

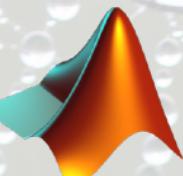
Computational Optimal Transport

<http://optimaltransport.github.io>

Unbalanced OT

Gabriel Peyré

www.numerical-tours.com



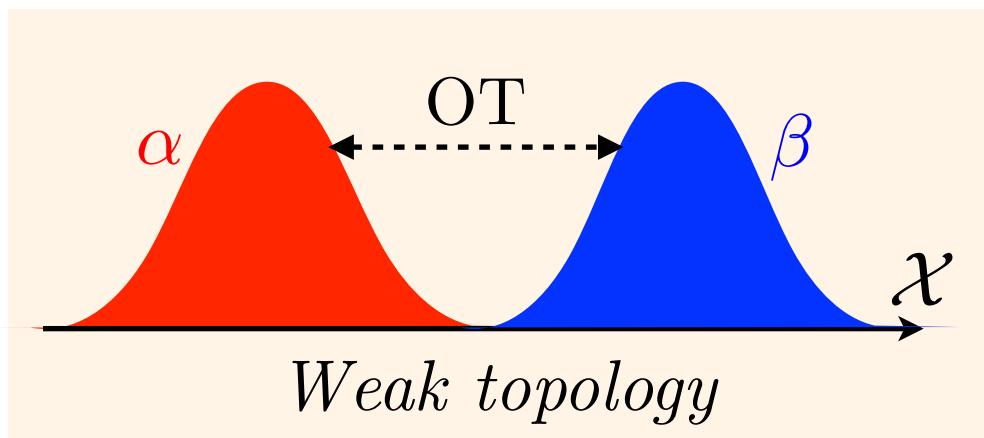
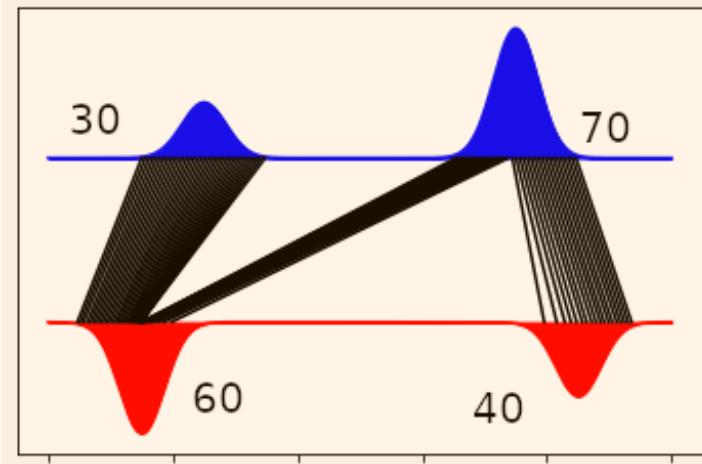
Total Variation Norm

“Balanced” OT: imposes $\alpha(\mathcal{X}) = \beta(\mathcal{X})$

Robust to support shift.

Not robust to

- outliers
- mode variations
- missing parts



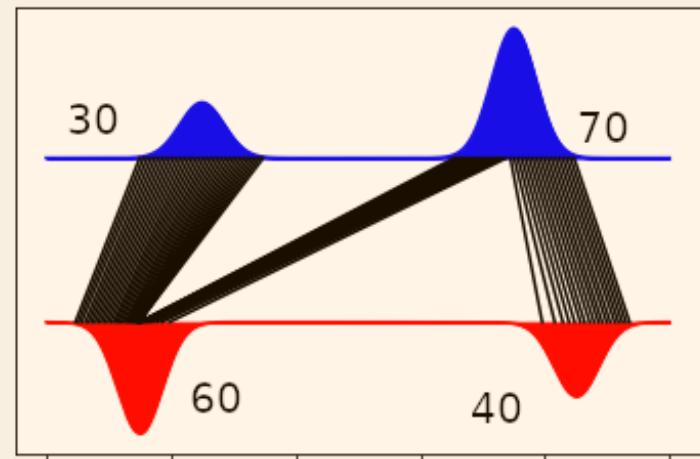
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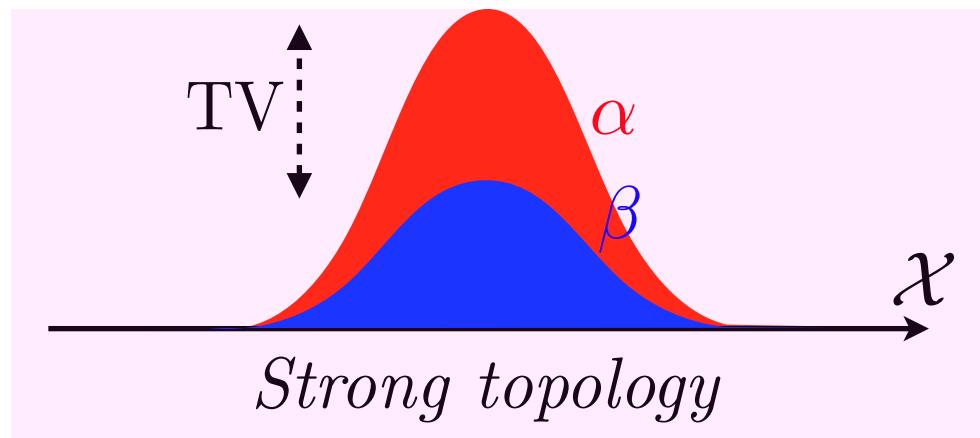
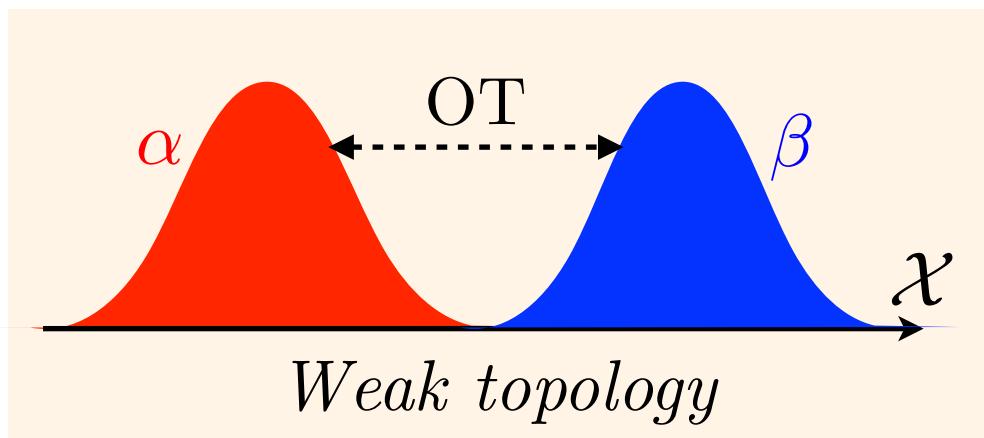
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$$\begin{aligned}\text{Total variation: } \|\alpha - \beta\|_{\text{TV}} &\triangleq \sup \left\{ \int f d(\alpha - \beta) : \|f\|_\infty \leq 1 \right\} \\ &= |\alpha - \beta|(\mathcal{X}) = \left\| \frac{d\alpha}{dx} - \frac{d\beta}{dx} \right\|_{L^1(dx)}\end{aligned}$$



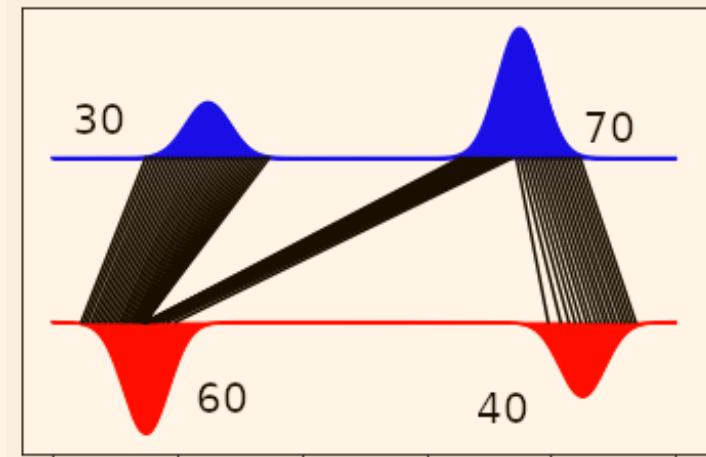
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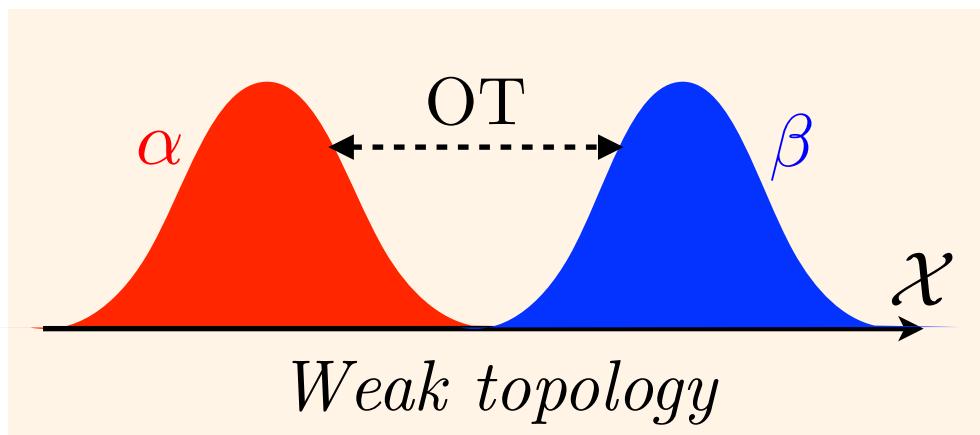
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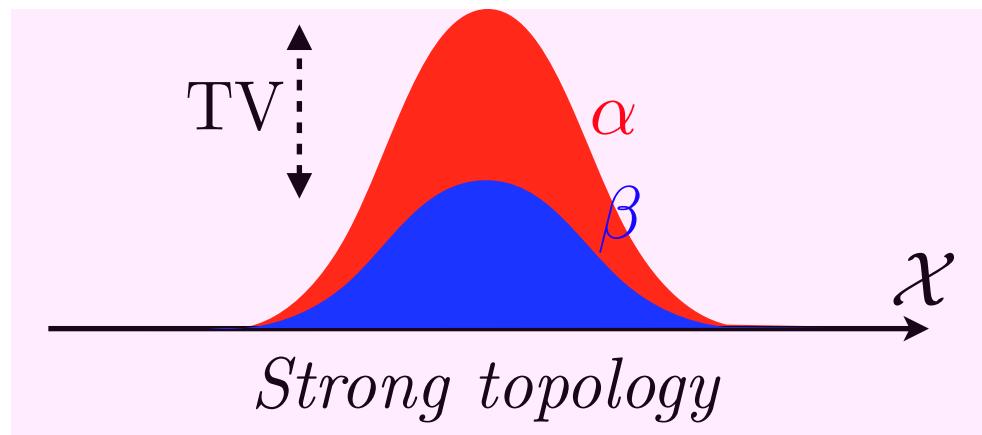
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Weak topology



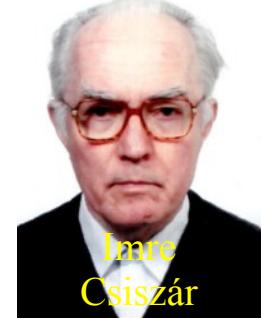
Strong topology

Unbalanced OT: hybridize the weak and strong topologies.

Csiszar Divergence

Comparing

$$\frac{d\alpha}{dx} \leftrightarrow \frac{d\beta}{dx} \longrightarrow \frac{d\alpha}{d\beta} \leftrightarrow 1$$

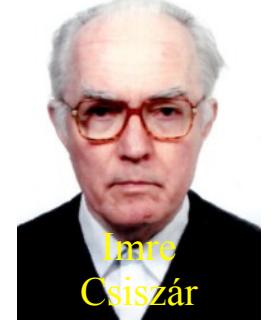


Imre
Csiszár

Csiszar Divergence

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φ convex, $\varphi(1) = 0$, $\boxed{\varphi \geqslant 0}$ \longrightarrow Important if $\alpha(\mathcal{X}) \neq \beta(\mathcal{X})$.

Recession constant: $\varphi'_\infty \triangleq \lim_{t \rightarrow +\infty} \frac{\varphi(t)}{t}$ $\alpha = \frac{d\alpha}{d\beta} + \alpha^\perp$

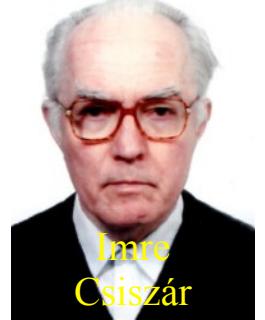
Csiszár φ -divergence: $D_\varphi(\alpha|\beta) \triangleq \int \varphi \left(\frac{d\alpha}{d\beta}(x) \right) d\beta(x) + \varphi'_\infty \alpha^\perp(\mathcal{X})$

Csiszar Divergence

Comparing

$$\frac{d\alpha}{dx} \leftrightarrow \frac{d\beta}{dx}$$

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Csiszár φ -divergence: $D_\varphi(\alpha|\beta) \triangleq \int \varphi\left(\frac{d\alpha}{d\beta}(x)\right) d\beta(x) + \varphi'_\infty \alpha^\perp(\mathcal{X})$

Proposition: $D_\varphi \geqslant 0$ is jointly convex,

$$D_\varphi(\alpha|\beta) = 0 \Leftrightarrow \alpha = \beta$$

Example of Csiszar Divergence

$$\begin{aligned} D_\varphi(\alpha \mid \beta) &\triangleq \int \varphi\left(\frac{d\alpha}{d\beta}(x)\right) d\beta(x) + \varphi'_\infty \alpha^\perp(\mathcal{X}) \\ &= \sum_{\mathbf{b}_i > 0} \varphi\left(\frac{\mathbf{a}_i}{\mathbf{b}_i}\right) \mathbf{b}_i + \varphi'_\infty \sum_{\mathbf{b}_i = 0} \mathbf{a}_i \end{aligned}$$

Discrete measures:

$$\alpha = \sum_i \mathbf{a}_i \delta_{x_i}$$

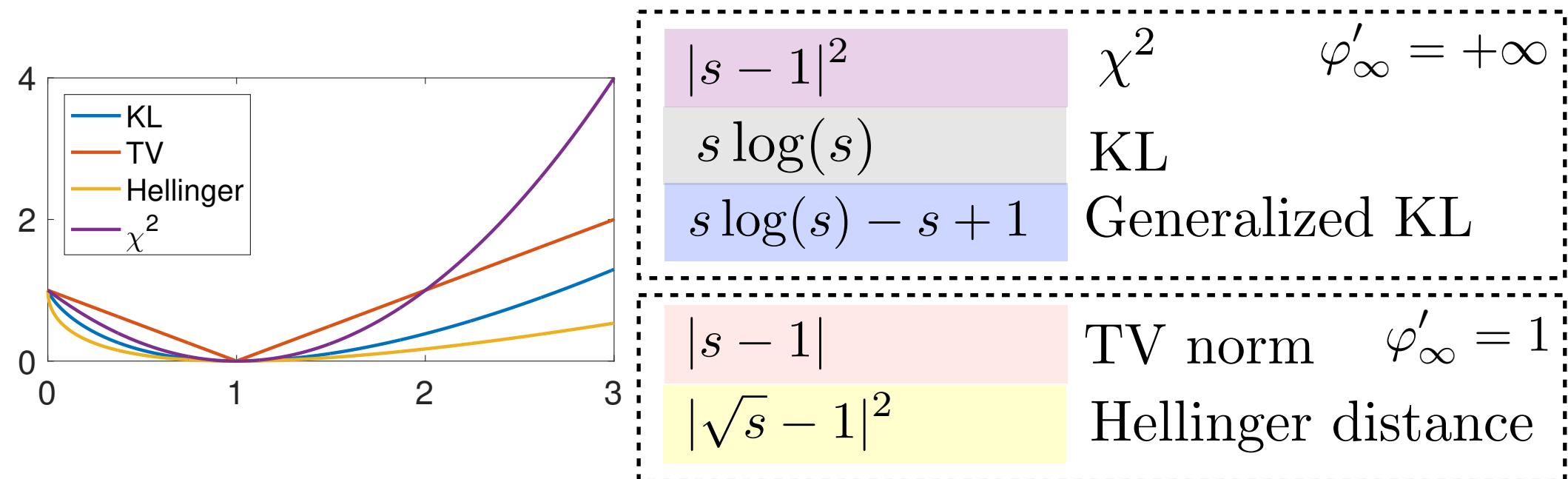
$$\beta = \sum_i \mathbf{b}_i \delta_{x_i}$$

Example of Csiszar Divergence

$$\begin{aligned}
 D_\varphi(\alpha|\beta) &\triangleq \int \varphi\left(\frac{d\alpha}{d\beta}(x)\right) d\beta(x) + \varphi'_\infty \alpha^\perp(\mathcal{X}) \\
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Discrete measures:

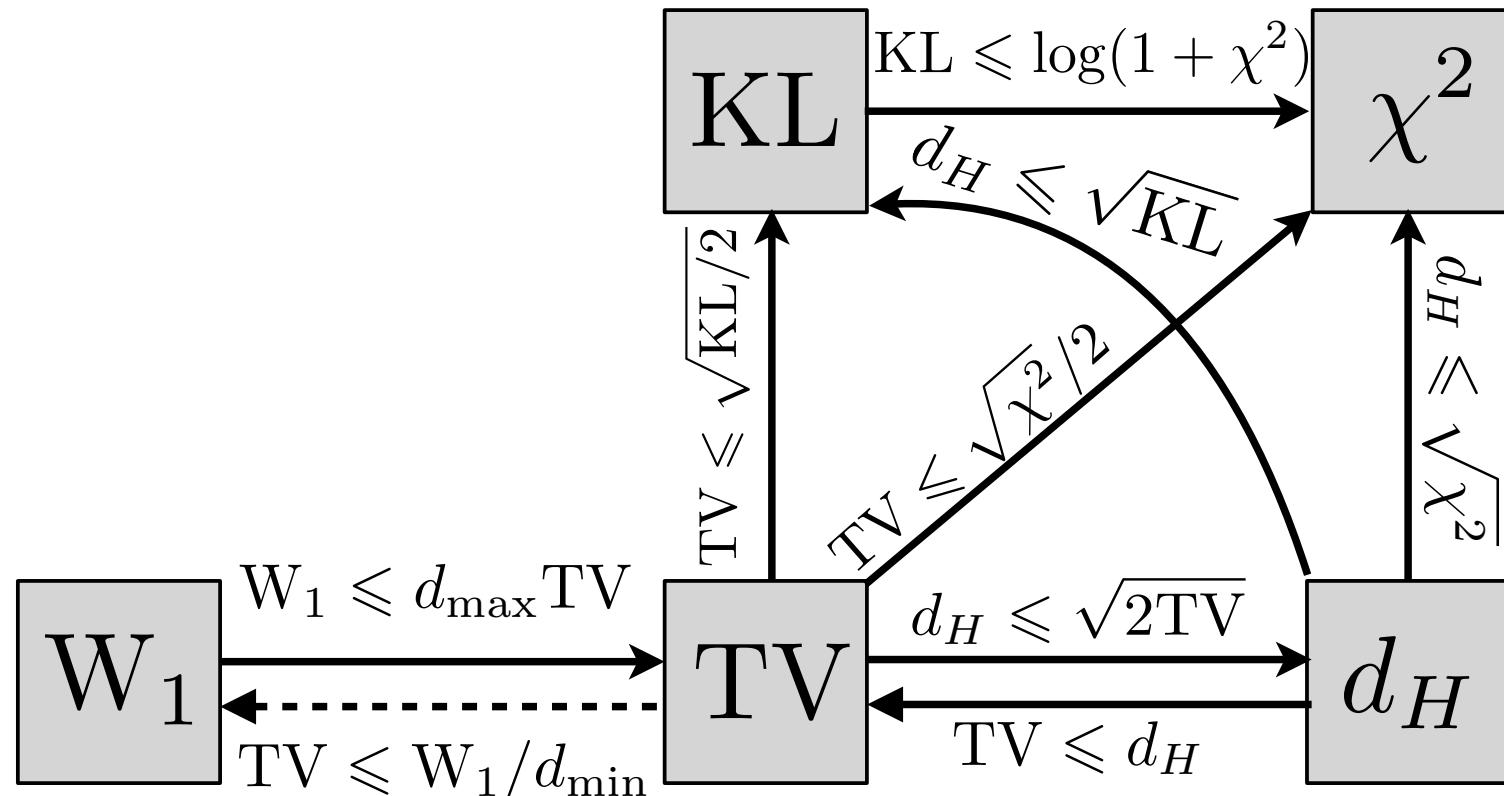
$$\alpha = \sum_i \mathbf{a}_i \delta_{x_i}$$

$$\beta = \sum_i \mathbf{b}_i \delta_{x_i}$$


$$\begin{aligned}
 \|\alpha - \beta\|_{\text{TV}} &= \left\| \frac{d\alpha}{dx} - \frac{d\beta}{dx} \right\|_{L^1(dx)} \\
 &= \sum_i |\mathbf{a}_i - \mathbf{b}_i|
 \end{aligned}$$

$$\begin{aligned}
 d_H(\alpha, \beta)^2 &= \left\| \sqrt{\frac{d\alpha}{dx}} - \sqrt{\frac{d\beta}{dx}} \right\|_{L^2(dx)}^2 \\
 &= \sum_i (\sqrt{\mathbf{a}_i} - \sqrt{\mathbf{b}_i})^2
 \end{aligned}$$

Equivalence and non-equivalence



$$d_{\max} = \sup_{(x, x')} d(x, x') \quad d_{\min} \stackrel{\text{def.}}{=} \min_{x \neq x'} d(x, x')$$

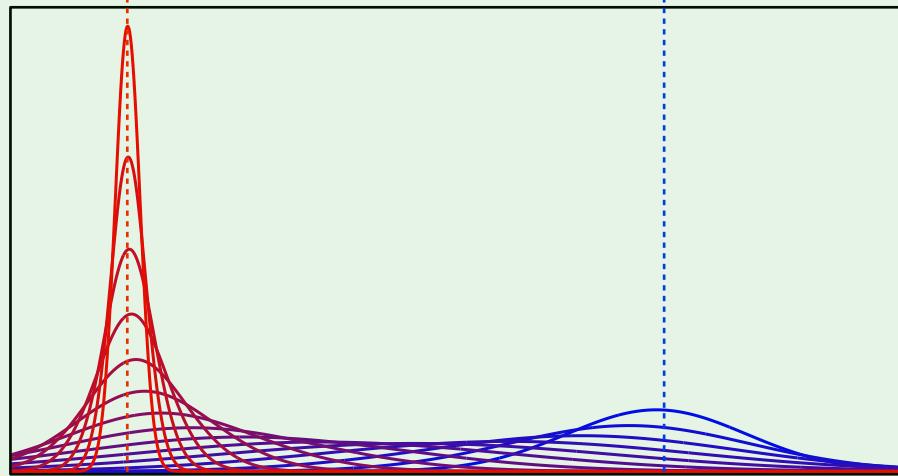
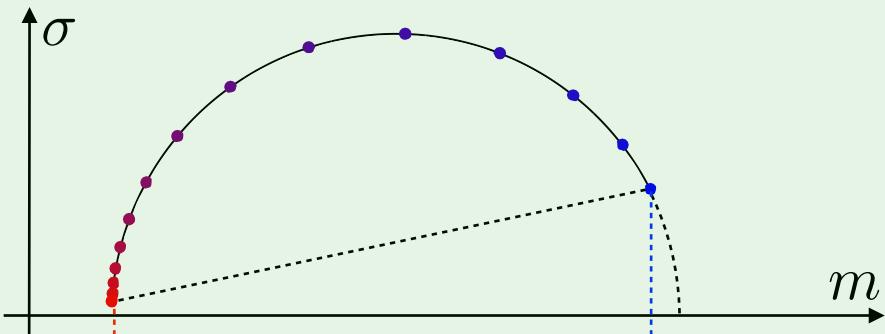
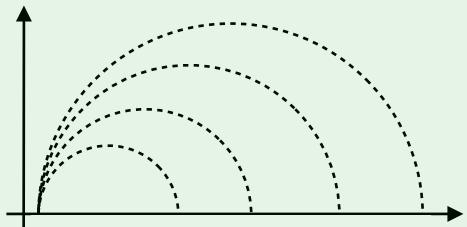
OT vs. KL (Fisher-Rao)

$$\mathcal{X} = \mathbb{R} \quad \alpha = \mathcal{N}(m_\alpha, \sigma_\alpha), \quad \beta = \mathcal{N}(m_\beta, \sigma_\beta)$$

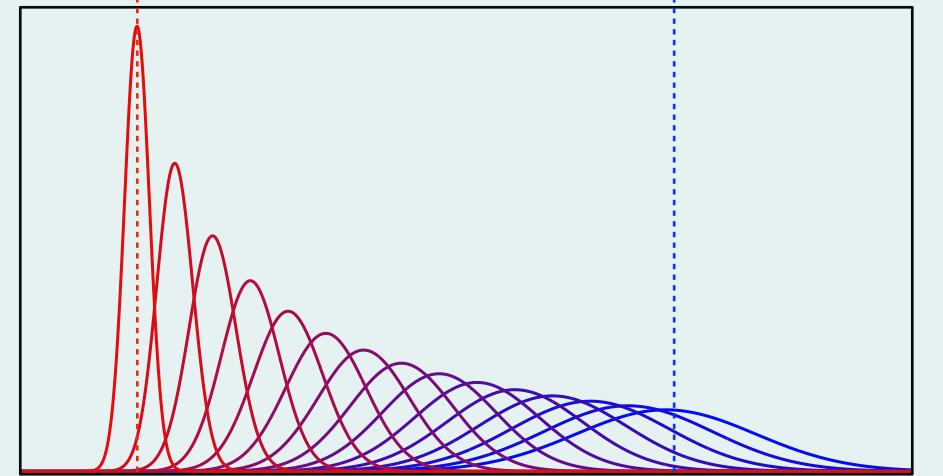
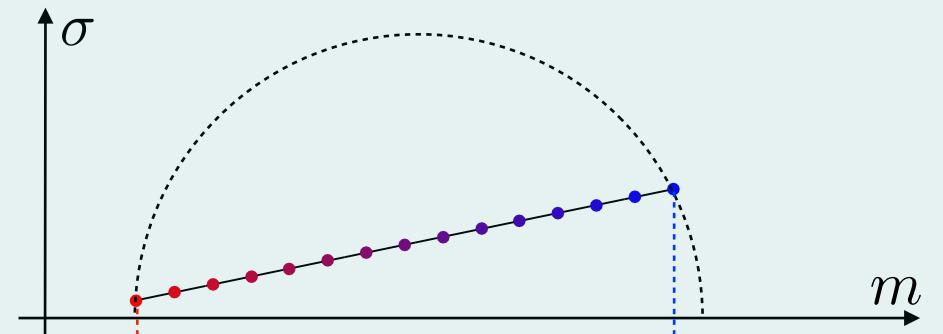
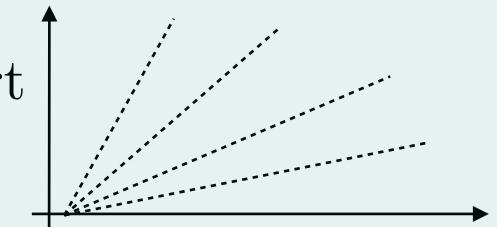
$$\text{KL}(\alpha|\beta) = \frac{1}{2} \left(\frac{\sigma_\alpha^2}{\sigma_\beta^2} + \log \left(\frac{\sigma_\beta^2}{\sigma_\alpha^2} \right) + \frac{|m_\alpha - m_\beta|}{\sigma_\beta^2} - 1 \right)$$

$$\text{W}_2^2(\alpha, \beta) = |m_\alpha - m_\beta|^2 + |\sigma_\alpha - \sigma_\beta|^2$$

Fisher-Rao
(hyperbolic)



Optimal Transport
(Euclidean)



Unbalanced OT

$$\text{OT}_\rho(\alpha, \beta) \triangleq$$

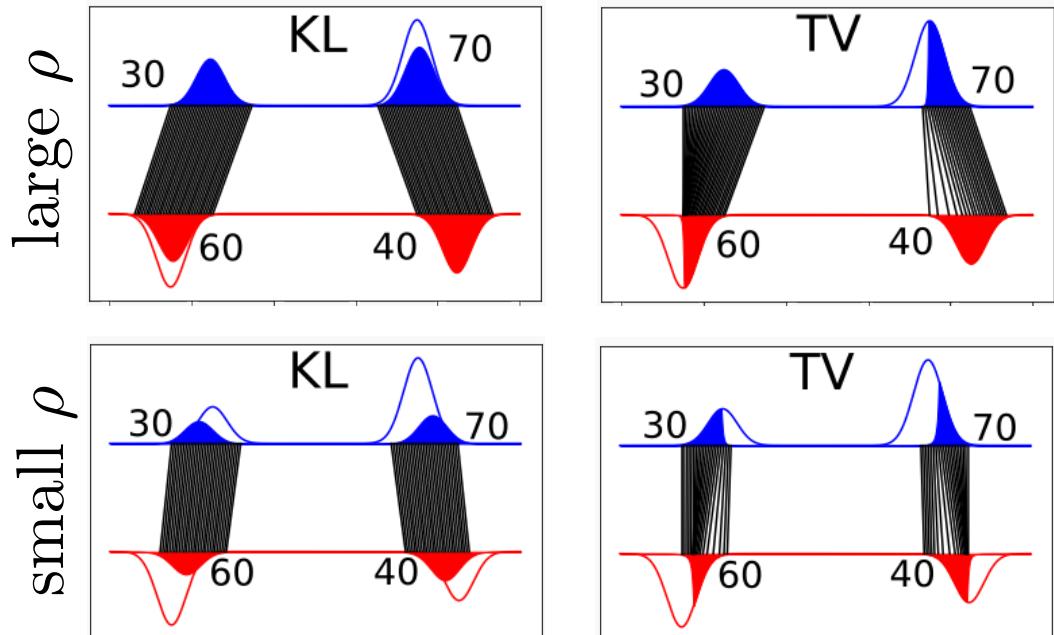
$$\min_{\pi \geq 0} \left\{ \int c(x, y) d\pi(x, y) + \rho D_\varphi(\pi_1 | \alpha) + \rho D_\varphi(\pi_2 | \alpha) ; \pi_1 = \alpha, \pi_2 = \beta \right\}$$

$\rho \approx$ transportation radius

Balanced OT:

$$\rho \rightarrow +\infty \text{ or } \varphi = \iota_{\{1\}}$$

[Liero, Mielke, Savare, 2018]



Unbalanced OT

$$\text{OT}_\rho(\alpha, \beta) \triangleq$$

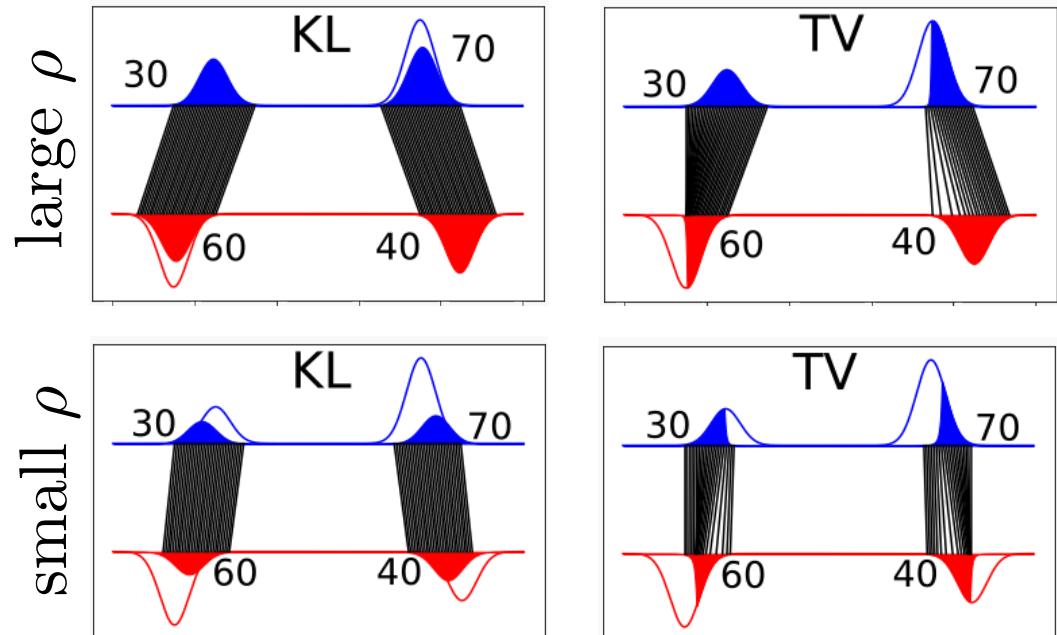
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$\rho \approx \text{transportation radius}$

Balanced OT:

$$\rho \rightarrow +\infty \text{ or } \varphi = \iota_{\{1\}}$$

[Liero, Mielke, Savare, 2018]



$$\frac{1}{\rho} \text{OT}_\rho(\alpha, \beta) \xrightarrow{\rho \rightarrow 0} \min_{\mu \geq 0} D_\varphi(\mu | \alpha) + D_\varphi(\mu | \beta)$$

$$= \left\| \sqrt{\frac{d\alpha}{d\beta}} - 1 \right\|_{L^2(d\beta)}^2$$

for KL

Unbalanced Sinkhorn

$$\min_{\pi_1=\alpha, \pi_2=\beta} \int c d\pi + D_\varphi(\pi_1|\alpha) + D_\varphi(\pi_2|\beta) + \varepsilon \text{KL}(\pi|\alpha \otimes \beta)$$

$$\pi = e^{\frac{f+g-c}{\varepsilon}} \alpha \otimes \beta$$

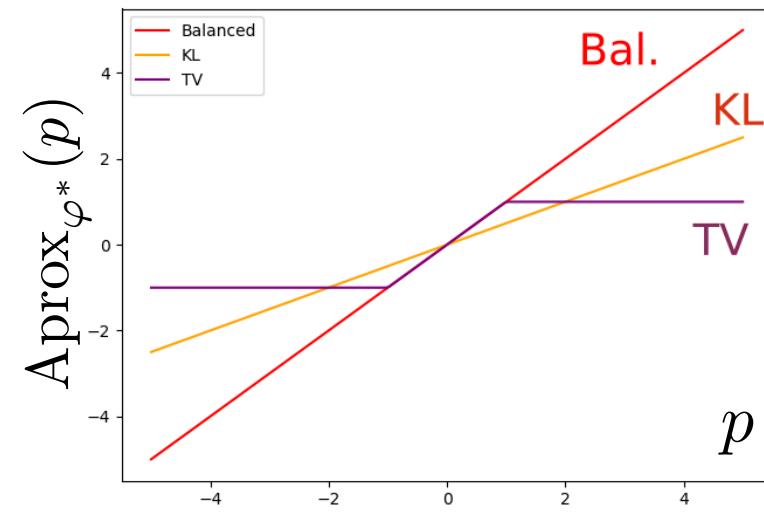
$$\sup_{f,g} - \int \varphi^*(f(x)) d\alpha(x) - \int \varphi^*(g(x)) d\beta(x) - \varepsilon \int e^{\frac{f+g-c}{\varepsilon}} \alpha \otimes \beta$$

Soft c -transforms:

$$f^{c,\varepsilon}(y) \triangleq -\varepsilon \log \int e^{\frac{c(x,y)-f(x)}{\varepsilon}} d\alpha(x)$$

Anisotropic prox:

$$\text{Aprox}_{\varphi^*}(p) \triangleq \underset{q \in \mathbb{R}}{\operatorname{argmin}} e^{p-q} + \varphi^*(q)$$



Proposition: Sinkhorn (alternate maximization)

$$f \leftarrow -\varepsilon \text{Aprox}_{\frac{\varphi^*}{\varepsilon}}(-g^{c,\varepsilon}) \quad g \leftarrow -\varepsilon \text{Aprox}_{\frac{\varphi^*}{\varepsilon}}(-f^{c,\varepsilon})$$

Example: $D_\varphi = \rho \text{KL}$ $f \leftarrow \frac{\rho}{\varepsilon+\rho} g^{c,\varepsilon}$ $g \leftarrow \frac{\rho}{\varepsilon+\rho} f^{c,\varepsilon}$

Distance Properties

$$\text{UOT}(\alpha, \beta)^2 \triangleq \min_{\pi_1 = \alpha, \pi_2 = \beta} \int c(x, y) d\pi(x, y) + \text{KL}(\pi_1 | \alpha) + \text{KL}(\pi_2 | \alpha)$$

Theorem: UOT is a distance on positive measure for

$$c(x, y) = d(x, y)^2$$

[Gaussian-Hellinger]

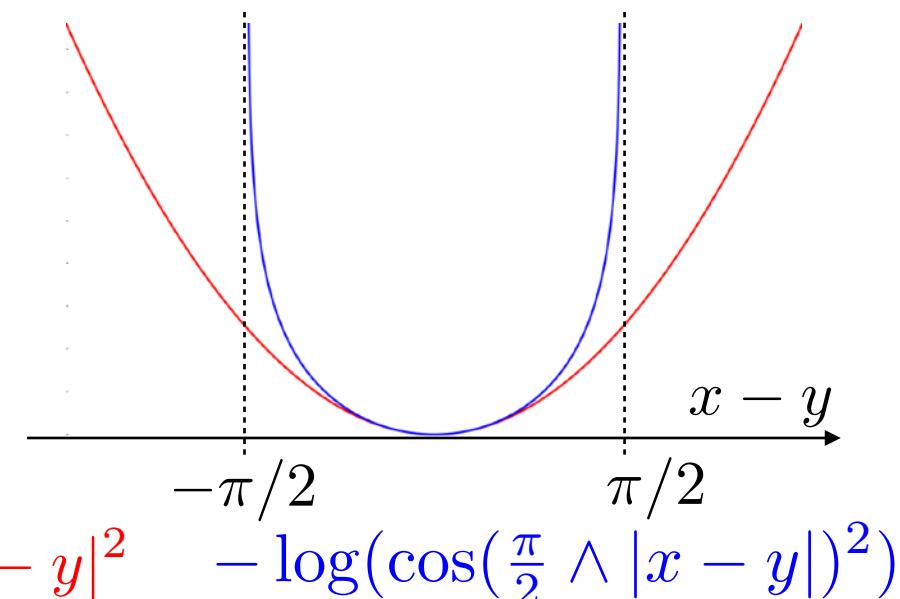
$$c(x, y) = -\log(\cos(\frac{\pi}{2} \wedge d(x, y)^2))$$

[Wasserstein-Fisher-Rao /
Kantorovitch-Hellinger]

[Kondratyev, Monsaingeon, Vorotnikov 2015]

[Liero, Mielke, Savaré 2015]

[Chizat, Schmitzer, Peyré, Vialard 2015]

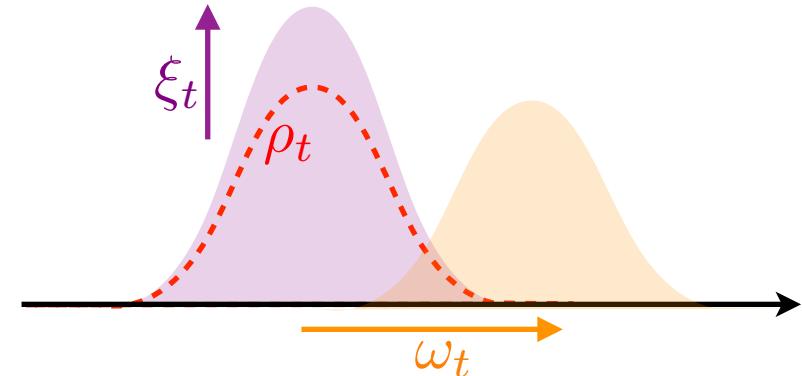


Dynamical Formulation

Wasserstein-Fisher-Rao /

Kantorovitch-Hellinger

$$c(x, y) = -\log(\cos(\frac{1}{2\rho}\|x - y\| \wedge \frac{\pi}{2})^2)$$



Theorem:

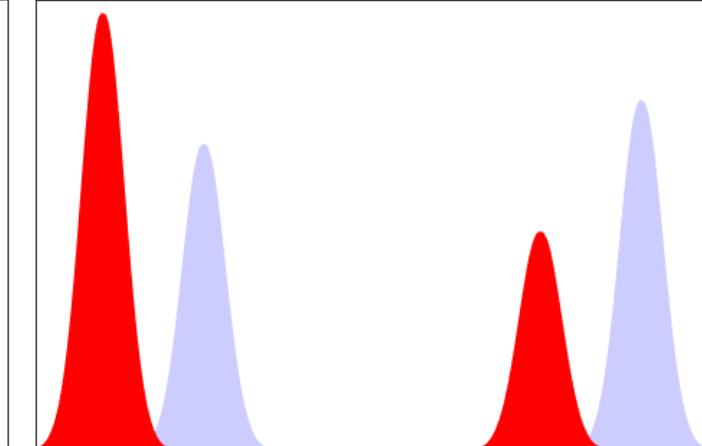
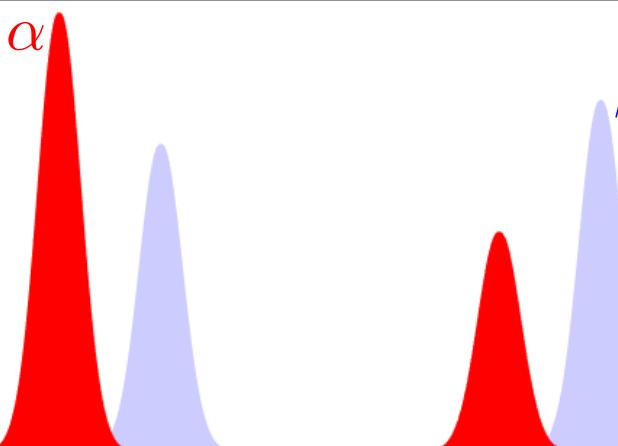
$$\text{UOT}(\alpha, \beta)^2 = \min_{\mu_0 = \alpha, \mu_1 = \beta} \left\{ \int_0^1 \int_{\mathbb{R}^d} \frac{\|\omega_t\|^2 + \rho \xi_t^2}{\mu_t} dx dt : \partial_t \mu_t + \text{div}(\omega_t) = \xi_t \right\}$$

$$\int (\sqrt{\alpha} - \sqrt{\beta})^2 \xleftarrow{\rho \rightarrow 0} \text{Unbalanced} \xrightarrow{\rho \rightarrow +\infty} \text{Balanced}$$

Hellinger

α

β

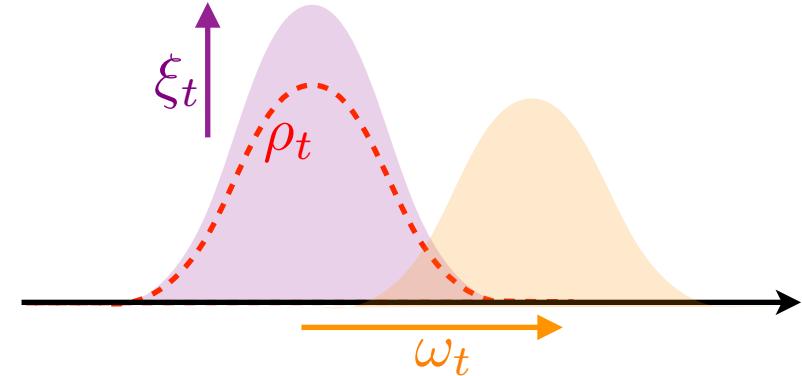


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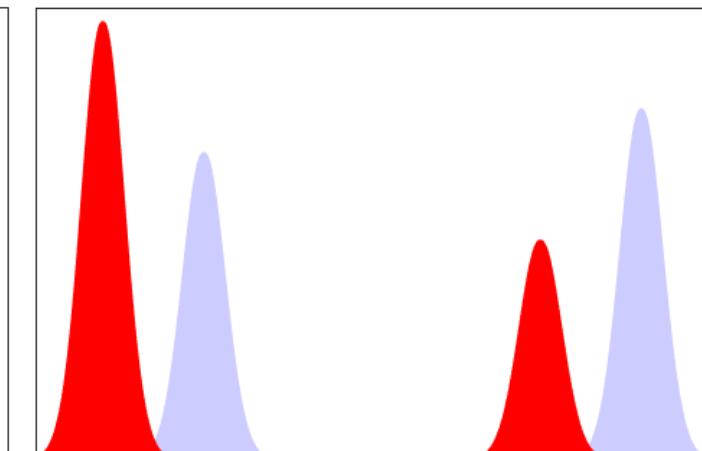
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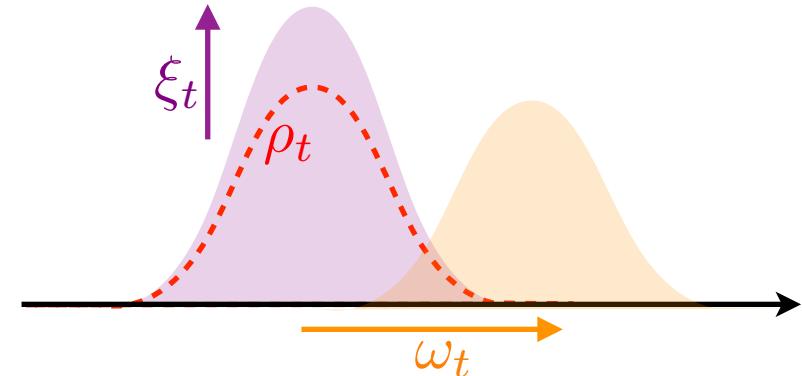


Dynamical Formulation

Wasserstein-Fisher-Rao /

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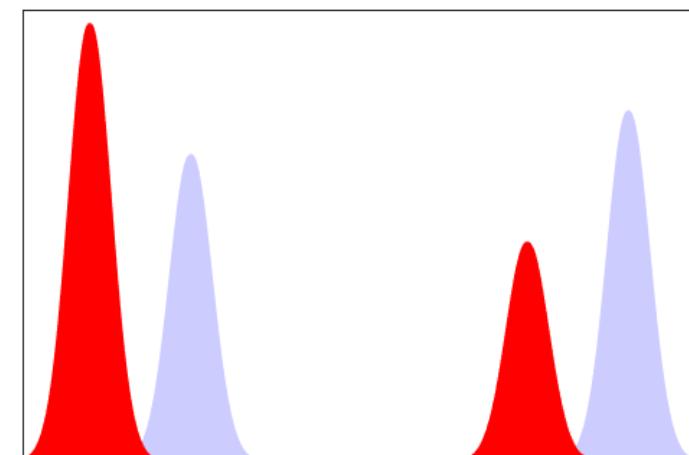
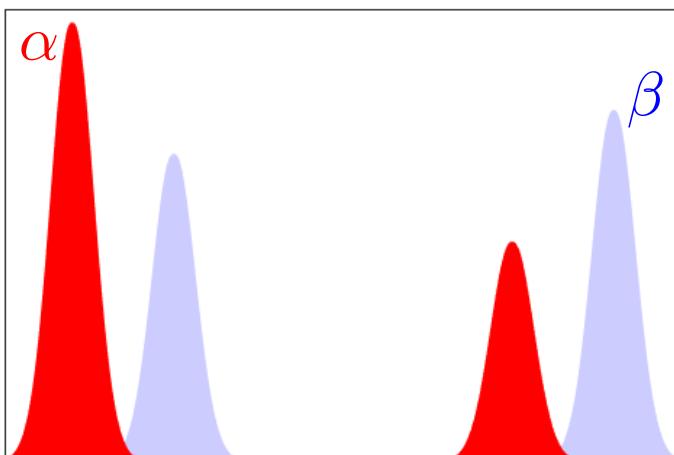
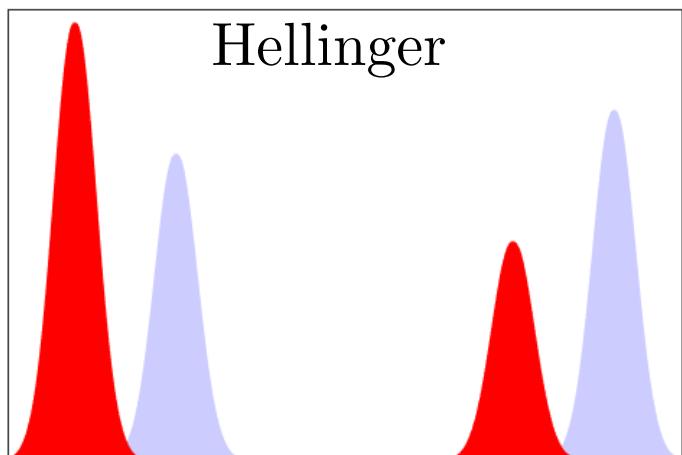
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Hellinger

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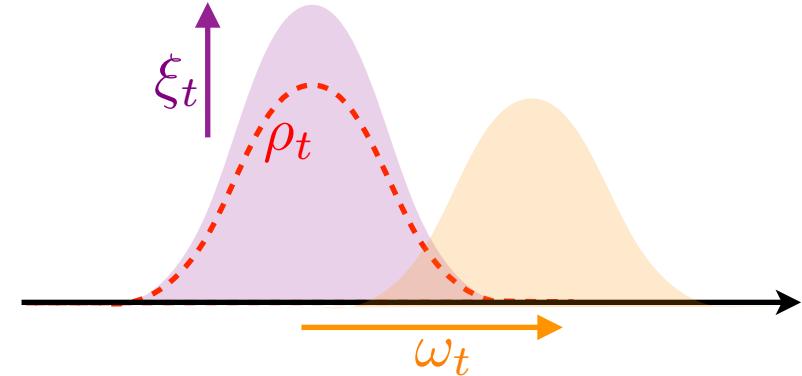


Dynamical Formulation

Wasserstein-Fisher-Rao /

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Hellinger

α

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α

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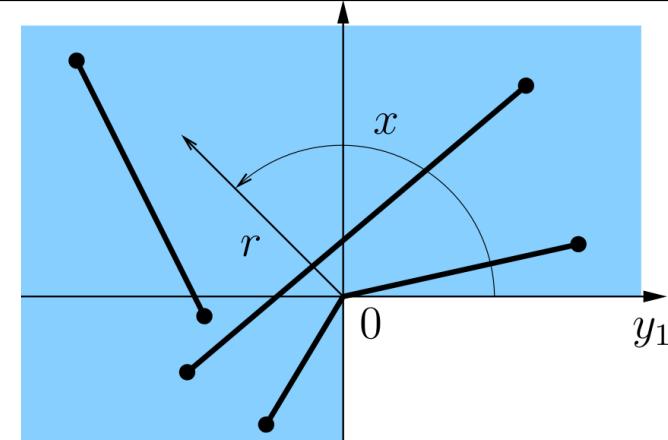
α

β

Conic Formulation

Conification of \mathcal{X} : $(x, r) \in \mathfrak{C}[\mathcal{X}] \triangleq \mathcal{X} \times \mathbb{R}^+$.

Cone distance: $d_{\mathfrak{C}[\mathcal{X}]}((x, r), (y, s))^2$
 $\triangleq r^2 + s^2 - 2rs \cos(\pi \wedge d_{\mathcal{X}}(x, y)))$



$$\sum_{i=1}^n r_i^2 \delta_{x_i} \in \mathcal{M}_+(\mathcal{X}) \xrightarrow{\text{Lifting}} \frac{1}{n} \sum_i \delta_{(r_i, x_i)} \in \mathcal{M}_+^1(\mathfrak{C}[\mathcal{X}])$$

$$\int_{\mathbb{R}^+} r^2 d\gamma(\cdot, r) \in \mathcal{M}_+(\mathcal{X}) \xleftarrow{\text{Projection}} \gamma \in \mathcal{M}_+^1(\mathfrak{C}[\mathcal{X}])$$

Theorem: $\text{UOT}(\alpha, \beta) = \inf_{\eta \in \mathcal{M}_+^1(\mathfrak{C}[\mathcal{X}])^2} \left\{ \int_{\mathfrak{C}[\mathcal{X}]^2} d_{\mathfrak{C}[\mathcal{X}]}^2 d\eta : \begin{array}{l} \int r^2 d\eta_1(\cdot, r) = \alpha \\ \int s^2 d\eta_2(\cdot, s) = \beta \end{array} \right\}$

