

OPTIMAL TRANSPORT
AND (RICCI) CURVATURE
THEOREMS AND PROBLEMS
(IN SEARCH OF THE GEOMETRIC MEANING
OF RICCI)

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Cédric Villani

University of Lyon
& Institut Henri Poincaré (Paris)

Analytic vs. Synthetic: an example

Def. (i) $\varphi \in C^2(\mathbb{R}^n; \mathbb{R})$ is convex if for any x ,

$$\nabla^2 \varphi(x) \geq 0$$

Def. (ii) $\varphi : \mathbb{R}^n \rightarrow \mathbb{R}$ is convex if for any x, y, t ,

$$\varphi((1-t)x + ty) \leq (1-t)\varphi(x) + t\varphi(y)$$

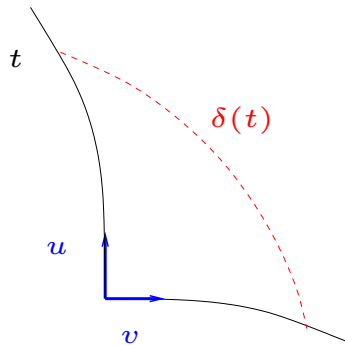
(i): simple, local, effective

(ii): useful, general, stable

– and implies some regularity in the end

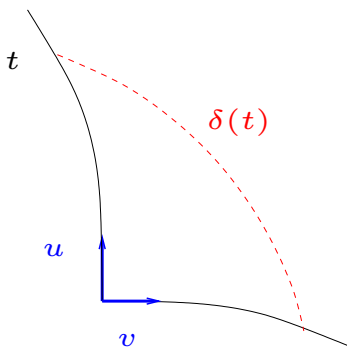
Geometric meaning of curvature

Let $u, v \in T_x M$ be orthogonal unit vectors. $\kappa(u, v)$ measures the divergence of geodesics, w.r.t. to Euclidean geometry: $d(\exp_x tu, \exp_x tv) = \sqrt{2} t \left(1 - \frac{\kappa}{12} t^2 + O(t^4) \right)$



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Ricci curvature = “average sectional curvature”

(e_1, e_2, \dots, e_n) orthonormal, then $\text{Ric}(e_1) := \sum_{j=2}^n \kappa(e_1, e_j)$

This extends to a quadratic form

(expressed in terms of second derivatives of the metric g)

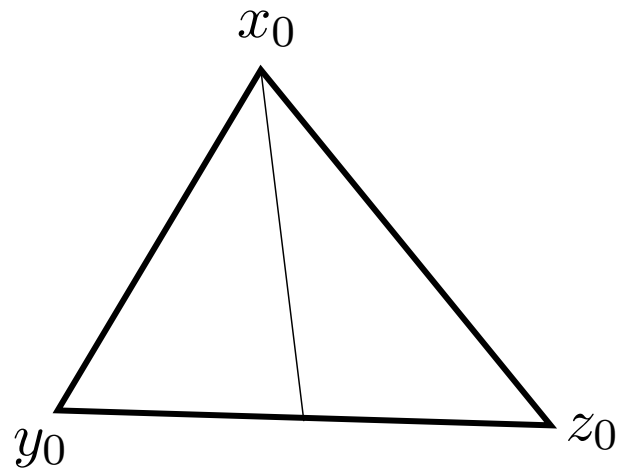
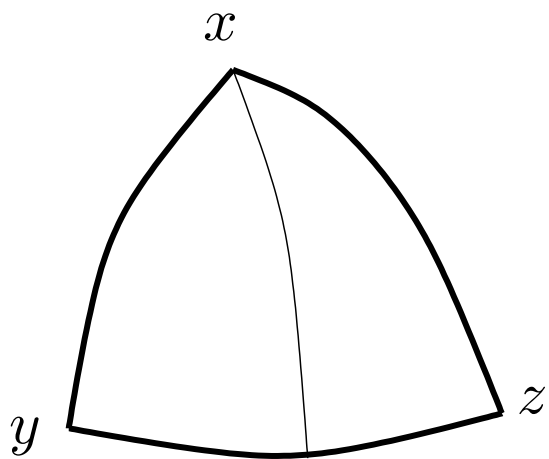
Metric spaces of nonnegative sectional curvature

(Cartan–Alexandrov–Toponogov)

$$\kappa \geq 0$$



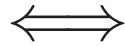
Triangles are **puffier** than Euclidean triangles



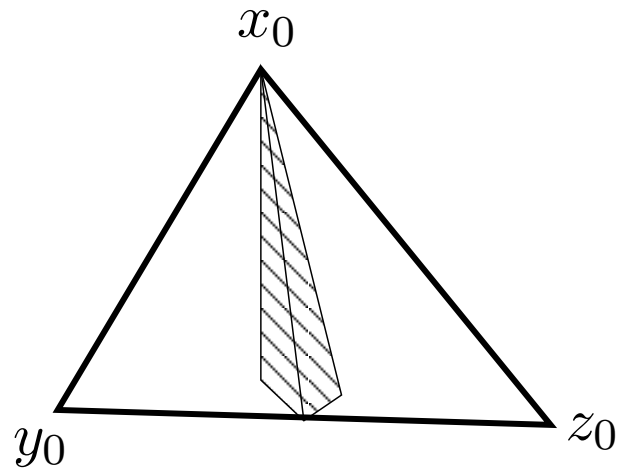
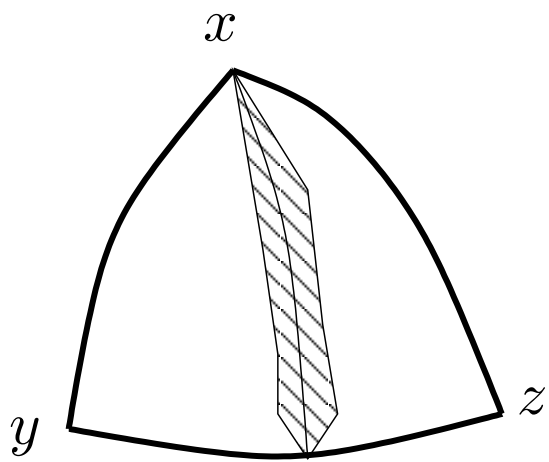
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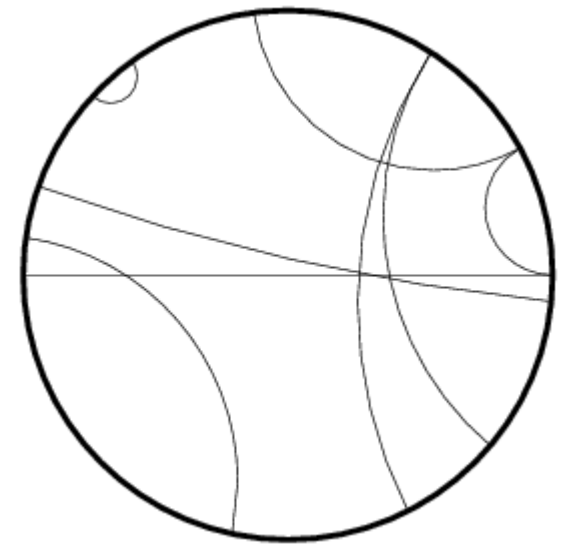
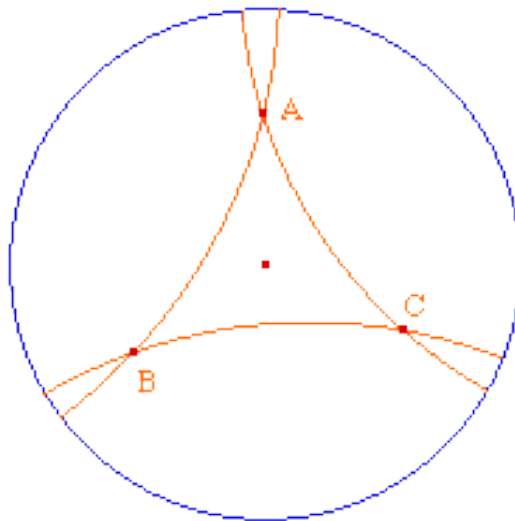
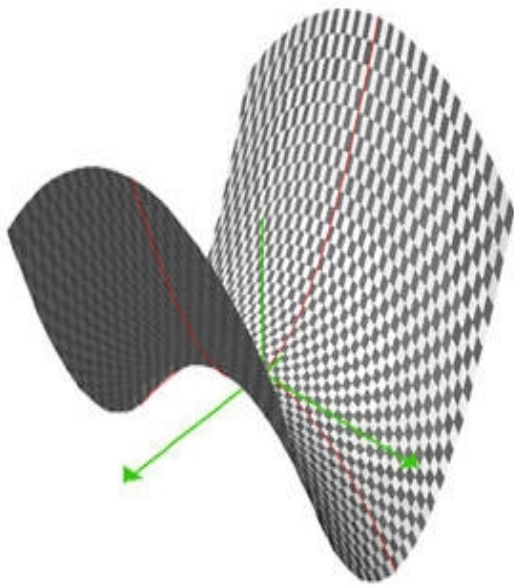
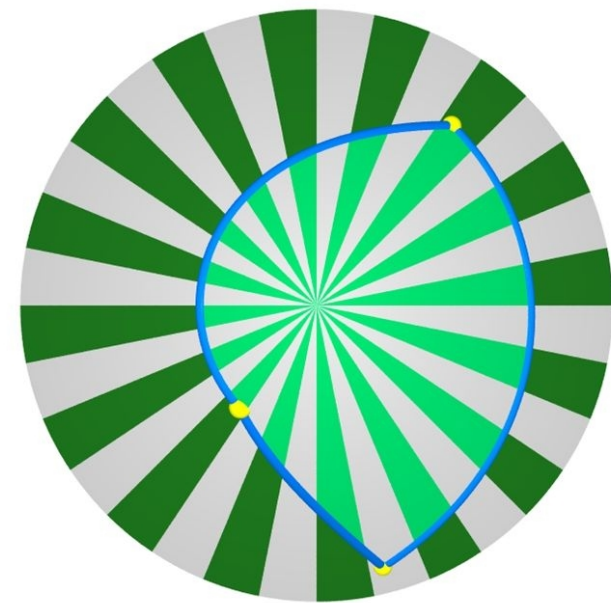
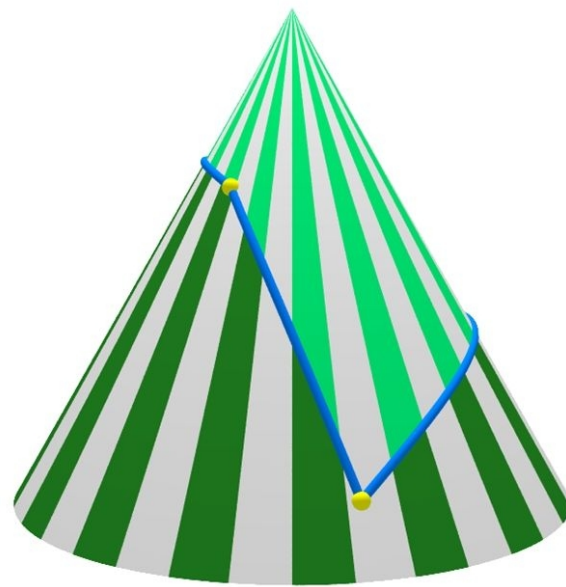
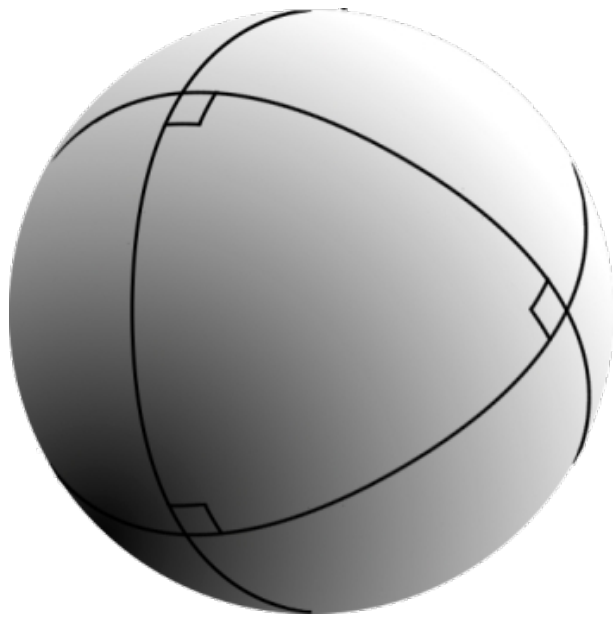
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Theory of Alexandrov spaces of positive curvature

Many results by Alexandrov, Burago, Perelman, Petrunin, Ohta, Lytchak, Kuwae, Otsu, Shioya...

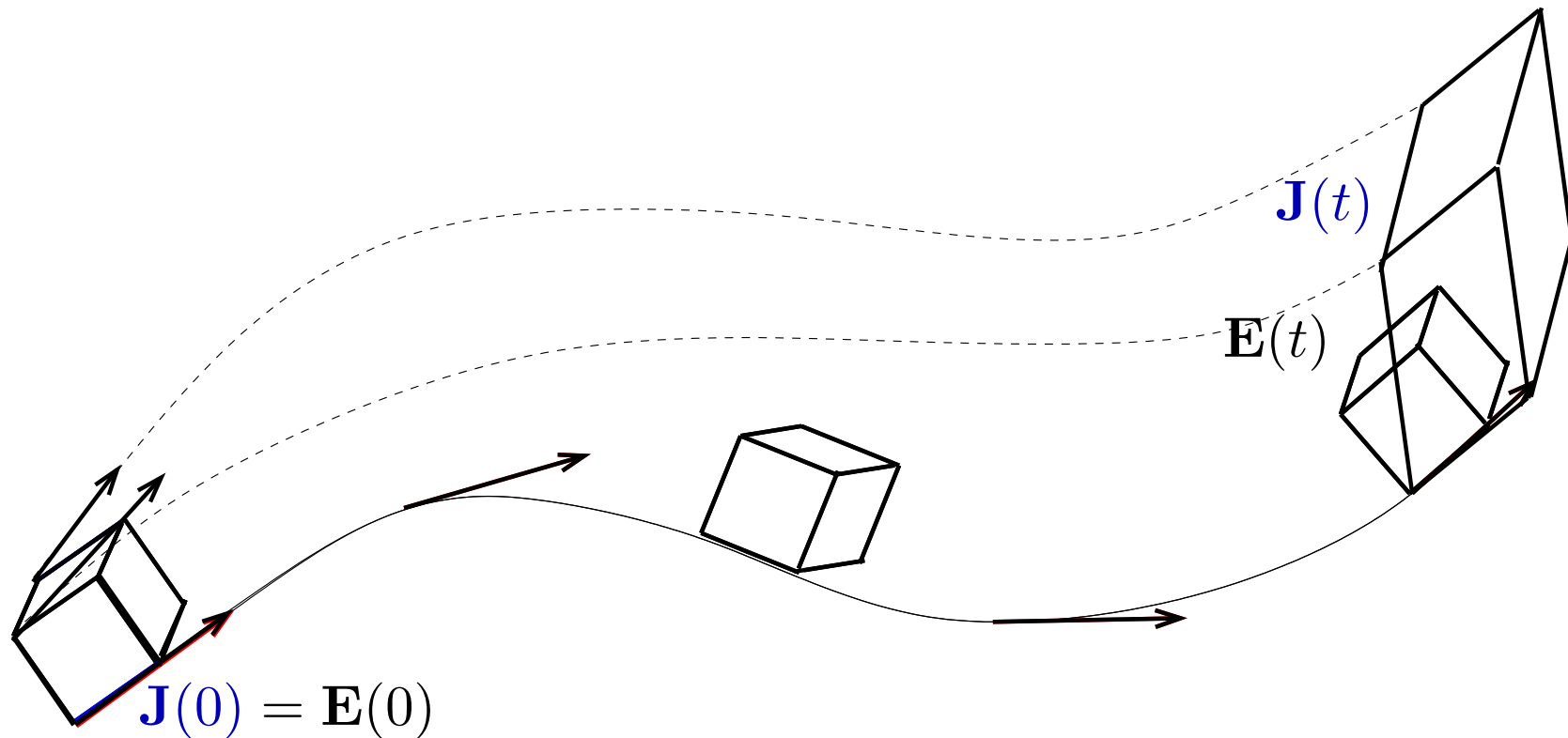
First and second-order calculus, parallel transport, quasigeodesics (replacement for exponential map), basis, gradient flows, smoothing ...

Theory of Alexandrov spaces of negative curvature

Also exists, very different



The meaning of Ricci curvature, I



$$\gamma(t) = \exp_x(tv), \quad (e_1(t), \dots, e_n(t)) \quad e_1(0) = v/|v|$$

$$R_{ij}(t) = \left\langle \text{Riem}_{\gamma(t)}(\dot{\gamma}(t), e_i(t)) \dot{\gamma}(t), e_j(t) \right\rangle_{\gamma(t)}$$

$$\ddot{\mathbf{J}}(t) + \mathbf{R}(t)\mathbf{J}(t) = 0$$

$$\mathbf{J}(0) = I_n, \quad \dot{\mathbf{J}}(0) = \nabla^2 \psi, \quad \text{tr } \mathbf{R} = \text{Ric}$$

$$R_{ij}(t) = \left\langle \text{Riem}_{\gamma(t)}(\dot{\gamma}(t), e_i(t)) \dot{\gamma}(t), e_j(t) \right\rangle_{\gamma(t)}$$

$$\ddot{J}(t) + R(t)J(t) = 0$$

$$J(0) = I_n \quad \dot{J}(0) = \nabla^2 \psi$$

$$\mathcal{J}(t) = \det J(t) \quad \dot{\mathcal{J}}/\mathcal{J} = \text{tr}(\dot{J}J^{-1}) =: \text{tr} U(t)$$

$$\dots \dot{U}(t) + U(t)^2 + R(t) = 0 \quad \text{So } U(t) \text{ is symmetric!}$$

$$(\text{tr} U)^\cdot + \text{tr} U^2 + \text{Ric} = 0 \implies (\text{tr} U)^\cdot + \frac{(\text{tr} U)^2}{n} + \text{Ric} \leq 0$$

$$(\dot{\mathcal{J}}/\mathcal{J})^\cdot + n^{-1}(\dot{\mathcal{J}}/\mathcal{J})^2 + \text{Ric} \leq 0$$

$$(\mathcal{J}^{\frac{1}{n}})^\cdot(t) \leq -\frac{1}{n} \text{Ric}(\dot{\gamma}(t)) \mathcal{J}(t)^{1/n}$$

Lagrangian: If $E(t)$ is an orthonormal matrix of Jacobi fields (infinitesimal geodesic variations of a geodesic γ), then $U := E' E^{-1}$ satisfies the Riccati equation

$$(\operatorname{tr} U)' + \operatorname{tr} (U^2) + \operatorname{Ric}(\dot{\gamma}, \dot{\gamma}) = 0$$

Eulerian: If $u \in C^3(M)$, then

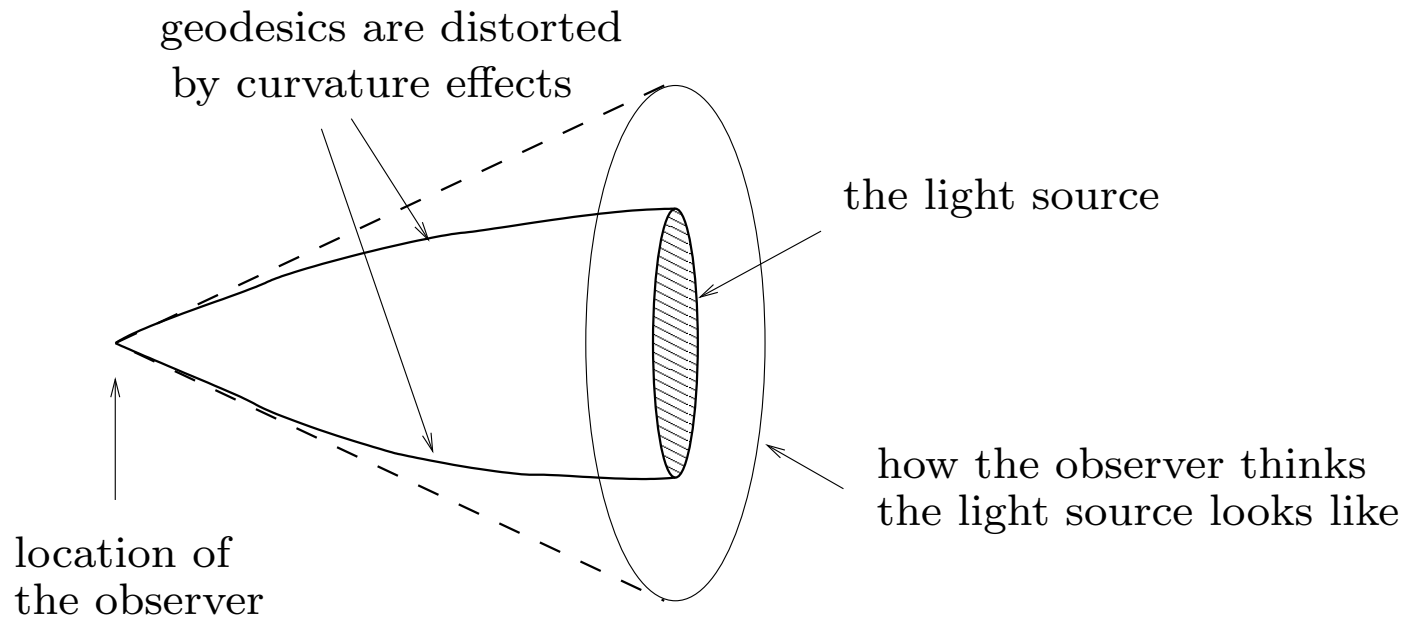
$$-\nabla u \cdot \nabla \Delta u + \Delta \frac{|\nabla u|^2}{2} = \|D^2 u\|^2 + \operatorname{Ric}(\nabla u, \nabla u)$$

Bochner formula

The start of **many** theorems and estimates

Note: Passing from one to the other: Hamilton–Jacobi theory $\partial_t \psi + |\nabla \psi|^2/2 = 0$

The meaning of Ricci curvature, II



Because of nonnegative curvature, the observer overestimates the **surface** of the light source; in negative curvature this would be the contrary.

$$[\text{Distortion coefficients always } \geq 1] \iff [\text{Ric} \geq 0]$$

The meaning of Ricci curvature, III

Otto's (formal) differential calculus on $P_2(M^n)$, which is the “manifold” of probability measures on M^n , equipped with the **distance**

$$\begin{aligned} W_2(\mu_0, \mu_1) &= \sqrt{\inf \left\{ \int_0^1 \int |v(t, x)|^2 \mu_t(dx); \quad \partial_t \mu + \nabla_x \cdot (v\mu) = 0 \right\}} \\ &= \sqrt{\inf_{T\#\mu_0=\mu_1} \int d(x, T(x))^2 \mu_0(dx)} \end{aligned}$$

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$$\partial_t \rho + \nabla \cdot (\rho \nabla \phi) = 0 \implies$$

$$\left\langle \text{Hess}_{\rho \text{vol}}(H) \cdot \partial_t \rho, \partial_t \rho \right\rangle = \int \left(\|D^2 \phi\|^2 + \langle \text{Ric} \cdot \nabla \phi, \nabla \phi \rangle \right) \rho \, d\text{vol}$$

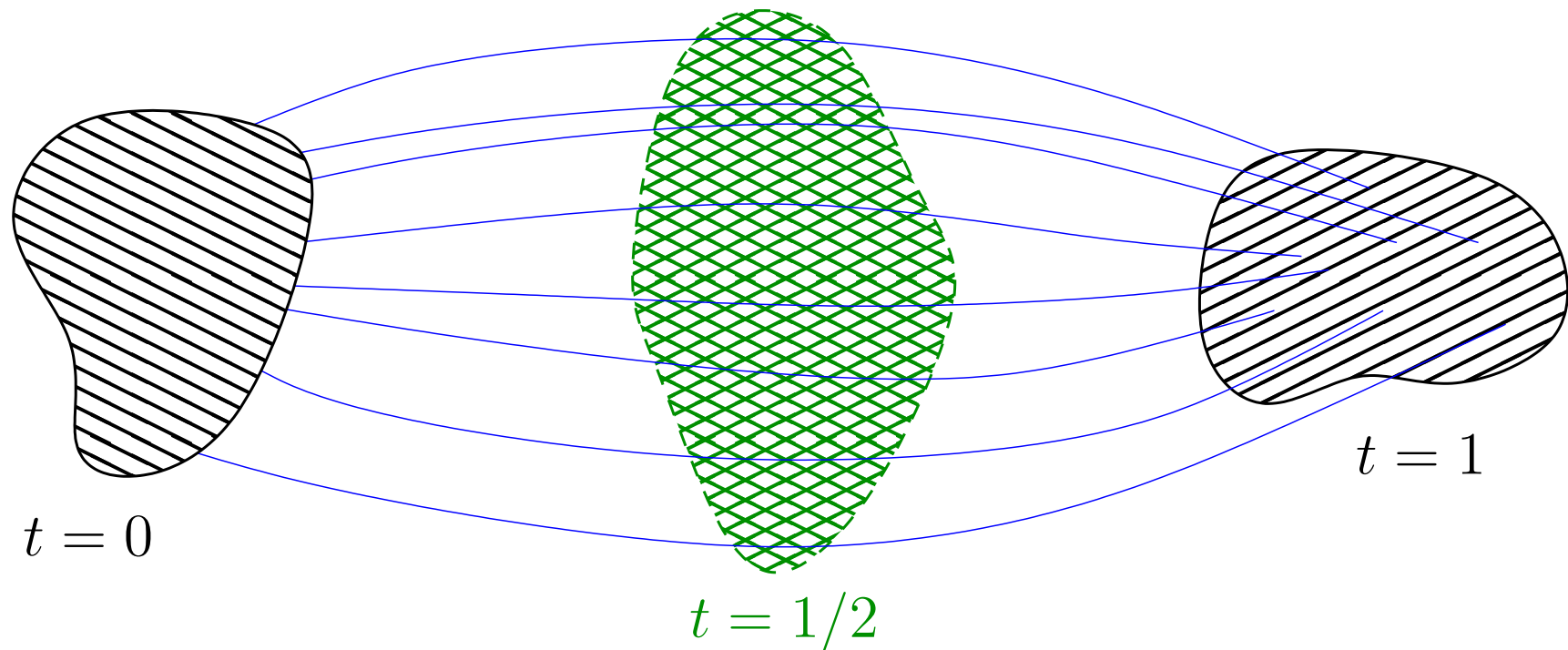
$$H(\rho) = \int \rho \log \rho \, d\text{vol}$$

Consequences of Ricci curvature lower bounds

- isoperimetric inequalities (Lévy–Gromov)
- heat kernel estimates (Li–Yau)
- Sobolev inequalities
- diameter control (Bonnet–Myers)
- spectral gap inequalities (Lichnérowicz)
- Poincaré inequalities (Cheeger...)
- volume growth estimates (Bishop–Gromov)
- compactness of families of manifolds (Gromov)
- concentration (Lévy, Gromov, Talagrand...)
- volume of intermediate points

(Brunn–Minkowski)

Example: curved Brunn–Minkowski for Ric ≥ 0



$$\text{vol}^{\frac{1}{n}} m(X, Y) \geq \frac{\text{vol}^{\frac{1}{n}}(X) + \text{vol}^{\frac{1}{n}}(Y)}{2} \quad (\text{midpoints})$$

NB: In \mathbb{R}^n , recover classical B–M

$|X + Y|^{\frac{1}{n}} \geq |X|^{\frac{1}{n}} + |Y|^{\frac{1}{n}}$ by homogeneity

Inequalities

$$-\nabla u \cdot \nabla \Delta u + \Delta \frac{|\nabla u|^2}{2} = \|D^2 u\|^2 + \text{Ric}(\nabla u)$$

$$\implies -\nabla u \cdot \nabla \Delta u + \Delta \frac{|\nabla u|^2}{2} \geq \frac{(\Delta u)^2}{N} + K |\nabla u|^2$$

if $n \leq N$, $\text{Ric} \geq K$

→ **criterion** $\text{CD}(K, N)$: **the** inequality involving Ricci curvature and dimension

(Also has Lagrangian counterparts of course)

Generalizations

If the **reference volume** is $e^{-V(x)} \text{vol}(dx)$ then $\text{CD}(K, N)$ (“Ricci $\geq K$, dimension $\leq N$ ”), should be changed into

$$-\nabla u \cdot \nabla \Delta_\nu u + \Delta_\nu \frac{|\nabla u|^2}{2} \geq \frac{(\Delta_\nu u)^2}{N} + K |\nabla u|^2$$

where $\Delta_\nu = \Delta - \nabla V \cdot \nabla$

Equivalently, $\text{Ric}_{N,\nu} \geq K g$

where $\text{Ric}_{N,\nu} = \text{Ric} + \nabla^2 V - \frac{\nabla V \otimes \nabla V}{N - n}$

Theory of $CD(K, N)$ bounds

Geometric/analytic consequences have been developed by Bakry, Émery, Ledoux, Li & Yau, and many others.

There it is (often) considered a property of the **Laplace operator**, or heat equation...

Ex: If $CD(K, N)$ then

$$\|f\|_{L^{\frac{2N}{N-2}}}^2 \leq \|f\|_{L^2}^2 + \frac{4}{KN(N-2)} \|\nabla f\|_{L^2}^2$$

Ex: $CD(K, \infty)$ corresponds to:

$$|\nabla H_t f|^2 \leq e^{-2Kt} H_t |\nabla f|^2 \dots$$

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Lott–Sturm–Villani

(Building on Otto–Villani,
Cordero-Erausquin–McCann-Schmuckenschläger,
Sturm–Von Renesse)

The **synthetic** $CD(K, N)$ criterion goes through the interplay of **optimal transport** and **entropy-type functionals**

Recently pushed very far in the “Riemannian” setting

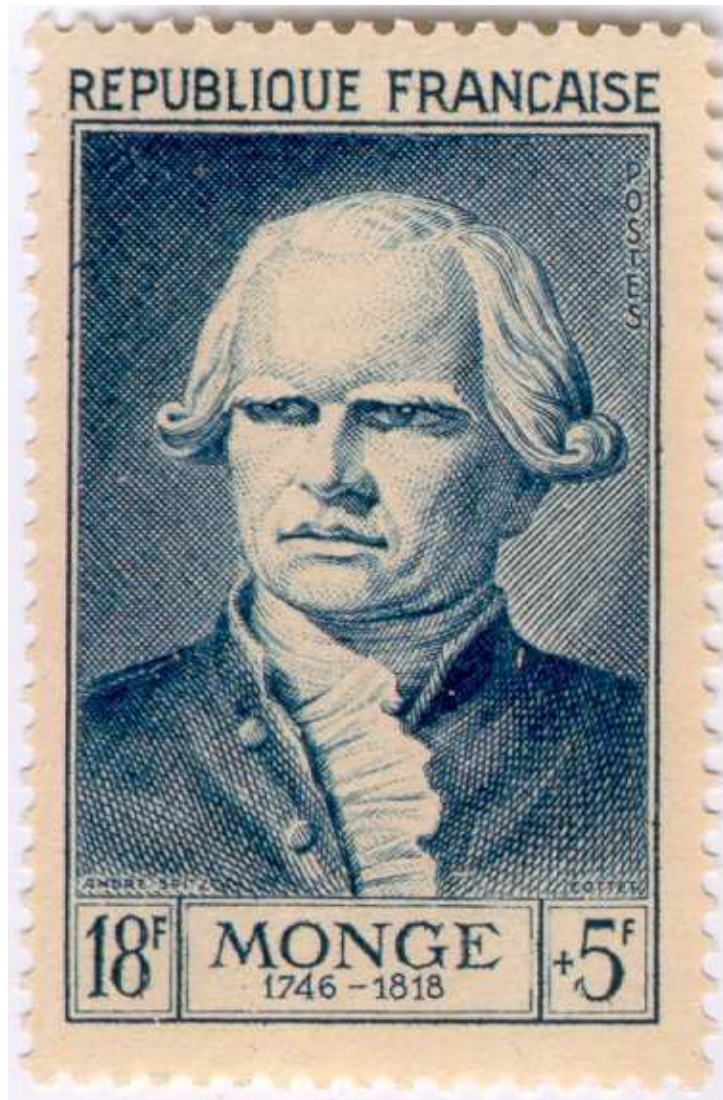
Optimal transport

$$\inf_{T_{\#}\mu_0=\mu_1} \int d(x, T(x))^2 \mu_0(dx)$$

Boltzmann Entropy

$$S(\rho) = - \int \rho \log \rho = -H(\rho)$$

Optimal transport



The Kantorovich problem

(Kantorovich, 1942)

- \mathcal{X}, \mathcal{Y} two complete separable metric spaces
- $\mu \in P(\mathcal{X}), \nu \in P(\mathcal{Y})$
- $c \in C(\mathcal{X} \times \mathcal{Y}; \mathbb{R}),$ say $c(x, y) = d(x, y)^2$

$$\Pi(\mu, \nu) = \left\{ \pi \in P(\mathcal{X} \times \mathcal{Y}); \text{ marginals of } \pi \text{ are } \mu \text{ and } \nu \right\}$$

$$\forall h \quad \int h(x) \pi(dx dy) = \int h d\mu \quad \int h(y) \pi(dx dy) = \int h d\nu$$

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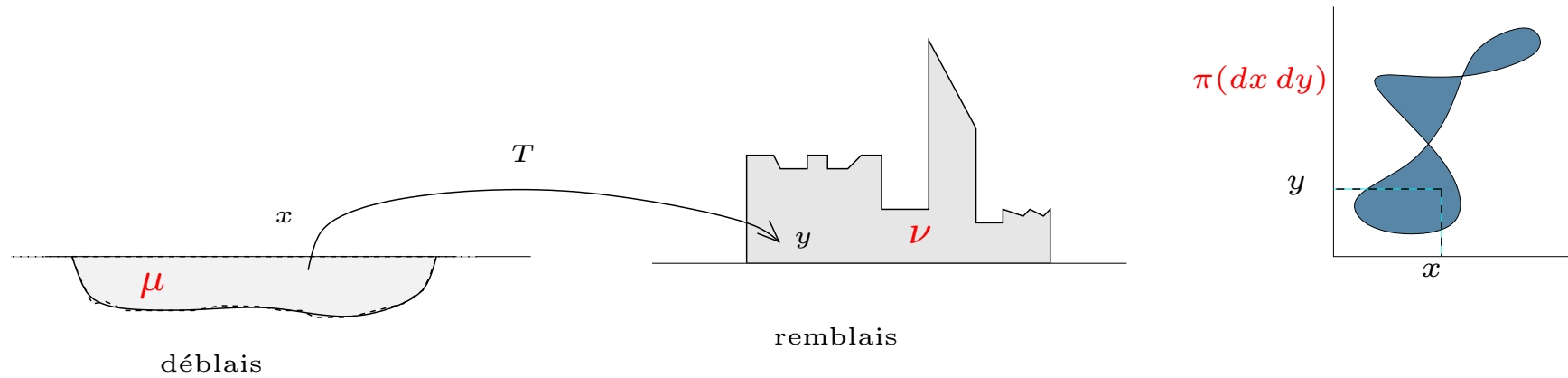
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(K)

$$\inf_{\pi \in \Pi(\mu, \nu)} \int c(x, y) \pi(dx dy)$$

Engineer's interpretation



Given the initial and final distributions, transport matter at lowest possible cost

Information theory

The **Shannon–Boltzmann entropy** $S = - \int f \log f$ quantifies how much information there is in a “random” signal Y , or a language.

$$H_{\mu}(\nu) = \int \rho \log \rho d\mu; \quad \nu = \rho \mu.$$

... Entropy = mean value of $\log \frac{1}{\rho(Y)}$...

Microscopic meaning of the entropy functional

Measures the **volume** of **microstates** associated,
to some degree of accuracy in macroscopic observables,
to a given **macroscopic** configuration (observable
distribution function)

⇒ How exceptional is the observed configuration?

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Boltzmann's formula

$$S = k \log W$$

→ How to go from $S = k \log W$ to $S = - \int f \log f$?

Famous computation by Boltzmann

N particles in k boxes

f_1, \dots, f_k some (rational) frequencies; $\sum f_j = 1$

N_j = number of particles in box # j

$\Omega_N(f)$ = number of configurations such that $N_j/N = f_j$

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$$\boxed{\Omega_N(f) = 1}$$

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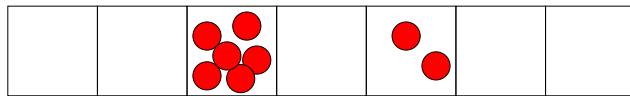
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$$f = (0, 0, 3/4, 0, 1/4, 0, 0)$$

$$\Omega_8(f) = \frac{8!}{6! 2!}$$

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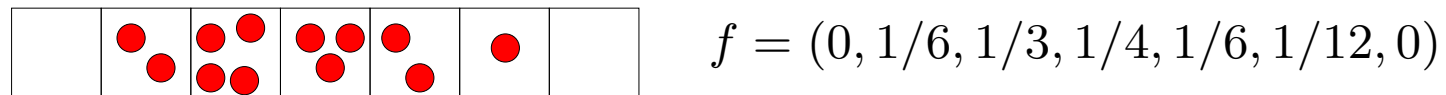
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$$\Omega_N(f) = \frac{N!}{N_1! \dots N_k!}$$

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Then as $N \rightarrow \infty$

$$\#\Omega_N(f_1, \dots, f_k) \sim e^{-N \sum f_j \log f_j}$$

$$\frac{1}{N} \log \#\Omega_N(f_1, \dots, f_k) \simeq - \sum f_j \log f_j$$

Recall: Sanov's Theorem

Mathematical translation of the Boltzmann formula

x_1, x_2, \dots (“microscopic r.v.”) i.i.d. law ν ;

$$\hat{\mu}^N := \frac{1}{N} \sum_{i=1}^N \delta_{x_i} \text{ (random, “empirical” measure)}$$

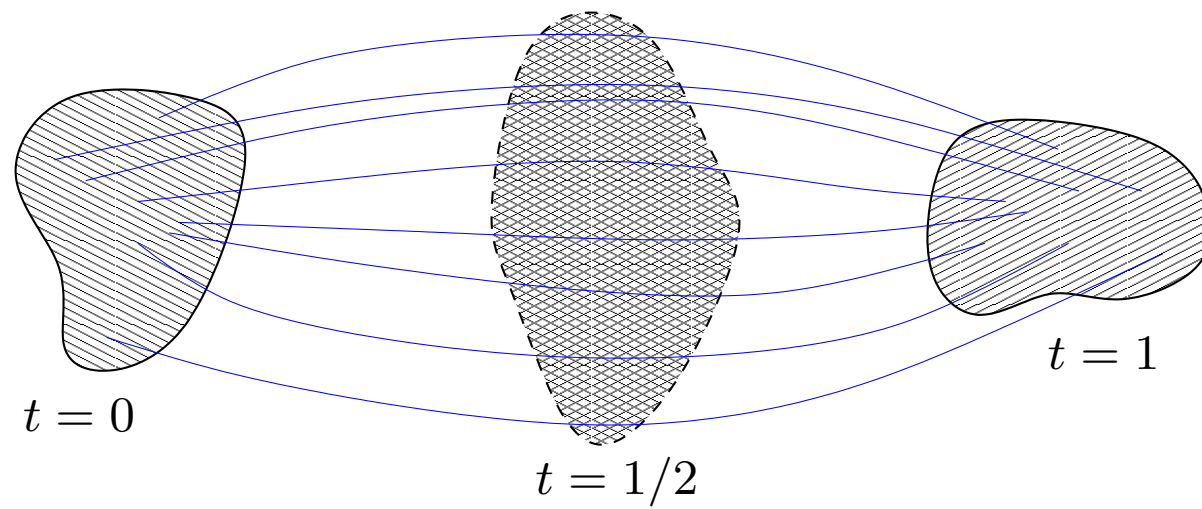
What measure shall we observe??

Informal: $\mathbb{P} [\hat{\mu}^N \simeq \mu] \sim e^{-N H_\nu(\mu)}$

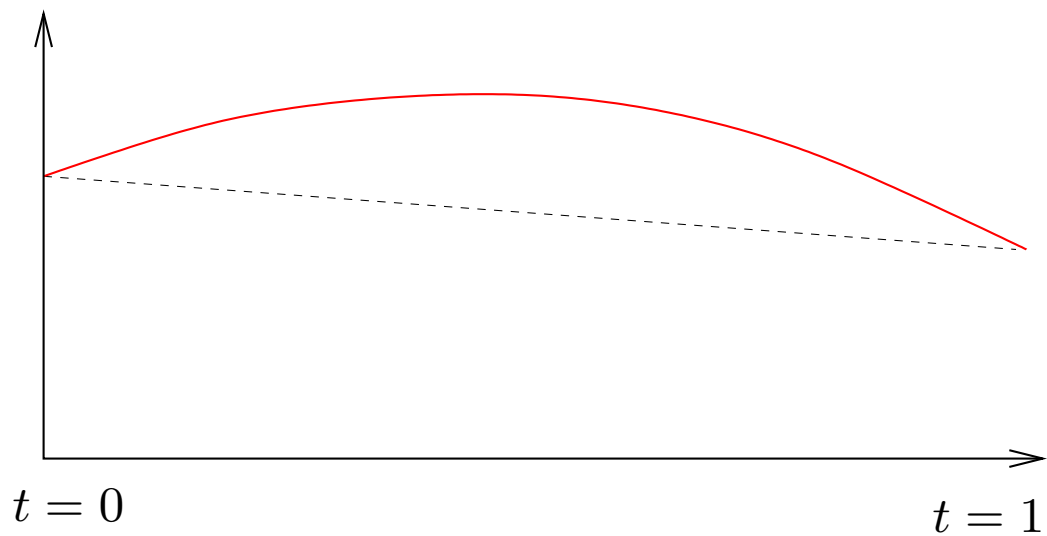
$$H_\nu(\mu) = \int \rho \log \rho \, d\nu, \quad \rho = \frac{d\mu}{d\nu}$$

Rigorously: $H_\nu =$ Large Deviation Rate Function of $\hat{\mu}^N$.

The lazy gas experiment



$$S = - \int \rho \log \rho$$



Relation between transport and Ricci

$$\text{Ric} \geq 0$$

if and only if

$$H(\mu_t) = \int \rho_t \log \rho_t \, d\text{vol} \quad \text{is a convex function of } t$$

$$\rho_t = \frac{d\mu_t}{d\text{vol}}$$

(convexity along geodesics of optimal transport!)



Metric-measure spaces of nonnegative Ricci curvature

(Lott–Sturm–Villani)

Definition: A compact metric-measured space (\mathcal{X}, d, ν) has **Ricci curvature ≥ 0** (in weak sense) if

$\forall \mu_0, \mu_1 \in P(\mathcal{X}) \quad \exists (\mu_t)_{0 \leq t \leq 1}, \quad \text{geodesic in } P(\mathcal{X}), \quad \text{s.t.}$

$\forall t \in [0, 1],$

$$\int \rho_t \log \rho_t d\nu \leq (1 - t) \int \rho_0 \log \rho_0 d\nu + t \int \rho_1 \log \rho_1 d\nu$$

(Some slight variants: a.c. or not? More general $\rho \log \rho$ -type nonlinearities?)

Metric-measure spaces of positive Ricci curvature

(Lott–Sturm–Villani)

Definition: A compact metric-measured space (\mathcal{X}, d, ν) has **Ricci curvature $\geq K$** (in weak sense) if

$\forall \mu_0, \mu_1 \in P(\mathcal{X}) \quad \exists (\mu_t)_{0 \leq t \leq 1}$, geodesic in $P(\mathcal{X})$, s.t.

$\forall t \in [0, 1]$,

$$\int \rho_t \log \rho_t d\nu \leq (1 - t) \int \rho_0 \log \rho_0 d\nu + t \int \rho_1 \log \rho_1 d\nu - \frac{K}{2} t(1 - t) C(\mu, \nu)$$

General CD(K, N): no unanimity yet!

- Change the class of nonlinearities: in dimension N , replace $\rho \log \rho$ by $U(\rho)$, where $s^N U(s^{-N})$ is convex

- Introduce distortion coefficients in the functional:

$$\int U(\rho_t) d\nu \leq (1-t) \int U\left(\frac{\rho_0(x)}{\beta_t(x,y)}\right) \beta_t(x,y) \pi(dy|x) \nu(dx) + \dots$$

where π is optimal, $\beta_t(x, y) =$ reference distortion coeff

Two competing choices of reference distortion coefficients

$$\beta_t(x, y) = \left(\frac{\sin(t\alpha)}{t \sin \alpha}\right)^{N-1}, \quad \alpha = \sqrt{\frac{K}{N-1}} d(x, y) \quad [\text{CD}]$$

$$\beta_t(x, y) = \left(\frac{\sin(t\alpha)}{t \sin \alpha}\right)^N, \quad \alpha = \sqrt{\frac{K}{N}} d(x, y) \quad [\text{CD}^*]$$

Consistency

The weak definition coincides with the usual one if the space is smooth (Riemannian manifold)

Core of proof of (\Rightarrow) Take $\mu_0 = \rho_0 \text{ vol}$, $\mu_1 = \rho_1 \text{ vol}$.

1. The optimal transport takes the following form: each starting point x is related to the final point y by a **minimizing geodesic** $\gamma_x(t)$, with initial velocity $\dot{\gamma}_x(0) = \nabla\psi(x)$ for some function ψ having some convexity-type properties.

2. The interpolation μ_t between μ_0 and μ_1 is obtained by stopping the geodesic at time t : **$\mu_t = (\exp t\nabla\psi)_\# \mu_0$**

3. Change variables:

$$H(\mu_t) = H(\mu_0) - \int \log \text{Jac}(\exp t\nabla\psi) d\mu_0$$

$$4. \text{ Ric} \geq 0 \implies \frac{d^2}{dt^2} \log \text{ Jac}(\exp t \nabla \psi) \leq 0$$

.... All the rest is “analysis” and approximation...

Note:

- The entropy is an “integrated” way to involve the logarithmic Jacobian determinant of the exponential map
- With optimal transport we have only access to gradient velocity fields, which is rich enough (Hamilton–Jacobi eq.)

Locality

With the second (weakest) definition of distortion coefficients, the definition is **local** as soon as the space is nonbranching. Probably the “right” def!

This is because of the underlying differential inequality

$$\ddot{D} + \frac{K}{N} D \leq 0$$

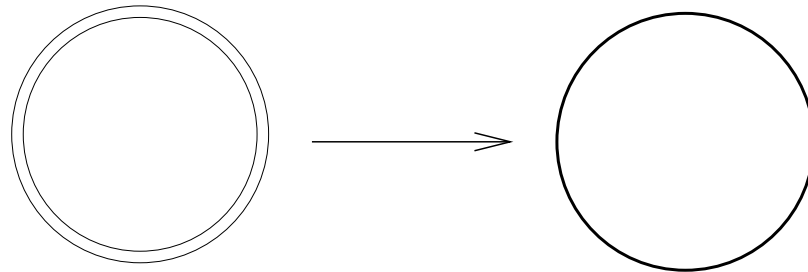
It is open whether the two choices of distortion coefficients are equivalent (true for all examples – cones, Finsler/Alexandrov spaces, warped products...)

It is known that for the nonbranching spaces $CD^*(K, N)$ is equivalent to Boltzmann’s information H satisfying $H'' \geq K + (H')^2/N$ along geodesics

Stability

Def: $(\mathcal{X}_k, d_k, \nu_k)_{k \in \mathbb{N}}$ converges to (\mathcal{X}, d, ν) in **measured Gromov–Hausdorff** topology if there are $f_k : \mathcal{X}_k \rightarrow \mathcal{X}$

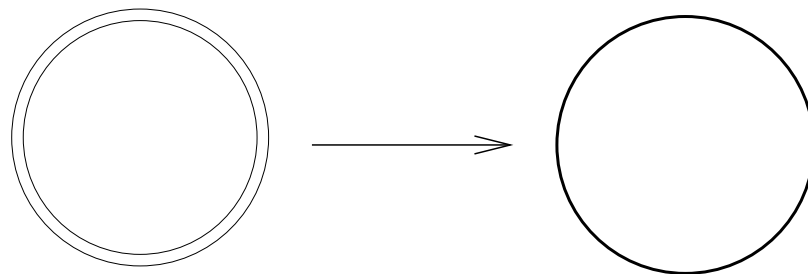
$$\begin{cases} |d(f_k(x), f_k(y)) - d_k(x, y)| \leq \varepsilon_k \rightarrow 0 \\ \forall x \in X, \quad d(x, f_k(X_k)) \leq \varepsilon_k \\ (f_k)_\# \nu_k \longrightarrow \nu \quad \text{weakly} \end{cases}$$



Stability

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Thm: If $(\mathcal{X}_k, d_k, \nu_k)$ has $\text{Ric} \geq K$ and converges to (\mathcal{X}, d, ν) then (\mathcal{X}, d, ν) has $\text{Ric} \geq K$.

(no need for convergence of the second derivatives!)

Strategy of proof of stability (say for $N = \infty$)

Step 1: Reformulate the condition “ $\text{Ric} + \nabla^2 V \geq 0$ ”:

For any two probability measures μ_0 and μ_1 , there is a geodesic $(\mu_t)_{0 \leq t \leq 1}$ in the Wasserstein space $(P(\mathcal{X}), W_2)$, s.t. $H_\nu(\mu_t) \leq (1 - t) H_\nu(\mu_0) + t H_\nu(\mu_1)$

Step 2: $P_2(X)$ is stable under MGH:

If $f_k : X_k \rightarrow X$ is an approximate isometry, then $(f_k)_\# : P_2(X_k) \rightarrow P_2(X)$ also

Combining with a compactness argument, find a limit geodesic in the space of measures.

Step 3: Use the properties of the entropy to pass to the limit in the inequality.

If $U : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ is convex and continuous, then

$$U_\nu(\mu) := \int U \left(\frac{d\mu}{d\nu} \right) d\nu$$

is *lower semicontinuous* w.r.t. μ and ν ,

and satisfies a *contraction principle*:

$$\text{for any } f, \quad U_{f\#\nu}(f\#\mu) \leq U_\nu(\mu)$$

Conclude that the same property holds true in the limit space, deduce $\text{Ric} + \nabla^2 V \geq 0$.

Compatibility (Petrunin 2009)

If (\mathcal{X}, d) is a compact finite-dimensional Alexandrov space with “sectional” curvature ≥ 0 then also $(\mathcal{X}, d, \text{vol})$ has “Ricci” curvature ≥ 0 .

This establishes a **direct link** between Cartan–Alexandrov–Toponogov and Lott–Sturm–V and ensures the compatibility of weak definitions

This was generalized to “sectional curvature $\geq \kappa$ ”, providing examples of $\text{CD}(K, N)$ spaces.

But weak $\text{CD}(K, N)$ spaces are **more general** and include all MGH limits of $\text{CD}(K, N)$ manifolds, all normed $\mathbb{R}^N \dots$

Properties derived from the synthetic formulation

Sobolev inequalities, Brunn–Minkowski, Bishop–Gromov,
Poincaré, Lichnérowicz...

Example: Prove the Curved Brunn–Minkowski inequality

A_0, A_1 given

$$\mu_0 := \nu|_{A_0}, \quad \mu_1 := \nu|_{A_1}; \quad (\mu_t)_{0 \leq t \leq 1}$$

$$\int \rho_{1/2}^{1-1/N} d\nu \geq \frac{1}{2} (|A_0|^{1/N} + |A_1|^{1/N}),$$

Apply Jensen to conclude.

Isoperimetric inequalities, concentration

The transport approach gives a grip on measures/sets

Used for concentration inequalities

Recently used by Funano to prove: under $\text{CD}(0, \infty)$,
 $\lambda_k(M, \nu) \leq C^k \lambda_1(M, \nu)$ for some **universal** C .

The key is the entropy interpretation and a recursive estimate on the **separation**: $\text{Sep}(M, \nu, \alpha_1, \dots, \alpha_N) :=$ maximum min-distance between sets A_1, \dots, A_N satisfying $\nu[A_j] = \alpha_j$,

obtained through displacement convexity of H

Also inequalities on isoperimetric-type constants...

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Why does the Lévy–Gromov inequality remain elusive?

Rough heat flow (Ambrosio–Gigli–Savaré 2011)

If (\mathcal{X}, d, ν) has “Ricci” curvature $\geq -K$, one can define a (nonlinear) heat flow on the space of probability densities,

- either as gradient flow of H_ν in P_2
- or as L^2 grad flow of Dirichlet form $\int |\nabla \rho|^2 d\nu$

Origin: Jordan–Kinderlehrer–Otto (1998)

On M compact Riemannian manifold (or $M = \mathbb{R}^n$)
there is a link between

- heat/Fourier equation $\frac{\partial \rho}{\partial t} = \Delta \rho$ on M
- Boltzmann's H functional: $H(\rho) = \int \rho \log \rho$
- optimal transport

$$C(\mu, \nu) = \inf_{T \# \mu = \nu} \int d(x, T(x))^2 \mu(dx)$$

Monge solution of Fourier equation

Unorthodox gradient flow scheme. Time discretize.

From time t to time $t + \Delta t$: Given $\rho(t)$, search for $\rho(t + \Delta t)$ as the **minimizer** of $H(\rho) + \frac{C(\rho(t), \rho)}{2 \Delta t}$

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Note: Interpretation (Peletier et al.)

The occurrence of H can be related to Sanov's Theorem;
the exponent 2 to the (log) Central Limit Theorem

Theorem (Ambrosio–Gigli–Savaré)

This procedure works the same in weak $CD(K, \infty)$ spaces. In fact as soon as $|\nabla^- H_\nu|$ is lower semi-continuous; in that case this is the square root of the **Fisher information**.

Side PDE remark

Nonsmooth Hamilton–Jacobi theory is crucial here!

For this purpose it was developed in general metric spaces (Lott, V, Gozlan, Roberto, Samson, Ambrosio, Gigli, Savaré...)

$$Q_t f(x) = \min \left[f(y) + \frac{d(x,y)^2}{2t} \right]$$

\implies In any geodesic space, $\partial_t Q_t f + \frac{|\nabla Q_t f|^2}{2} = 0$ (except at countably many times)

How wide is this generalization?

Nonbranching $CD(K, N)$ spaces satisfy many properties of smooth ones.

But the flow is in general **nonlinear** and the **splitting theorem** does not hold; **normed spaces are allowed**,
Finsler geometry is included

RCD(K, N) Spaces / RCD $^*(K, N)$ Spaces

If one makes the **additional assumption** that $W^{1,2}$ is Hilbert (Ambrosio–Gigli–Savaré), or equivalently (!) that the heat flow is linear, then one obtains a narrower class of weak CD(K, N) spaces, which satisfies a lot, and is **still stable** (!)

- Laplace operator
- Bochner inequality; link to Bakry–Émery formalism (equivalence: Erbar–Kuwada–Sturm); cone property, etc.
- Splitting Theorem (Gigli), in quantitative form; sharp inequalities for RCD *
- Almost everywhere existence of (unique?) finite-dimensional tangent spaces

An intermediate theory?

Can one develop a good calculus without restricting to the “Riemannian” assumption, keeping Finsler spaces along the way?

Maybe if the Sobolev space $W^{1,2}$ is strictly convex?

Note: Exponent 2 is there in the heat equation (even nonlinear) and in the curvature!

Adaptation to discrete spaces

Many different theories in discrete spaces (approximate geodesics, or change the distance through a discretized Riemannian structure, etc.)

Ollivier, Sturm–Bonciocat, Maas, Erbar, Mielke,
Gozlan–Roberto–Samson–Tetali, Hillion...

The Ricci curvature of the discrete hypercube?

(Question by D. Stroock, 1998)

Ollivier–V: A and B two nonempty subsets of $\{0, 1\}^N$.

M the set of midpoints of A and B . Then

$$\log |M| \geq \frac{1}{2} (\log |A| + \log |B|) + \frac{K}{8} d(A, B)^2, \quad K = \frac{1}{2N}$$

Maas: Can be made more precise, $K = 1/(2N)$ is (in some sense) the discrete Ricci curvature of the hypercube.

