A Generalization of Caffarelli's Contraction Theorem via (reverse) Heat-Flow

Emanuel Milman

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Fields Institute November 5, 2010

joint with Young-Heon Kim, UBC.

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Outline

- Optimal Transport and Caffarelli's Contraction Theorem.
- Recall some applications of CCT.
- State Generalization of CCT.
- New Applications.
- Ideas in Proof.
- Challenge.

Monge (Monge–Kantorovich) Transport Problem (~ 1781)

Let μ, ν be two Borel probability measures on \mathbb{R}^n , $\mu << Leb$, $\int |x|^2 d\mu$, $\int |x|^2 d\nu < \infty$.

Among all maps $T : \mathbb{R}^n \to \mathbb{R}^n$ pushing forward μ onto ν , $(\nu = \mu \circ T^{-1}, \text{"}T : \mu \mapsto \nu\text{"})$, minimize $\int |T(x) - x|^2 d\mu(x)$.

Thm (Brenier '91, McCann '95)

Minimizing $T = T_{opt}$ exists, unique (μ -a.e.), and characterized by $T_{opt} = \nabla \varphi$, $\varphi : \mathbb{R}^n \to \mathbb{R}$ convex.

Thms (Caffarelli 90's)

Regularity Theory for the Monge-Ampére equation

$$det D^2 \varphi(x) = \frac{f(x)}{g(\nabla \varphi(x))}$$
, $\mu = f(x) dx$, $\nu = g(x) dx$

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Then $T_{opt}: \mu \mapsto \nu$ is a contraction:

$$|T_{opt}(x) - T_{opt}(y)| \leq |x - y| \quad \forall x, y \in \mathbb{R}^n$$
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Applications

- Transferring isoperimetric and Sobolev inequalities.
- Transferring Poincaré inequalities (Brascamp–Lieb, B-conjecture).
- Correlation Inequalities.
- More...

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- K, L two convex subsets of \mathbb{R}^n , K = -K, L = -L.

Gaussian Correlation Conjecture (Das Gupta, Eaton, Olkin, Perlman, Savage and Sobel 1972)

$$\gamma_n(K \cap L) \geq \gamma_n(K)\gamma_n(L)$$
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Pitt (1977) confirmed for n = 2, $n \ge 3$ still open.

Thm (Hargé 1999, Cordero-Erausquin 2002)

True if K (or L) is a centered ellipsoid.

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If $\mathcal{E} = A(B_2^n)$, set $\mu = \gamma_n \circ A$. Want to show:

$$\mu(B_2^n \cap L) \ge \mu(B_2^n)\mu(L) \quad \forall L = -L \text{ convex }$$

Set $\nu = (\mu \mathbf{1}_L)/\mu(L)$. Want to show:

$$\nu(B_2^n) = \frac{\mu(B_2^n \cap L)}{\mu(L)} \ge \mu(B_2^n) .$$

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Very useful in applications.

However, leaves room for improvement:

- $\mu = Gaussian$.
- *T_{opt}* optimal-transport map:
 - Non-constructive.
 - Analysis requires Caffarelli's regularity theory.

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Fix $\mathbb{R}^n = \underline{E_0} \oplus \underline{E_1} \oplus \ldots \oplus \underline{E_k}$ orthogonal decomposition.

Assume $\mu = \exp(-U(x))dx$ and $\nu = \mu \exp(-V)$, where:

$$U(x) = Q(P_{E_0}x) + \sum_{i=1}^{\kappa} \rho_i(|P_{E_i}x|),$$

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$$|T(x)-T(y)| \leq |x-y| \quad \forall x,y \in \mathbb{R}^n$$
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- $E_0 = \mathbb{R}^n$ recovers Caffarelli's Thm (with different T).
- $E_1 = \mathbb{R}^n$ $U = \rho(|x|)$, V = v(|x|) are radial.
- $E_0 = 0$ and $dim(E_i) = 1 U = \sum \rho_i(|x_i|) \Rightarrow \mu$ is product; V is convex and unconditional.

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Applications

Generalizes all the applications mentioned.

Corollary (Generalized Correlation Inequality)

Fix $\mathbb{R}^n = E_0 \oplus E_1 \oplus \ldots \oplus E_k$ orthogonal decomposition

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Let L = -L convex such that:

$$\exists C_L \subset \mathbb{R}^{dimE_0+k} \quad \mathbf{1}_L(x) = \mathbf{1}_{C_L}(P_{E_0}x, |P_{E_1}x|, \dots, |P_{E_k}x|) \ .$$

Let K = -K such that if $(x_0, x_1, \dots, x_k) \in K$ then:

$$\forall y_0 \in E_0 \ \|y_0\|_{\mathcal{E}} \le \|x_0\|_{\mathcal{E}} \ \forall t_i \in [-1,1] \ (y_0, t_1x_1, \ldots, t_kx_k) \in K.$$

Then:

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Other Applications: Transferring isoperimetric inequalities

Fact: Lipschitz maps transfer isoperimetric inequalities

Assume
$$T:(\Omega_1, d_1, \mu_1) \rightarrow (\Omega_2, d_2, \mu_2), T: \mu_1 \mapsto \mu_2$$
 and:

$$d_2(T(x), T(y)) \leq d_1(x, y) \quad \forall x, y \in \Omega_1.$$

If
$$\mu_1(\partial A) \geq \mathcal{I}(\mu_1(A)) \ \forall A$$
, then $\mu_2(\partial B) \geq \mathcal{I}(\mu_2(B)) \ \forall B$.

Corollary of Generalized CCT (particular case)

Let $\mu = c \exp(-\sum_{i=1}^{n} |x_i|^p), p \in (0, 2]$. It is known that:

$$\mu(\partial A) \geq \mathcal{I}_{p,n}(\mu(A))$$

Set $\nu=(\mu\mathbf{1}_L)/\mu(L),\,L\subset\mathbb{R}^n$ unconditional and convex. Then:

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$$\frac{d}{dt}f = Lf := \Delta f - \langle \nabla f, \nabla U \rangle , \ f|_{t=0} = f_0 .$$

$$P_t(\exp(-V)) \rightarrow \int \exp(-V)d\mu = |\nu| = 1$$
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$$u_0 =
u = \mu \exp(-V) \quad o \quad
u_t := \mu P_t(\exp(-V)) \quad o \quad
u_\infty = \mu \ .$$

We construct $T^{-1}: \nu \mapsto \mu$, and show it is expanding.

 T^{-1} is constructed by following heat-flow with drift, transforming $\nu = \mu \exp(-V)$ into $\mu = \exp(-U(x))dx$.

Denote by $P_t(f_0)$ the solution to:

$$\frac{d}{dt}f = Lf := \Delta f - \langle \nabla f, \nabla U \rangle , \ f|_{t=0} = f_0 .$$

 $P_t = \exp(tL)$ is the associated semi-group.

L and P_t are self-adjoint on $L_2(\mu)$, $\mu = \exp(-U(x))dx$.

 P_t preserves total μ -mass, and (under mild assumptions) converges to the constant stationary distribution:

$$P_t(\exp(-V)) o \int \exp(-V) d\mu = |\nu| = 1$$
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Interpolation:

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u = \mu \exp(-V) \rightarrow
u_t := \mu P_t(\exp(-V)) \rightarrow
u_\infty = \mu.$$

 $T^{-1} := \lim_{t \to \infty} S_t$, where $S_t : \nu \mapsto \nu_t$ are diffeomorphisms

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 $P_t = \exp(tL)$ is the associated semi-group.

L and P_t are self-adjoint on $L_2(\mu)$, $\mu = \exp(-U(x))dx$. P_t preserves total μ -mass, and (under mild assumptions) converges to the constant stationary distribution:

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The Reduction

Reduction

When does heat-flow w.r.t. $\mu = \exp(-U(x))dx$:

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preserve log-concavity: $-\log P_t(f_0)$ remains convex $\forall t \geq 0$?

Example: $\mu=$ Gaussian ($\emph{U}=\emph{Q}$) "Ornstein–Uhlenbeck"

By the Mehler formula, it is known that:

$$P_t(f_0) = \operatorname{rescaled}_{t} f_0 * \operatorname{Gaussian}_{t}$$
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The Reduction (continued)

Thm (Kolesnikov '01)

For general initial log-concave data $f_0 = \exp(-V)$, only Ornstein–Uhlenbeck (U = Q) preserves log-concavity.

Observation ("inherent tradeoff")

For less general convex V, log-concavity may still be preserved by more general U.

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Classical PDE problem (Korevaar, Caffarelli–Spruck, Kawohl ...). One of key methods is maximum principle.

New - Geometric ideas + technical points previously not treated:

• Reduce to Dirichlet boundary valued problem on $B(R) \times [0, T]$:

$$\frac{d}{dt}f = (\Delta - \langle \nabla f, \nabla U \rangle)f, \ f|_{t=0} = f_0, \ f|_{\partial B(R) \times [0,T]} \equiv \mathbf{0}.$$

- Show that f remains log-concave near the parabolic boundary $\partial B(R) \times [0, T]$: $D^2(-\log f) = -\frac{D^2 f}{f} + \frac{\nabla f \otimes \nabla f}{f^2} \ge 0$?
 - Problem: $f \notin C^{2;1}(\overline{B(R)} \times [0, T])$!
 - $\partial_{n,n}$ assume $\langle \nabla f_0, n \rangle > 0$ and use Hopf strong principle.
 - $\partial_{t,*}$ use strong convexity of $\partial B(R)$ + extra regularity.
- Set $V := -\log f$, and assume V_0 is strictly convex. V satisfies:

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To obtain contradiction, need:

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Intuitively, $T \neq T_{opt}$ generically.

 $T = T_{opt}$ in dimension 1, or in 1-dimensional situations

Example (where everything is computable):

$$\mu = \exp(-\langle Ax, x \rangle) \;,\; \nu = \mu \exp(-\langle Bx, x \rangle) \;,\; A, B \ge 0 \;.$$
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Fact

When A, B commute, $T = T_{opt}$.

Conjecture

When *A* and *B* do not commute, $T \neq T_{opt}$ generically.

Can show that generically for $n \ge 2$, along the flow, DS_t is not symmetric except at discrete set of times, so S_t is not the gradient of a potential, i.e. not interpolating optimal map.

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