

Ricci curvature of finite Markov chains via convexity of the entropy

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Overview

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What we are talking about

RICCI CURVATURE

OPTIMAL TRANSPORT

- ▶ Wasserstein geometry
- ▶ Convexity of Shannon's entropy

MARKOV CHAINS

General theoretical framework

The heat flow is the gradient flow of the entropy **in the W_2 space**

$\text{Ric} \geq \kappa \iff \kappa\text{-convexity of the entropy} \iff \kappa\text{-contractivity of the heat flow}$

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Interpret the continuous time Markov chain as the heat flow
(via semigroup)

The generator of the Markov chain equals generator of the heat flow, the Laplacian operator

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- * Define a geometry \mathcal{W} such that heat flow with a Markov kernel is the gradient flow of entropy *

Why do we care?

Mainly three motivations:

- ▶ obtain convergence to equilibrium of Markov chains
- ▶ study the geometry induced by Markov kernel (e.g. random walk on the hypercube, graphs)
- ▶ obtain discrete counterpart of powerful inequalities (e.g. mass concentration, Sobolev inequalities, spectral results)

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History on Ricci curvature and evolution of the heat flow

- ▶ McCann [1997] (displacement convexity on \mathbb{R}^n)
- ▶ Jordan-Kinderlehrer-Otto seminal work [1998]
- ▶ Otto–Villani [2000] (extension to manifold, Hessian of entropy on $\mathcal{P}(M)$)
- ▶ Cordero–Erausquin, McCann, Schmuckenschläger & von Renesse–Sturm [2005] (rigorous result on convexity and Ricci)
- ▶ Lott–Villani [2009] & Sturm [2006] (Ricci for metric measure spaces)
- ▶ Maas [2011] & Erbar–Maas [2012] among others (Ricci for discrete spaces)

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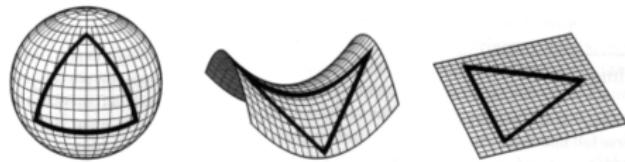
Applications and other results

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Ricci Curvature

Ricci curvature governs how volumes are distorted on the space

$$\text{Ric}_{\mathbb{R}^n} \equiv 0$$



Positive Curvature

Negative Curvature

Flat Curvature

Why a lower bound? $(X, Y) \rightarrow \text{Ric}(X, Y) \in \mathbb{R}$

- ▶ Analytical results (functional inequalities)
- ▶ Contraction properties
- ▶ Topological obstruction

Optimal transport I

Metric space (\mathcal{X}, d)

Space of probability measures

$$\mathcal{P}(\mathcal{X}) = \{\mu : X \rightarrow \mathbb{R}_+ : \mu \text{ additive, } \mu(\mathcal{X}) = 1\}$$

- ▶ The optimal transport problem:

$$\inf_{\gamma} \left\{ \int_{X \times X} c(x, y) \, d\gamma(x, y) : \gamma \in \Gamma(\mu_0, \mu_1) \right\} \quad (\text{K})$$

for $\mu_0, \mu_1 \in \mathcal{P}(\mathcal{X})$,

- ▶ Endow $\mathcal{P}(\mathcal{X})$ with the *2-Wasserstein distance* W_2 :

$$W_2^2(\mu_0, \mu_1) := \min_{\gamma} \left\{ \int_{X \times X} d^2(x, y) \, d\gamma(x, y) : \gamma \in \Gamma(\mu_0, \mu_1) \right\}$$

Optimal transport II

- Dynamic formulation relevant for us (Benamou-Brenier):
Given b vector field and μ measure,

$$\mathcal{A}(b, \mu) := \int_{\mathcal{X}} |b|^2 d\mu$$

Take μ_t curve on the space of measures
 $\mu : [0, 1] \rightarrow \mathcal{P}(\mathcal{X}), t \mapsto \mu_t$ from μ_0 to μ_1

$$W_2^2(\mu_0, \mu_1) = \min_{b, \mu} \left\{ \int_0^1 \mathcal{A}(b_t, \mu_t) dt : \frac{d}{dt} \mu_t + \text{div}(b_t \mu_t) = 0 \right\}$$

The minimizer is a geodesic.

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The minimizer is a geodesic.

Optimal transport provides the space of probability measures a geometry in the space of probability measures

Optimal transport III

We consider a reference measure $\pi \in \mathcal{P}(\mathcal{X})$ and absolutely continuous measures $\mu = \rho\pi$, ρ density

- ▶ W convexity of the entropy:

$$\mathcal{H}(\mu_t) \leq (1-t)\mathcal{H}(\mu_0) + t\mathcal{H}(\mu_1) - \frac{\kappa}{2}t(1-t)W_2^2(\mu_0, \mu_1)$$

- ▶ Gradient flow (high-level!): given a function f with $Dom(f) \subset \mathcal{X}$, $x_t : I \rightarrow Dom(f)$ is a gradient flow for f if

$$x'_t = -\nabla f(x_t)$$

Heat flow

Consider heat propagating on a space \mathcal{X} and a temperature function $u(x, t)$ for $x \in \mathcal{X}$ and $t \in [0, T]$,
the heat equation is

$$\frac{d}{dt}u(t) = \operatorname{div} \nabla u = \Delta u$$

Heat semigroup $P_t := e^{t\Delta}$

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* Interpret our continuous time Markov chain as the heat flow *

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Finite space of states \mathcal{X} , irreducible, reversible Markov kernel K

$$K(x_i, x_j) = K_{ij} = \Pr(X_t = x_j \mid X_{t-1} = x_i), \quad \sum_j K(x_i, x_j) = 1$$

Unique steady state $\pi = \pi K$

Continuous time Markov semigroup

$P_t := e^{t(K-I)}$ Markov generator

$$\Delta := \operatorname{div} \nabla = K - I$$

Space of probability densities

$$\mathcal{P}(\mathcal{X}) := \left\{ \rho : \mathcal{X} \rightarrow \mathbb{R}_+ : \sum_{x \in \mathcal{X}} \rho(x) \pi(x) = 1 \right\}$$

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* We would like to study the geometry induced by K *

New distance \mathcal{W}

Discrete action:

$$\mathcal{A}(\psi, \rho) := \frac{1}{2} \sum_{x,y \in \mathcal{X}} (\psi(y) - \psi(x))^2 \hat{\rho}(x, y) K(x, y) \pi(x) = \|\nabla \psi\|_{\rho}^2$$

Definition

For $\rho_0, \rho_1 \in \mathcal{P}(\mathcal{X})$ we define

$$\mathcal{W}^2(\rho_0, \rho_1) := \inf_{\psi, \rho} \left\{ \int_0^1 \mathcal{A}(\psi_t, \rho_t) dt : \frac{d}{dt} \rho_t + \operatorname{div}(\hat{\rho}_t \nabla \psi_t) = 0 \right\}$$

with ρ_t, ψ_t sufficiently regular.

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with ρ_t, ψ_t sufficiently regular.

Theorem

The heat flow $\rho_t := P_t \rho$ is the gradient flow of Shannon's entropy
 $\mathcal{H}(\rho) = \sum_x \rho \log \rho \pi$

$$\operatorname{grad}_{\mathcal{W}} \mathcal{H}(\rho_t) = \nabla \log(\rho_t) = -\nabla \psi_t$$

Defining Ricci

Definition

We say that K has a Ricci curvature bounded by below by $\kappa \in \mathbb{R}$ if for any geodesic $\{\rho_t\}_{t \in [0,1]}$ in $(\mathcal{P}(\mathcal{X}), \mathcal{W})$ we have

$$\mathcal{H}(\rho_t) \leq (1-t)\mathcal{H}(\rho_0) + t\mathcal{H}(\rho_1) - \frac{\kappa}{2}t(1-t)\mathcal{W}^2(\rho_0, \rho_1)$$

and we write

$$\text{Ric}_K \geq \kappa$$

Equivalent notions to Ricci

Theorem

Let $\kappa \in \mathbb{R}$. For an irreducible and reversible Markov kernel (\mathcal{X}, K) TFAE:

- (i) $\text{Ric}_K \geq \kappa$;
- (ii) For all $\rho_0, \rho_1 \in \mathcal{P}(\mathcal{X})$ the following ‘evolution variational inequality’ holds for all $t \geq 0$:

$$\frac{1}{2} \frac{d^+}{dt} \mathcal{W}^2(P_t \rho_0, \rho_1) + \frac{\kappa}{2} \mathcal{W}^2(P_t \rho_0, \rho_1) \leq \mathcal{H}(\rho_1) - \mathcal{H}(P_t \rho_0);$$

- (iii) For all $\rho \in \mathcal{P}(\mathcal{X})$
 $\text{Hess } \mathcal{H}(\rho) \geq \kappa$;

- (iv) For all $\rho_0, \rho_1 \in \mathcal{P}(\mathcal{X})$, there exists a constant speed geodesic $(\rho_t)_{t \in [0, T]}$ that connects them along which Shannon’s entropy is κ -convex

κ -contractivity

Proposition

Let (\mathcal{X}, K) be as before, with $\text{Ric}_K \geq \kappa$. Then the continuous time Markov semigroup $(P_t)_{t \geq 0}$ satisfies

$$\mathcal{W}(P_t \rho_0, P_t \rho_1) \leq e^{-\kappa t} \mathcal{W}(\rho_0, \rho_1)$$

for all $\rho_0, \rho_1 \in \mathcal{P}(\mathcal{X})$ and $t \geq 0$.

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Tensorisation result

Stability of our definition of Ricci for operations on the Markov chain

$\mathcal{X} = \prod_{i=1}^n \mathcal{X}_i$, $\sum_{i=1}^n \alpha_i = 1$, $X = (X_1, \dots, X_n)$, Kernel of the product chain on \mathcal{X} is K_α

$$K_\alpha(x, y) = \begin{cases} \sum_i \alpha_i K_i(x_i, x_i), & x_i = x_i \forall i \\ \alpha_i K_i(x_i, y_i) & x_i \neq y_i \text{ and } x_j = y_j \forall j \neq i \\ 0 & \text{otherwise} \end{cases}$$

Theorem

Assume that $\text{Ric}_{K_i} \geq \kappa_i$ for $i = 1, \dots, n$. Then we have

$$\text{Ric}_{K_\alpha} \geq \min_i \alpha_i \kappa_i$$

Ricci of a random walk on the discrete hypercube

Let $\mathcal{Q} = \{0, 1\}$, $(\mathcal{Q}, K_{p,q})$, $K(0, 1) = p, K(1, 0) = q$ for $p, q \in (0, 1)$

Any measure $\mu \in \mathcal{P}(\mathcal{Q})$ is $\mu = (1 - \lambda)\delta_0 + \lambda\delta_1$ for $\lambda \in [0, 1]$

Steady state is π with $\lambda = \frac{p}{p+q}$

Let us look at (\mathcal{Q}^n, K_p) simple random walk on n -dimensional hypercube, with $\alpha_i = 1/n$. Maas proves

$$\text{Ric}_{K_p} \geq \kappa_p := p + p \cdot \frac{1}{2} \inf_{\lambda} \left\{ \frac{1}{\lambda(1-\lambda)} \cdot \theta(\lambda, 1-\lambda) \right\}$$

Then by tensorisation

$$\text{Ric}_{K_{p,n}} \geq \frac{1}{n} 2p$$

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Thank you!



Extra: Functional inequalities

Theorem

Let K be an irreducible and reversible Markov kernel on a finite set \mathcal{X} with $\text{Ric}_K \geq \kappa$ or $\text{Ric} \geq \lambda > 0$. The following inequalities hold:

$$\mathcal{H}(\rho) \leq \mathcal{W}(\rho, \mathbf{1}) \sqrt{\mathcal{I}(\rho)} - \frac{\kappa}{2} \mathcal{W}(\rho, \mathbf{1})^2 \quad (\text{HWI}(\kappa))$$

$$\mathcal{H}(\rho) \leq \frac{1}{2\lambda} \mathcal{I}(\rho) \quad (\text{MLSI}(\lambda))$$

$$\mathcal{W}(\rho, \mathbf{1}) \leq \sqrt{\frac{2}{\lambda} \mathcal{H}(\rho)} \quad (\text{TW}(\lambda))$$

$$\|\varphi\|_{\pi}^2 \leq \frac{1}{\lambda} \|\nabla \varphi\|_{\pi}^2 \quad (\mathsf{P}(\lambda))$$

holds for all functions $\psi : \mathcal{X} \rightarrow \mathbb{R}$.