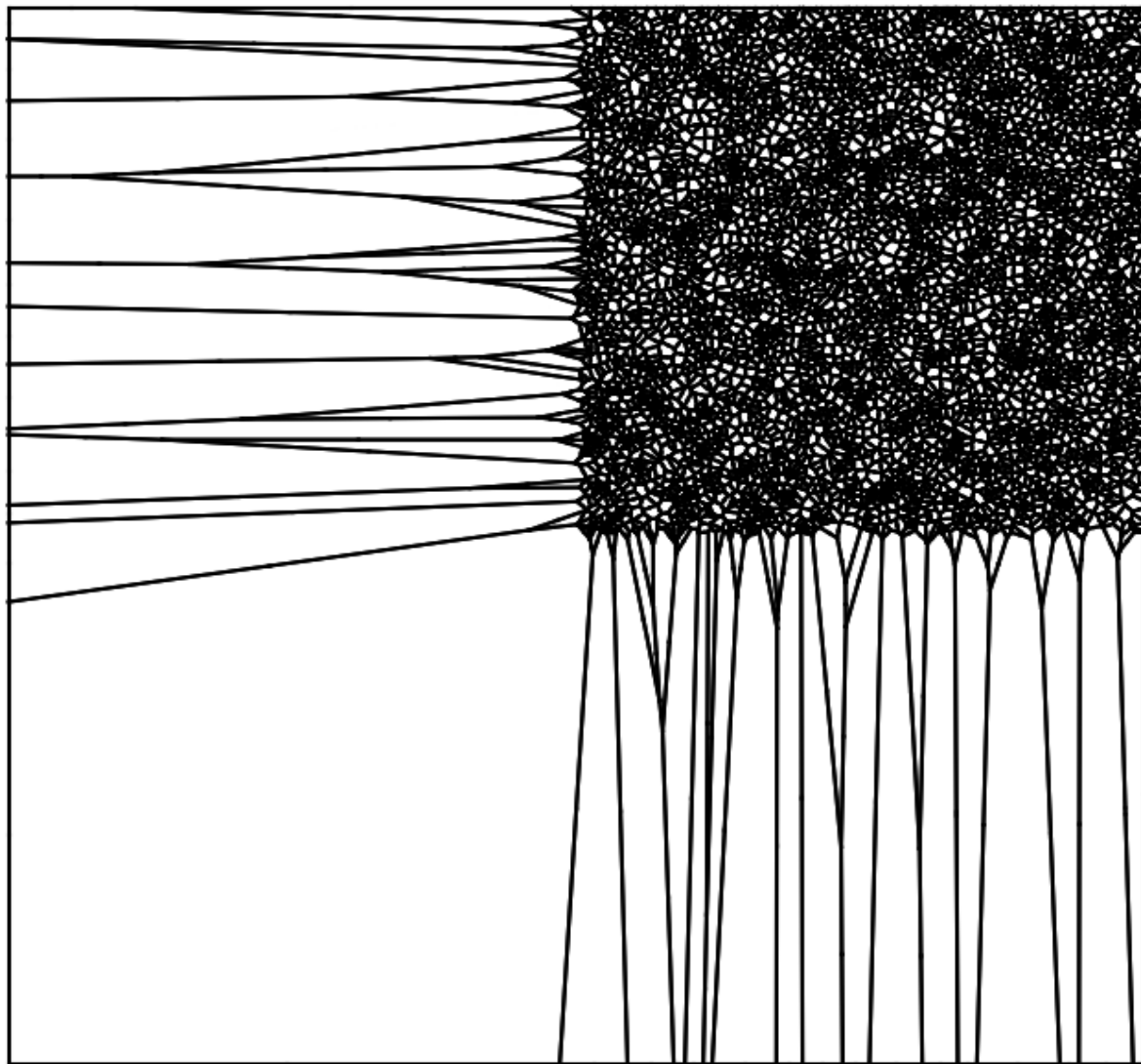
Theorem: [Boissonnat-Wormser-Yvinec '07]. For any family $(\lambda_i, \mu_i)_i \subset \mathbb{R}$, and $(y_i)_i \subset \mathbb{R}^d$ there exists $(r_i)_i \subset \mathbb{R}$ and $(c_i)_i \subset \mathbb{R}^{d+1}$ such that

$$\text{Mob}_i(y, \lambda, \mu) = \Pi(\text{Pow}_i(c, r) \cap P)$$

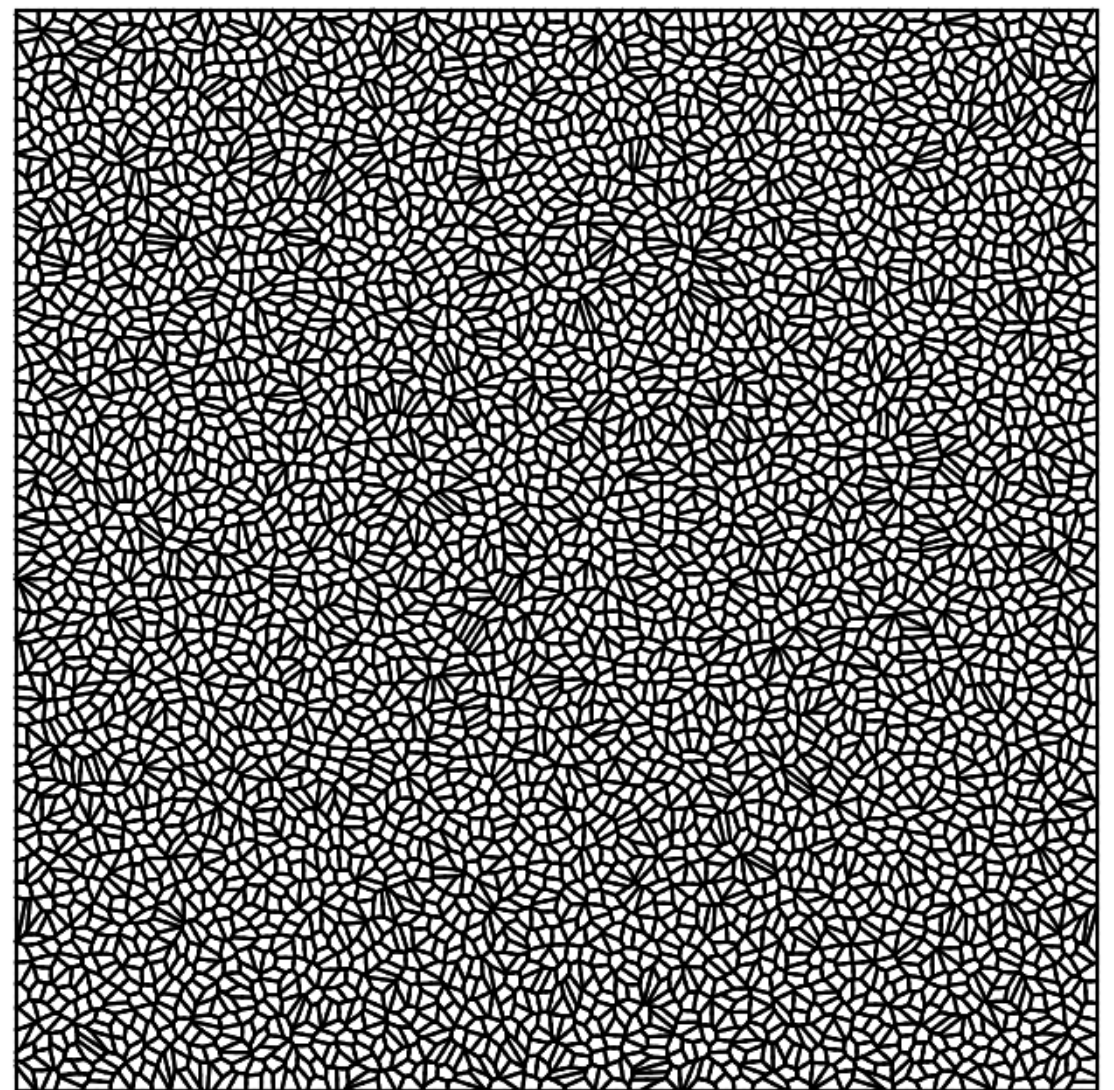
where $P = \{(x, \|x\|^2), x \in \mathbb{R}^d\}$ and Π is the orthogonal projection of \mathbb{R}^{d+1} on $\mathbb{R}^d \times \{0\}$.

Numerical experiments

- $\mathcal{X} = [-1, 1]^2$ with μ uniform
- $\mathcal{Y} \subset [0, 1]^2$, with ν uniform and $N = 5000$.



Initial diagram

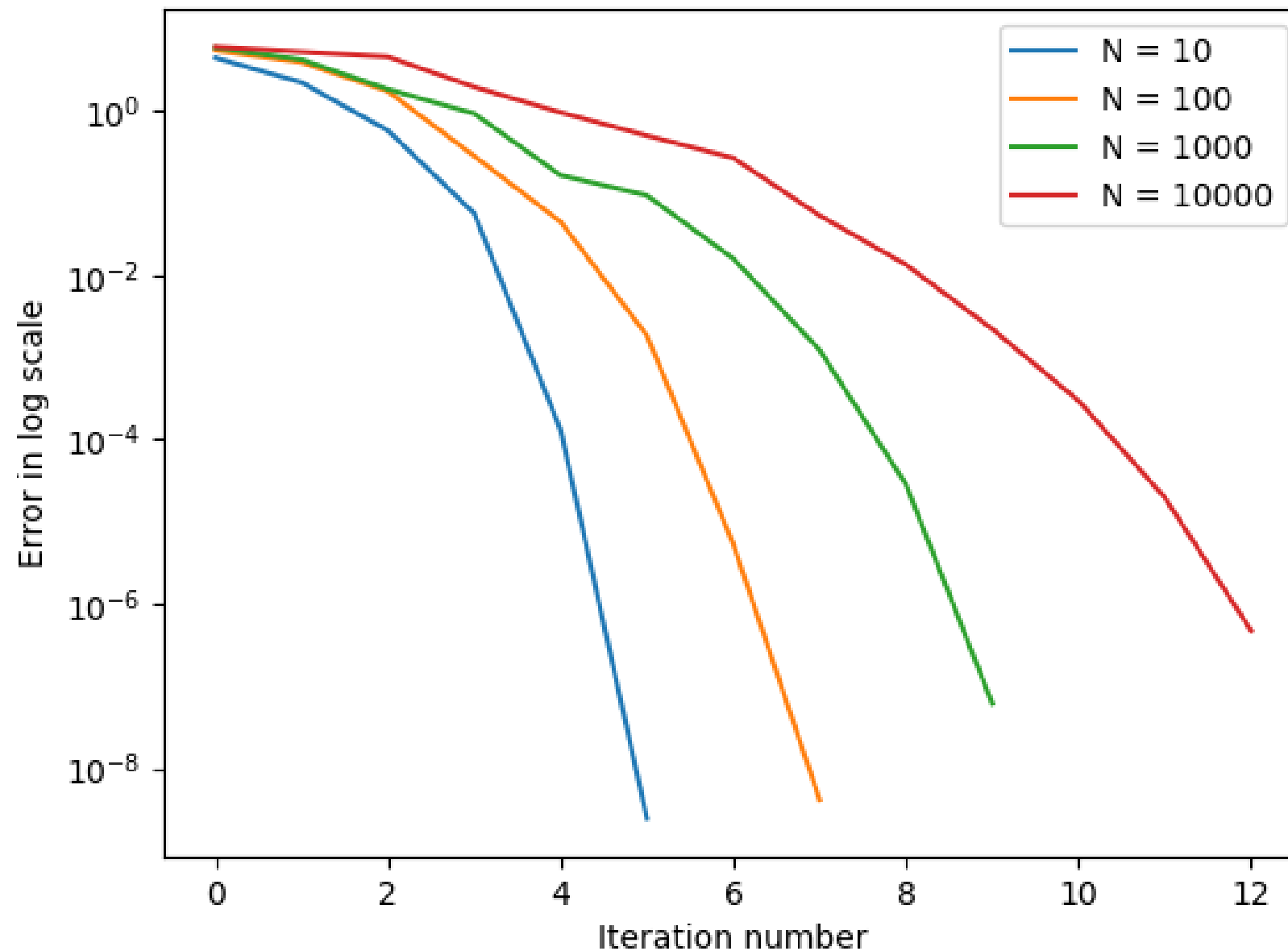


Final diagram

Laguerre diagram before and after convergence of the Newton algorithm

Numerical experiments

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- $\mathcal{Y} \subset [0, 1]^2$, with ν uniform



Convergence rate for different values of N .

Thank you for your attention

Appendix

Generating Function:

- $G(x, y, v)$ is \mathcal{C}^1 in x and v and $\sup_{\mathcal{X} \times \mathcal{Y} \times [\alpha, \beta]} |\nabla_x G(x, y, v)| < +\infty$ (Reg)
- $\forall (x, y, v) : \partial_v G(x, y, v) < 0$ (Mono)
- $\forall x \in \mathcal{X}, (y, v) \mapsto (G(x, y, v), \nabla_x G(x, y, v))$ is injective on $\mathcal{Y} \times \mathbb{R}$ (Twist)
- $\forall y \in Y, \lim_{v \rightarrow -\infty} \inf_{x \in \mathcal{X}} G(x, y, v) = +\infty$ (UC)

A stochastic algorithm for GJE

Entropic regularization:

- Regularized cells: $\mathcal{L}_{\varepsilon,i}[\psi](x) = \frac{e^{G(x,y_i,\psi_i)/\varepsilon}}{\sum_k e^{G(x,y_k,\psi_k)/\varepsilon}} \xrightarrow{\varepsilon \rightarrow 0} \begin{cases} 1 & \text{if } x \in \text{Lag}_i(\psi) \\ 0 & \text{otherwise} \end{cases}$
- Regularized mass function: $H_i^\varepsilon(\psi) = \int_X \mathcal{L}_{\varepsilon,i}[\psi](x) \, d\mu(x) \xrightarrow{\varepsilon \rightarrow 0} H_i(\psi)$

Regularized GJE: Find $\psi \in \mathbb{R}^N$ such that $H^\varepsilon(\psi) = \nu$

A stochastic algorithm for GJE

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Fixed point iterate: $\psi^{k+1} = \psi^k + \tau^k (H^\varepsilon(\psi) - \nu)$

A stochastic algorithm for GJE

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Regularized GJE: Find $\psi \in \mathbb{R}^N$ such that $H^\varepsilon(\psi) = \nu$

Stochastic fixed point iterate: $\psi^{k+1} = \psi^k + \tau^k (\mathcal{L}_\varepsilon[\psi](x_k) - \nu)$
where $x_k \sim \mu$ so that $\mathbb{E}(\mathcal{L}_\varepsilon[\psi](x_k)) = H^\varepsilon(\psi)$

- Stochastic gradient descent in the case of optimal transport.
- Numerical experiments converge for $\tau^k = \frac{1}{\sqrt{k}}$
- Proof of convergence is an open problem.