

Kantorovich optimal transport problem and Shannon's optimal channel problem

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*In honor of
Shun-ichi Amari*

Optimal transportation problems (OTPs)

Information and entropy

Optimal channel problem (OCP)

Geometry of information divergence and optimization

Dynamical OTP: Optimization of evolution

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Kantorovich's OTP

Optimal Transportation Problem (Kantorovich, 1939, 1942; Vasershtein, 1969; Dobrushin, 1970)

$$K_c(q, p) := \inf \left\{ \int_{X \times Y} c(x, y) dw : \pi_X w = q, \pi_Y w = p \right\}$$

where $c : X \times Y \rightarrow \mathbb{R}$ is a cost function (e.g. a metric).

$$\Gamma(q, p) := \{w \in \mathcal{P}(X \otimes Y) : \pi_X w = q, \pi_Y w = p\}$$

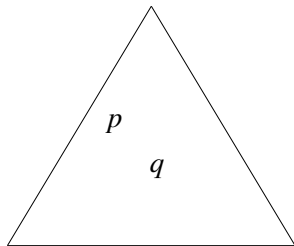
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$$\mathcal{P}(X) \leftrightarrow \mathcal{P}(X \otimes Y)$$

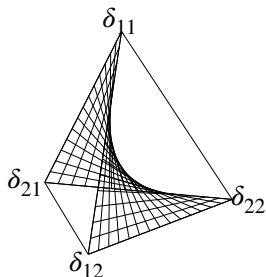
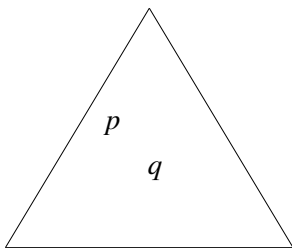
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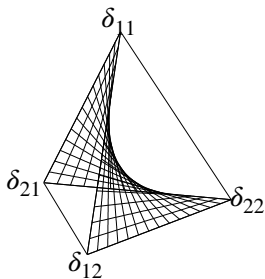


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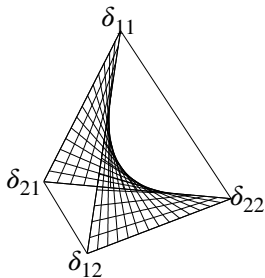
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$$T : \mathcal{P}(X) \rightarrow \mathcal{P}(Y):$$

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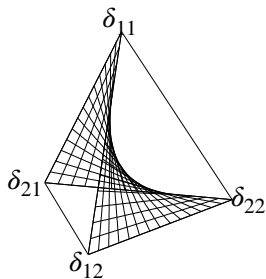
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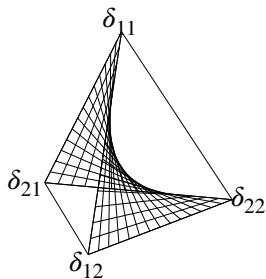
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- $p(\cdot | x)$ — Markov transition kernel
- T is determined by $w \in \mathcal{P}(X \otimes Y)$:

$$w = p(\cdot | x) \otimes q$$



Monge OTP

Optimal Transportation Problem (Monge, 1781)

$$K_c(q, p) := \inf \left\{ \int_X c(x, f(x)) dq : f : p = q \circ f^{-1} \right\}$$

where $p = q \circ f^{-1}$ is push-forward under measurable mapping $f : X \rightarrow Y$:

$$p(E) = q \circ f^{-1}(E) = q\{x : f(x) \in E\}$$

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- $p(\cdot | x)$ has the form:

$$\delta_{f(x)}(E) = \begin{cases} 1 & \text{if } f(x) \in E \\ 0 & \text{otherwise} \end{cases}$$

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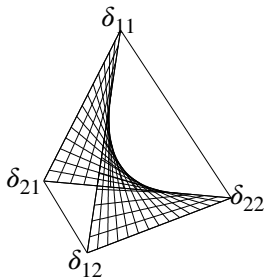
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- $w_f \in \partial \mathcal{P}(X \otimes Y)$:

$$w_f(X, Y \setminus f(X)) = 0$$



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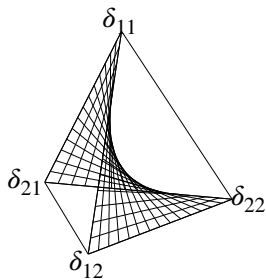
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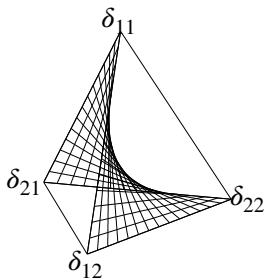
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For $w \in \Gamma(q, p) \subset \mathcal{P}(X \otimes Y)$:

$$\begin{aligned} I_w\{x, y\} &:= D_{KL}(w, q \otimes p) \\ &= H(q) - H(q(x | y)) \\ &= H(p) - H(p(y | x)) \end{aligned}$$



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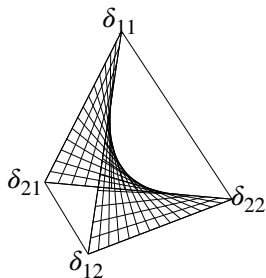
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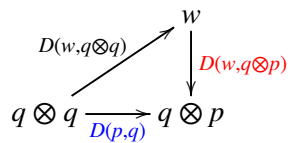
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Entropy $H(p) = - \int \ln p dp$

$$H(p) := \sup_{w: \pi_Y w = p} I_w\{x, y\} = I_w\{y, y\}$$



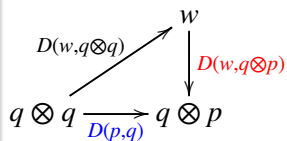


Theorem (Shannon-Pythagorean)

- $w \in \mathcal{P}(X \otimes Y)$, $\pi_X w = q$, $\pi_Y w = p$

$$D_{KL}(w, q \otimes q) = D_{KL}(w, q \otimes p) + D_{KL}(p, q)$$

(Belavkin, 2013a)

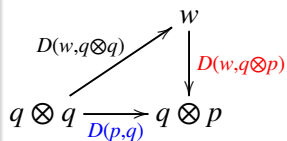


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Proof.

$$D(w, q \otimes q) = \underbrace{D(w, q \otimes p)}_{I_w\{x,y\}} + \underbrace{D(q \otimes p, q \otimes q)}_{D(p,q)} - \underbrace{\langle \ln q \otimes p - \ln q \otimes q, q \otimes p - w \rangle}_0$$

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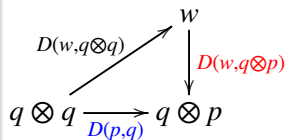
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Cross-Information (Belavkin, 2013a)

$$D_{KL}(w, q \otimes q) = \underbrace{-\langle \ln q, p \rangle}_{\text{Cross-entropy}} - \underbrace{[H(p) - D_{KL}(w, q \otimes p)]}_{H(p(y|x))}$$

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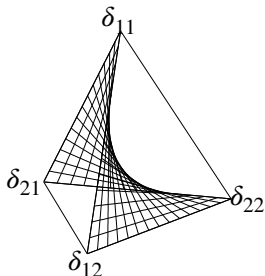
Optimal Channel Problem (Shannon, 1948)

$$S_c(q, \lambda) := \inf \left\{ \int_{X \times Y} c(x, y) d\omega : \pi_X \omega = q, I_\omega\{x, y\} \leq \lambda \right\}$$

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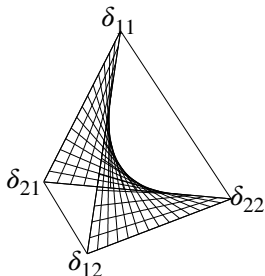
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Exponential family solutions

- Optimal $T : \mathcal{P}(X) \rightarrow \mathcal{P}(Y)$ is defined by

$$w = e^{-\beta c - \ln Z} q \otimes p, \quad \beta^{-1} = -dS_c(q, \lambda)/d\lambda$$



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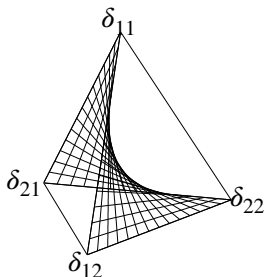
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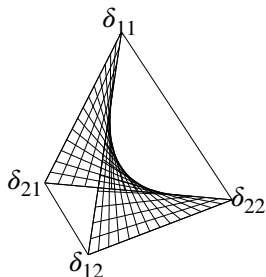
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Value of Information (Stratonovich, 1965)

$$V(\lambda) := S_c(q, 0) - S_c(q, \lambda) = \sup \{ \mathbb{E}_w \{u\} : I_w\{x, y\} \leq \lambda \}$$

Relation to Kantorovich OTP

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- q and p have entropies $H(q)$ and $H(p)$ and

$$0 \leq I_w\{x, y\} \leq \min[H(q), H(p)]$$

- $K_c(q, p)$ has implicit constraint $I_w\{x, y\} \leq \lambda = \min[H(q), H(p)]$ and

$$S_c(q, \lambda) \leq K_c(q, p)$$

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- These inverse values represent the smallest amount of Shannon's information required to achieve expected cost $\int c \, dw = v$.
- If $v = K_c(q, p)$, then

$$S_c^{-1}(q, v) \leq K_c^{-1}(q, p, v)$$

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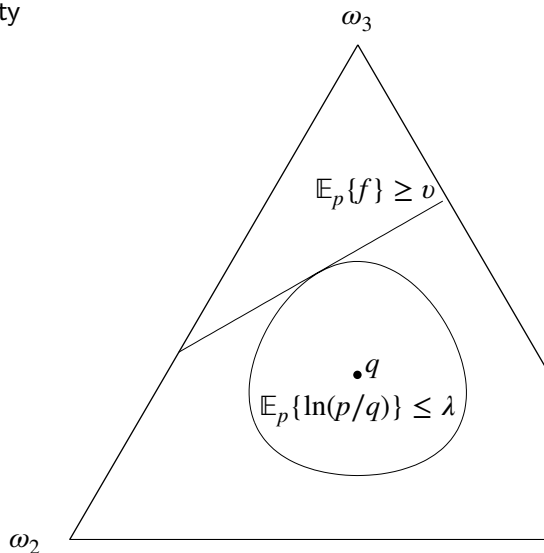
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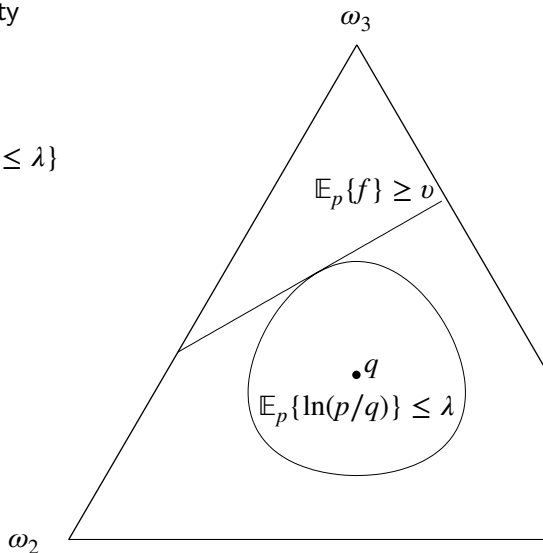
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$$v_u(\lambda) := \sup\{\langle u, p \rangle : F(p, q) \leq \lambda\}$$



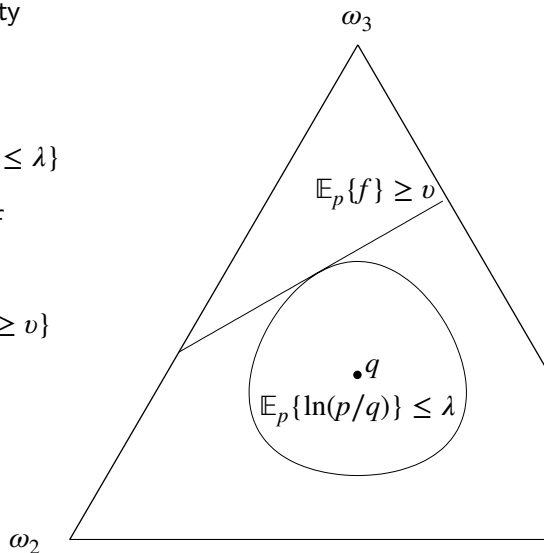
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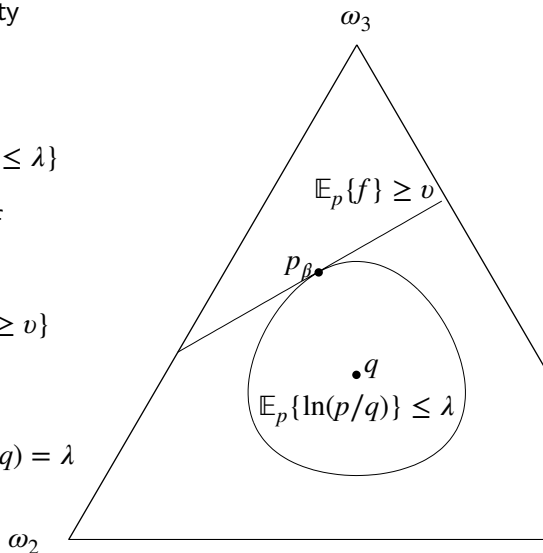
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$$p(\beta) \in \partial F^*(\beta u, q), \quad F(p(\beta), q) = \lambda$$



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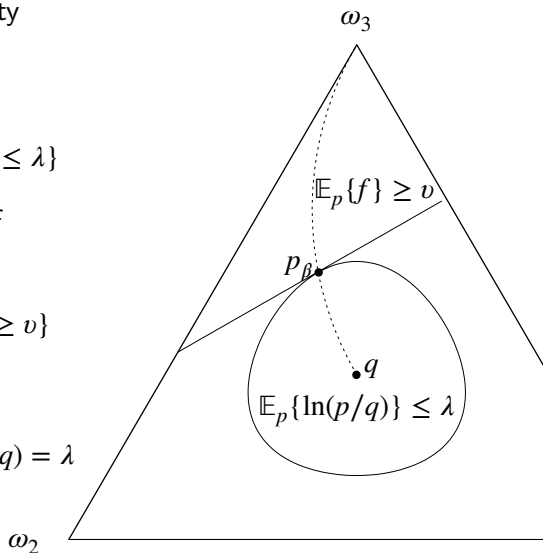
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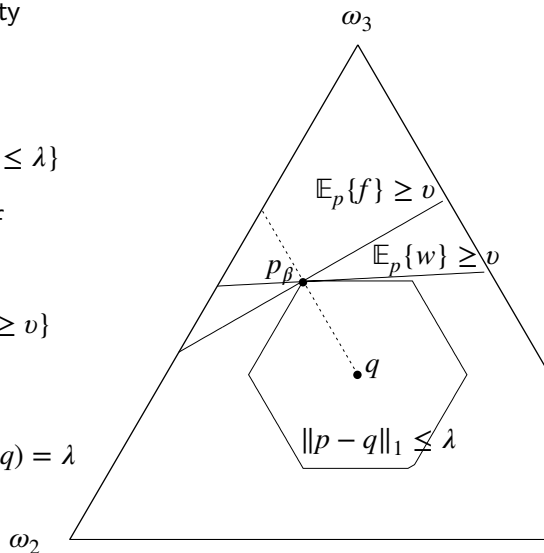
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General Solution

- Lagrange function for $v_u(\lambda) := \sup\{\langle u, p \rangle : F(p, q) \leq \lambda\}$
 $(\lambda_u(v) := \inf\{F(p, q) : \langle u, p \rangle \geq v\})$:

$$L(p, \beta^{-1}) = \langle u, p \rangle + \beta^{-1}[\lambda - F(p, q)]$$

$$\left(L(p, \beta) = F(p, q) + \beta[v - \langle u, p \rangle] \right)$$

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$$\left(L(p, \beta) = F(p, q) + \beta[v - \langle u, p \rangle] \right)$$

- Necessary and sufficient conditions $\partial L \ni 0$:

$$\partial_p L(p, \beta^{-1}) = \{\beta u\} - \partial_p F(p, q) \ni 0$$

$$\partial_{\beta^{-1}} L(p, \beta^{-1}) = \lambda - F(p, q) = 0$$

General Solution

- Lagrange function for $v_u(\lambda) := \sup\{\langle u, p \rangle : F(p, q) \leq \lambda\}$
 $(\lambda_u(v) := \inf\{F(p, q) : \langle u, p \rangle \geq v\})$:

$$\begin{aligned} L(p, \beta^{-1}) &= \langle u, p \rangle + \beta^{-1}[\lambda - F(p, q)] \\ \left(L(p, \beta) &= F(p, q) + \beta[v - \langle u, p \rangle] \right) \end{aligned}$$

- Necessary and sufficient conditions $\partial L \ni 0$:

$$\begin{aligned} \partial_p L(p, \beta^{-1}) &= \{\beta u\} - \partial_p F(p, q) \ni 0 \\ \partial_{\beta^{-1}} L(p, \beta^{-1}) &= \lambda - F(p, q) = 0 \end{aligned}$$

- Optimal solutions are subgradients of $F^*(u, q) = \sup\{\langle u, p \rangle - F(p, q)\}$:

$$p(\beta) \in \partial F^*(\beta u), \quad F(p, q) = \lambda \quad \left(\langle u, p(\beta) \rangle = v \right)$$

Example: Exponential Solution

- For $D_{KL}(p, q) = \langle \ln(p/q), p \rangle - \langle 1, p - q \rangle$:

$$L(p, \beta^{-1}) = \langle u, p \rangle + \beta^{-1}[\lambda - \langle \ln(p/q), p \rangle + \langle 1, p - q \rangle]$$

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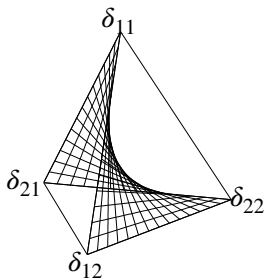
$$p(\beta) = e^{\beta u - \ln Z(\beta u)} q, \quad D_{KL}(p(\beta), q) = \lambda$$

Solution to Shannon's OCP

- The solution for

$$I_w\{x, y\} = D_{KL}(w, q \otimes p) \leq \lambda:$$

$$w(\beta) = e^{\beta u - \ln Z(\beta u)} q \otimes p$$



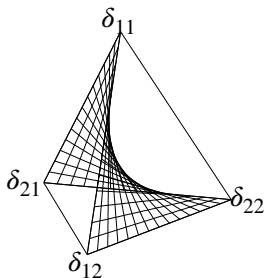
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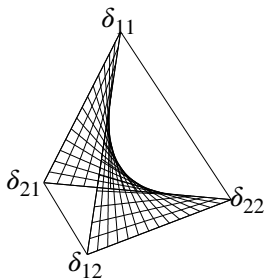
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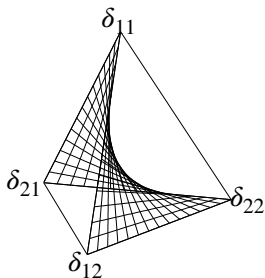
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- The dual is strictly convex:

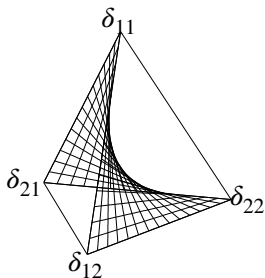
$$D_{KL}^*(u, q \otimes p) = \ln \int e^u q \otimes p$$



Solution to Kantorovich's OTP

- $\Gamma(q, p)$ is convex:

$$\pi_X((1-t)w_1 + tw_2) = (1-t)q + tq = q$$



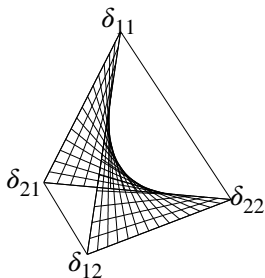
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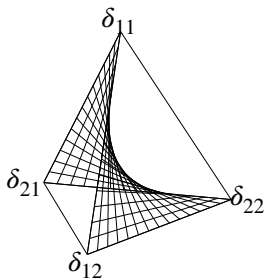
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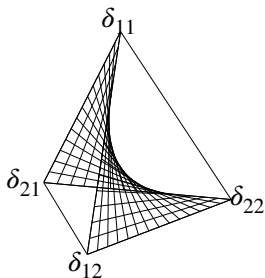
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Monge-Ampere equation

$$q = p \circ \nabla \varphi |\nabla^2 \varphi|$$

where $\varphi : X \rightarrow \mathbb{R} \cup \{\infty\}$ is convex, and $\nabla \varphi : X \rightarrow Y$ is such that $p = q \circ (\nabla \varphi)^{-1}$ (McCann, 1995; Villani, 2009).

Strict Inequalities

Theorem (Belavkin, 2013b)

- Let $\{w(\beta)\}_u$ be a family of $w(\beta) \in \mathcal{P}(X \otimes Y)$

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Strict Bounds for Monge OTP

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Optimal Transport and the Expected Utility Principle

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$$v \lesssim w \iff \lambda v \lesssim \lambda w, \quad \forall \lambda > 0 \quad (1)$$

$$v \lesssim w \iff v + r \lesssim w + r, \quad \forall r \in L \quad (2)$$

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Theorem

*Pre-ordered linear space (L, \lesssim) satisfies (1), (2) and (3) if and only if (L, \lesssim) has a utility representation by a closed **linear** functional $u : L \rightarrow \mathbb{R}$.*

Optimal transportation problems (OTPs)

Information and entropy

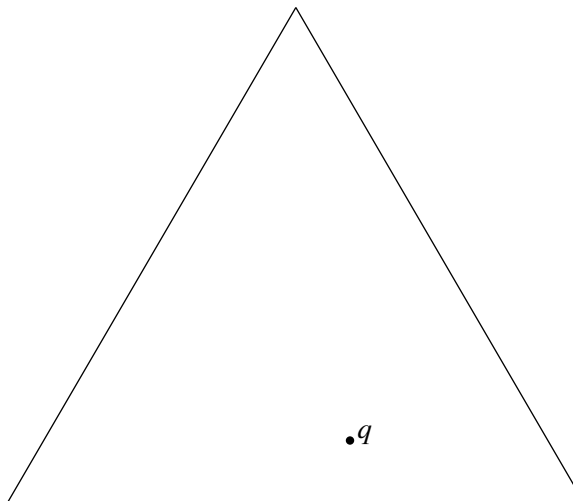
Optimal channel problem (OCP)

Geometry of information divergence and optimization

Dynamical OTP: Optimization of evolution

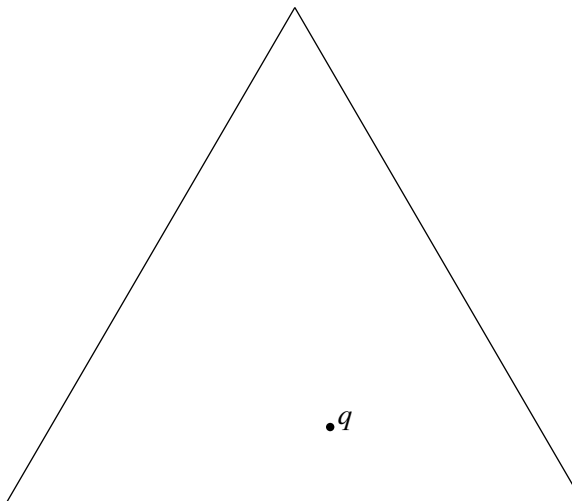
Dynamical Problems

- $q(t) \mapsto Tq(t) = q(t + 1)$



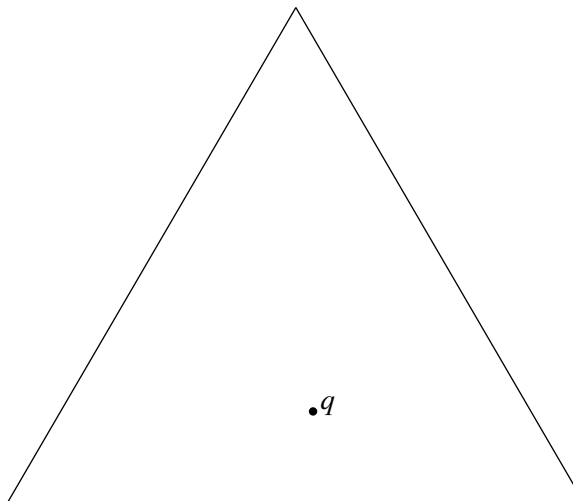
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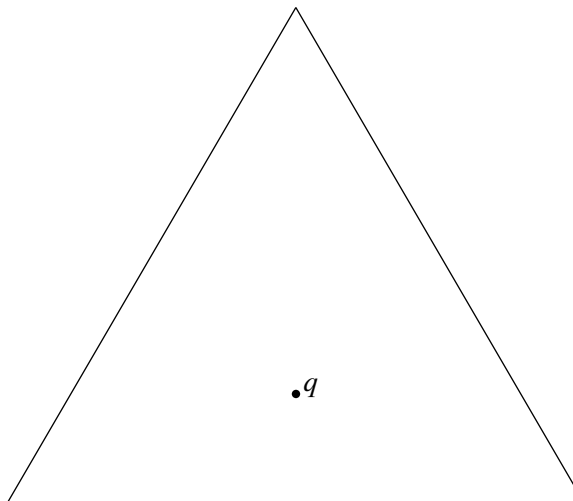
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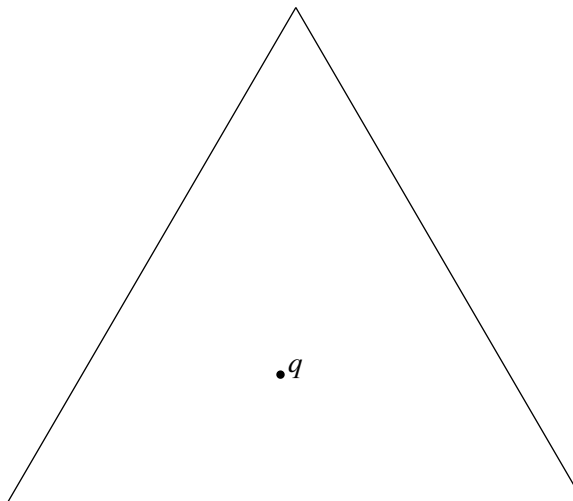
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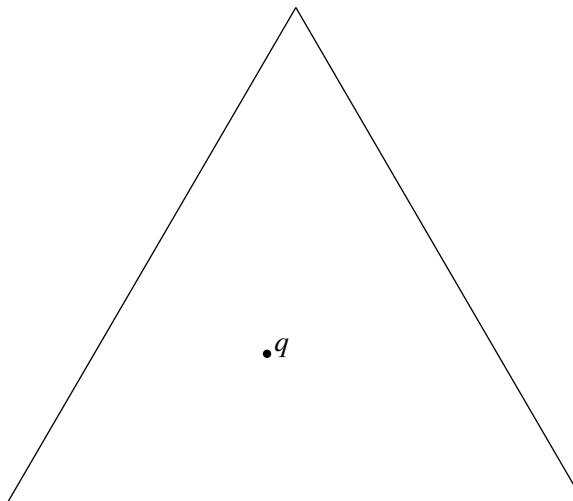
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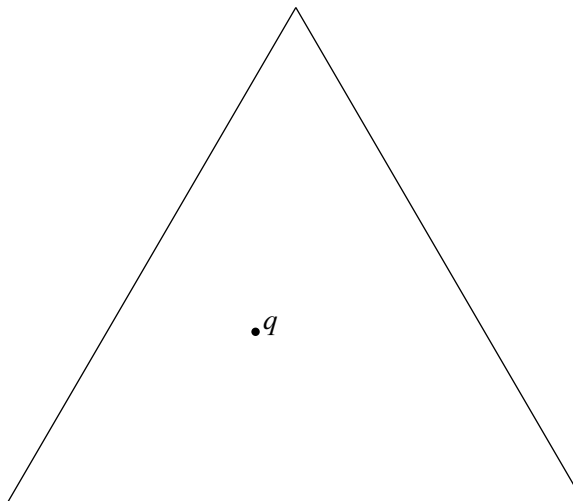
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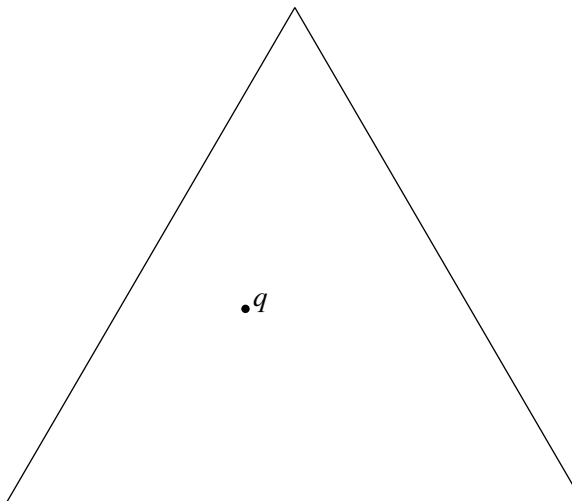
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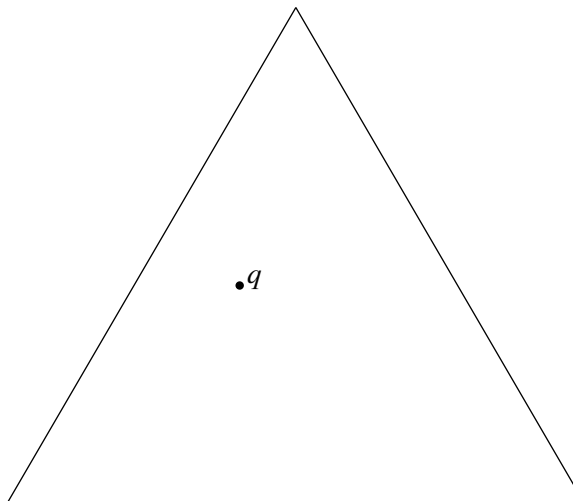
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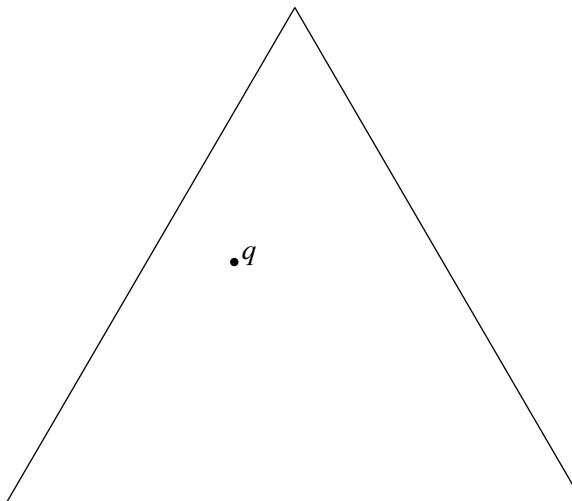
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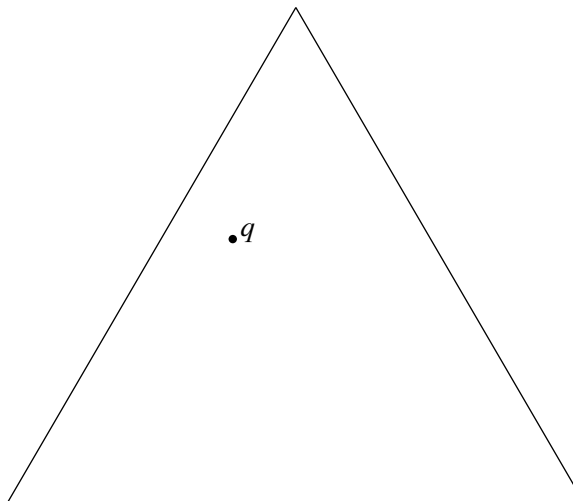
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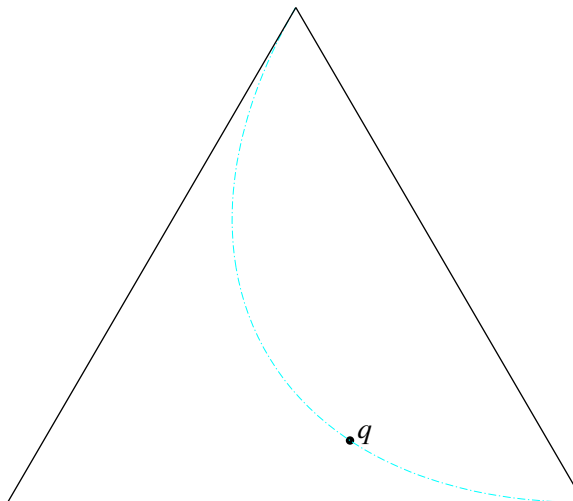
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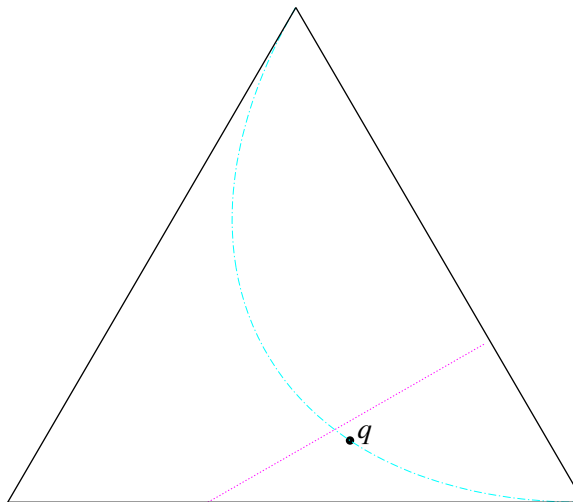
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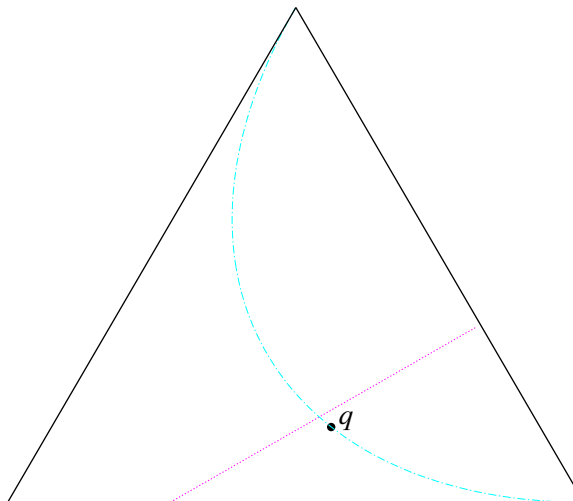
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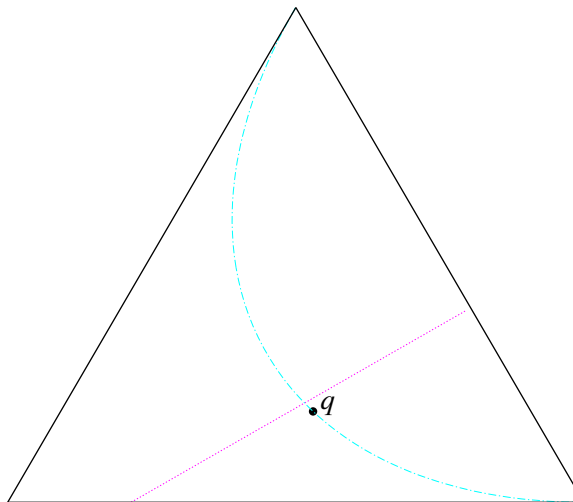
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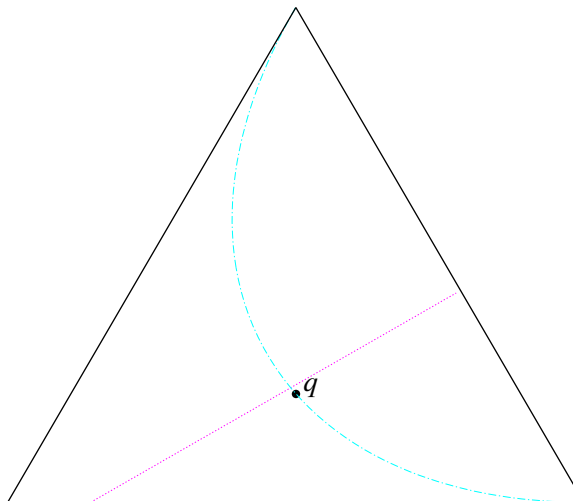
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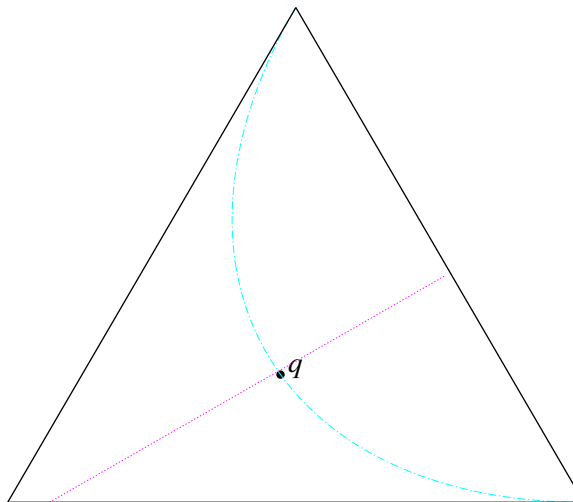
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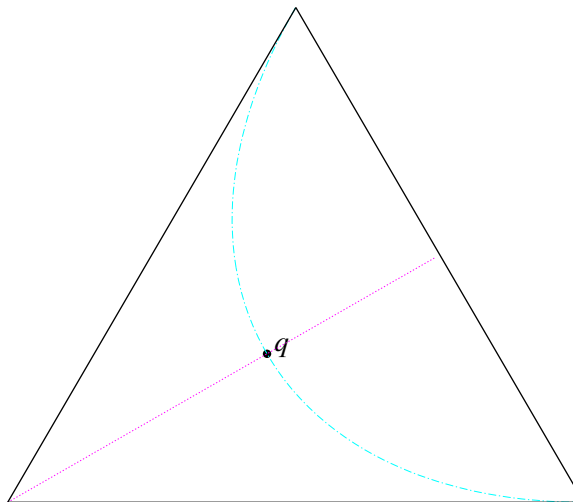
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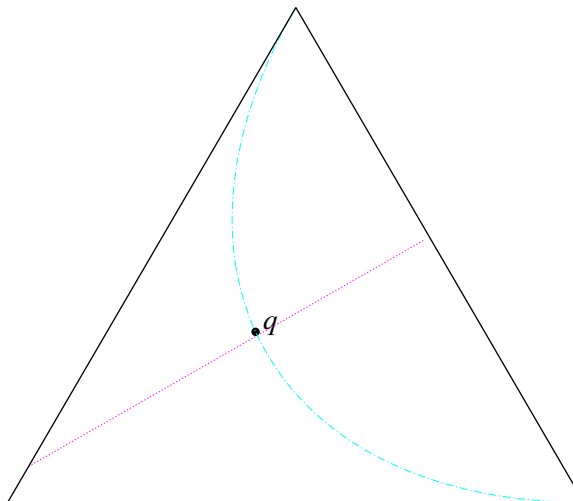
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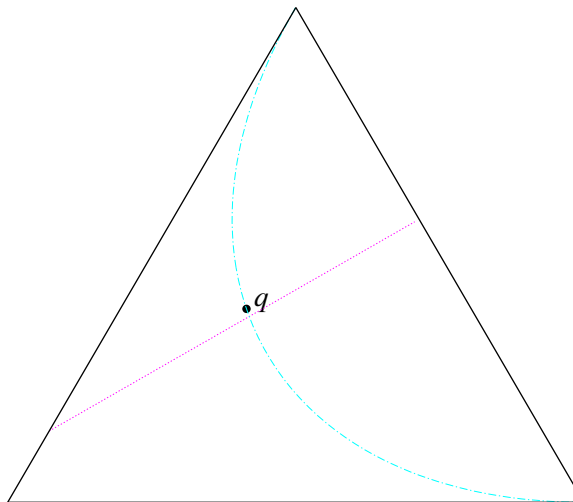
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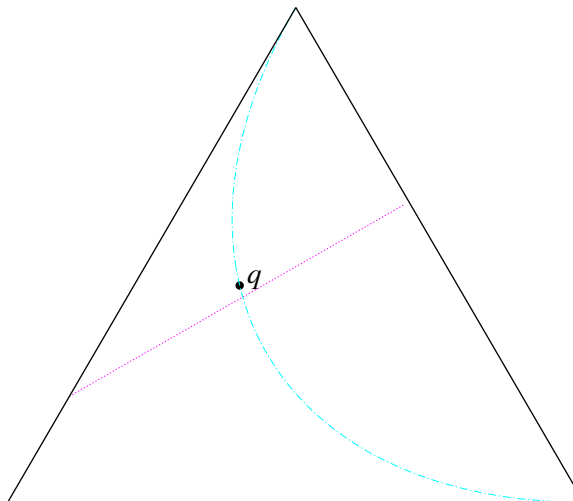
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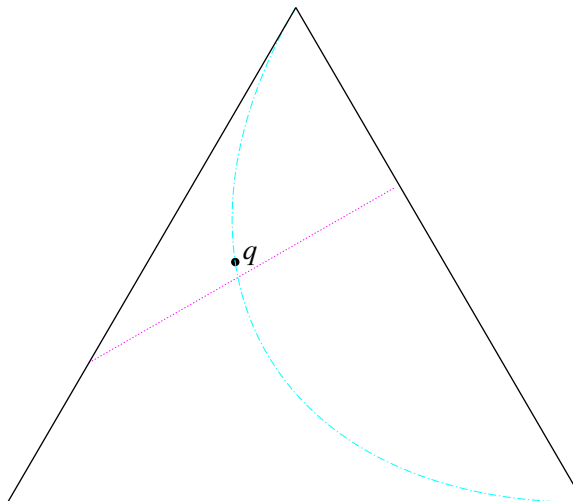
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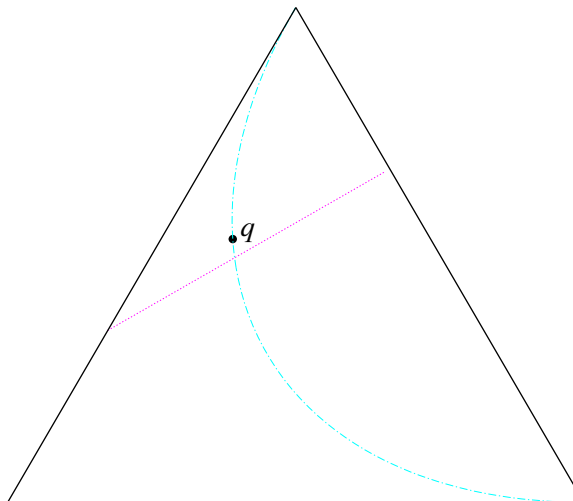


Dynamical Problems

- $q(t) \mapsto Tq(t) = q(t + 1)$
- $q(t) \mapsto T^s q(t) = q(t + s)$
- $q(t) \rightarrow \delta_T$
- Expected utility:

$$\mathbb{E}_{q(t)}\{u\} = \int_X u dq(t)$$

- Why not directly
 $q \mapsto Tq = \delta_T$?



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- For $l \geq 2$

$$\log_2(l + 1) < l \log_2 \alpha$$

Optimal Control of Mutation Rate

- Optimal transition kernels are

$$P_{\beta}(y | x) = \frac{e^{-\beta \|y-x\|_H}}{[1 + (\alpha - 1)e^{-\beta}]^l} = \prod_{i=1}^l \frac{e^{-\beta(1-\delta_{x_i y_i})}}{1 + (\alpha - 1)e^{-\beta}}$$

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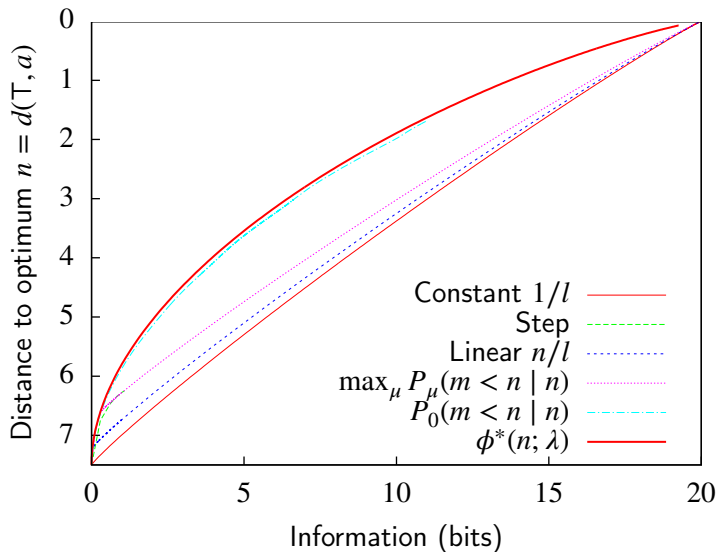
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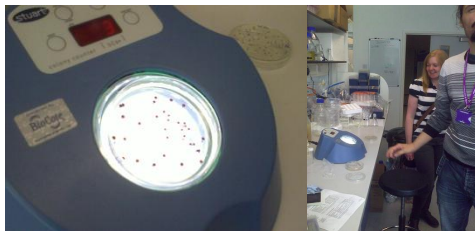
- Which $\mu(n)$?
- The CDF method:

$$\mu(n) = \sum_{m=0}^{n-1} \binom{l}{m} \frac{(\alpha - 1)^m}{\alpha^l}$$

Evolution of Fitness in Information



Mutation Rate Control in *E. coli*



- Used strains of *Escherichia coli* K-12 MG1665

Mutation Rate Control in *E. coli*



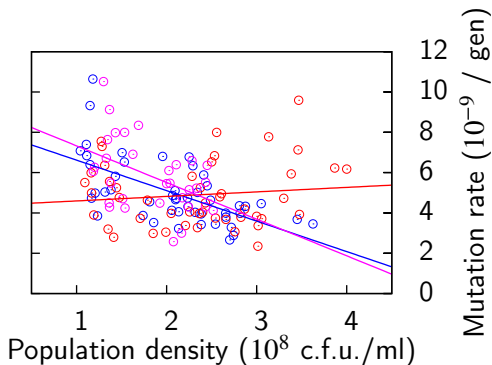
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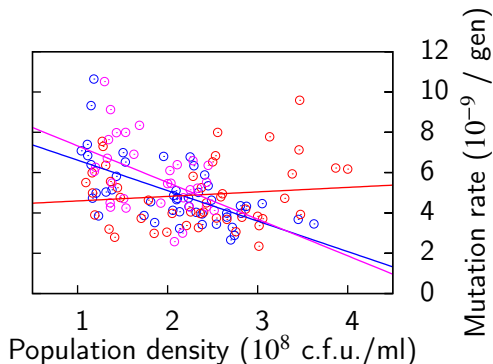
- Used strains of *Escherichia coli* K-12 MG1665
- Fluctuation test using media 50 μ g/ml of Rifampicin
- Estimated mutation rates μ in *E.coli* strains grown in Davis minimal medium with different amount of glucose.

Experimental Results (Krašovec et al., 2014)



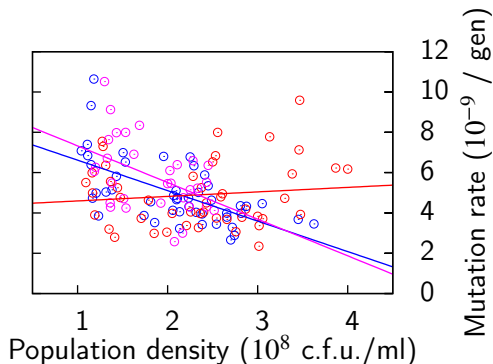
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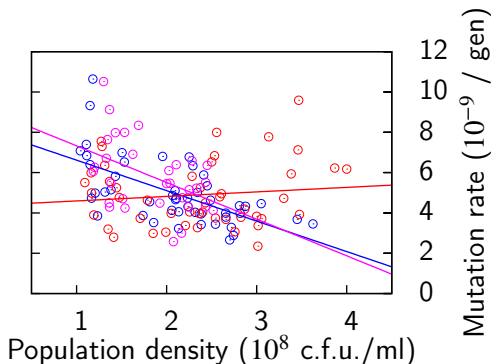
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Optimal transportation problems (OTPs)

Information and entropy

Optimal channel problem (OCP)

Geometry of information divergence and optimization

Dynamical OTP: Optimization of evolution

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