

Rice on graphs and functional inequalities

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I] Functional inequalities on graphs

ii] Rice in the continuous X obstructs

iii] Construction with \mathbb{Z}_2 (Dobrushin - Jullien - Oliveira - Sommer)

iv] Escher - Poiras

Sunyer \rightarrow Gorla - Polthouren - Perkins - R. - Tschali

I] 1) Definitions: $G = (V, E)$ finite graph, connected (undirected)

$$\mathcal{P}(G) = \{ \text{prob. measures on } G \}$$

$K = \left(K(x, y) \right)_{x, y \in V}$ is a Markov kernel if: $K(x, y) \geq 0$

$$\sum_y K(x, y) = 1 \quad \forall x$$

$$K(x, y) = 0 \text{ if } x \neq y$$

Assume for simplicity $K(x, x) > 0$

Def: For $C > 0$, $\mu \in \mathcal{P}(G)$ and a Markov kernel K ,

reversible w.r.t. μ (i.e. $\forall x, y \mu(x) K(x, y) = \mu(y) K(y, x)$)

Then,

i) (μ, K) satisfies the Poincaré inequality with constant C if for any $f: V \rightarrow \mathbb{R}$, it holds:

$$\text{Var}_\mu(f) \leq C \sum_{x, y} \mu(x) K(x, y) (f(y) - f(x))^2$$

where $\text{Var}_\mu(f) = \mu(f^2) - \mu(f)^2$

$$\text{and } \sum_{\mu, K} (f, g) = -\mu(f L g) \text{ with } L = I - K$$

$$= \frac{1}{2} \sum_{x, y} \mu(x) K(x, y) (g(y) - g(x)) (f(y) - f(x))$$

(ii) (μ, K) satisfies the modified log-Sobolev inequality with constant C if for all $f: V \rightarrow \mathbb{R}^+$, it holds:

$$\text{Ent}_\mu(f) \leq C \sum_{\mu, K} (f, \ln f)$$

$$\text{where } \text{Ent}_\mu(f) = \int f \log \frac{f}{\int f d\mu} d\mu$$

(iii) (μ, κ) satisfies the log-Sobolev inequality with constant C if for any $f: V \rightarrow \mathbb{R}$, it holds:

$$E_{\mu, \kappa}(f^2) \leq C E_{\mu, \kappa}(f, f)$$

The smallest C in (i) denoted by C_P

- (i) C_{PLS}
- (iii) C_{LS}

Prop In the continuous setting, for instance for a diffusion, $E(b, b) \approx \int \nabla f \nabla g d\mu$.
 Then (i) and (iii) are equivalent up to some factor (universal)

2) Two basic properties

Prop I.1: Let $\mu, \kappa, C_P, C_{PLS}, C_{LS}$ as before. Then,

$$0 \leq C_P \leq 2C_{PLS} \leq \frac{C_{LS}}{2}$$

Furthermore, either $C_P = \frac{C_{LS}}{2}$, or there exists $f: V \rightarrow \mathbb{R}_+^*$, with $\mu(f^2) = 1$, non constant and solution of
 (i) $L f_0 = -\frac{2}{C_{LS}} f_0 \ln f_0$

Similarly, either $C_P = 2C_{PLS}$ or there exists $f_1: V \rightarrow \mathbb{R}_+^*$ non constant, with $\mu(f_1) = 1$, which is solution of:
 (ii) $L f_1 + f_1 L \log f_1 = -\frac{1}{2C_{PLS}} f_1 \log f_1$

- Ref: (i) comes from Diaconis & Saloff-Coste '96
- (ii) ————— Bobkov & Tetali

Proof: $(a-b)^2 \leq \frac{1}{4} (a^2 - b^2) (\log a^2 - \log b^2) \quad a, b > 0$

shows that $E_{\mu, \kappa}(b, b) \leq \frac{1}{4} E_{\mu, \kappa}(b^2 \log b^2)$ for $b > 0$.

It implies $C_{TCS} \leq \frac{C_{LS}}{\epsilon}$. (3)

Take $b = 1 + \epsilon g$ with $\mu(g) = 0$

$$E_{\mu}(b) = \frac{\epsilon^2}{2} \text{Var}_{\mu}(g) + o(\epsilon^2)$$

$$E_{\mu}(b \cdot b) = \epsilon^2 E_{\mu}(g, g)$$

It implies $C_P \leq 2 C_{TCS}$ □

Prop. 1.2 (homomorphism property)

Consider a graph $(G)_{i=1}^n = (V_i, E_i)_{i=1}^n$, a probability measures $\mu_i \in \mathcal{P}(G)$, a Markov kernels $(K_i)_{i=1}^n$ on G_i , with K_i reversible w.r.t μ_i .

Let $\alpha_1, \dots, \alpha_n$ be s.t. $\sum_{i=1}^n \alpha_i = 1$, $\alpha_i \in [0, 1] \forall i$.

Then the product $\bigotimes_{i=1}^n \mu_i$ and the Markov kernel

$$K(x, y) = \sum_{i=1}^n \alpha_i \delta_{(x_i, y_i)} = \prod_{i=1}^n K_i(x_i, y_i) \delta_{(x_i, y_i)} \delta_{(x_{-i}, y_{-i})}$$

satisfies:

$$\min_i \{ \alpha_i^{-1} C_P^i \} \leq C_P \leq \max_i \{ \alpha_i^{-1} C_P^i \}$$

$$\min_i \{ \alpha_i^{-1} C_{TCS}^i \} \leq C_{TCS} \leq \max_i \{ \alpha_i^{-1} C_{TCS}^i \}$$

$$\min_i \{ \alpha_i^{-1} C_{LS}^i \} \leq C_{LS} \leq \max_i \{ \alpha_i^{-1} C_{LS}^i \}.$$

Proof: Easy consequence of:

$$E_{\mu, K}(b, b) = \sum_{i=1}^n \alpha_i \sum_{\vec{x}^i} E_i(b, b)(\vec{x}^i) \mu_i(\vec{x}^i)$$

where $\vec{x}^i = (x_1, \dots, x_i, x_{i+1}, \dots, x_n)$ $\mu_i = \bigotimes_{j \neq i} \mu_j$

$$\text{and } E_i(b, b)(\vec{x}^i) = \sum_{x_i, y_i} \mu_i(x_i) K_i(x_i, y_i) (b(\vec{x}^i, x_i) - b(\vec{x}^i, y_i))$$

(x_1, \dots, x_n) \parallel $(x_1, \dots, x_i, y_i, \dots, x_n)$

$$\text{Var}_\mu(f) \leq \sum_{i=1}^n \mu_i \left[\text{Var}_{\mu_i}(f) \right]$$

$$\text{Ent}_\mu(f) \leq \mu \left(\sum_i \text{Ent}_{\mu_i}(f) \right) \quad \square$$

Examples: a) Complete graph K_n :

$$K(x,y) = \frac{1}{n} \quad \forall x,y \quad \text{reversible w.r.t } \mu \equiv \frac{1}{n}$$

$$\sum_{\mu, K}(f,g) = \frac{1}{2} \sum_{x,y} \mu(x)\mu(y) (f(x)-f(y))(g(x)-g(y))$$

Prop 1.3: $C_p = 1$, $\frac{1}{2} \leq C_{TCS} \leq 1$, $C_{CS} = \frac{n \log(n-1)}{n-2}$.

(with $C_{CS} = \lim_n \frac{n \log(n-1)}{n-2} = 2$ for $n=2$)

Proof: $\text{Var}_\mu(f) = \sum_\mu (f,b) \quad \rightarrow C_p = 1$

$$\text{Ent}_\mu(f) = \int f \log f d\mu - \int f d\mu \log \int f d\mu$$

$$\leq \int f (\log f - \log \int f d\mu) d\mu$$

$$\stackrel{\text{reversibility}}{=} \frac{1}{2} \sum_{x,y} (f(x)-f(y)) (\log f(x) - \log f(y)) \mu(x)\mu(y)$$

$$= \sum_{\mu, K}(f, \log f) \quad \rightarrow C_{TCS} \leq 1$$

Rk: in fact, the equality is strict if f is not constant, thus, $C_{TCS} < 1$?

For C_{CS} , see Diaconis & Saloff-Coste 5.6

idea \otimes $C_{CS} = \left(\frac{p-q}{\log p - \log q} \right)^{-1}$ on the two points ($\mu = \beta(p)$)

show that $1 = C_p \leq \frac{C_{CS}}{2}$ (take a bad function)

This plus that $2f_0 = \frac{2}{C_{CS}} f_0 \log f_0$ for some maximal f_0

- f. takes only 2 values
- use \otimes with $\rho = \min_{x \in K_n} \mu(x) = \frac{1}{n}$

b) Hypercube $Q_n = \{0,1\}^n$

$$K(x,y) = \begin{cases} \frac{1}{2^n} & \text{if } x \sim y \\ \frac{1}{2} & \text{if } x=y \end{cases}$$

K reversible w.r.t $\mu \equiv \frac{1}{2^n}$

K corresponds to the product of n Markov kernels on $\{0,1\}$ defined by $K_i(x_i, y_i) = \frac{1}{2} \forall x_i, y_i \in \{0,1\}$ (reversible w.r.t $\mathbb{B}(\cdot)$) and $\pi_i = \frac{1}{2}$.

Prop: $c_P = n = 2 C_{\pi, K} = \frac{C_{K, S}}{2}$

4) Convergence to stationarity.

$$P_t = e^{-t(I-K)} = e^{-t} \sum_{n=0}^{\infty} \frac{t^n}{n!} K^n$$

Thm: Given K reversible w.r.t $\mu \in \mathcal{P}(S)$. The following are equivalent:

(i) $\text{Var}_{\mu}(f) \leq c \sum_{\mu, K}(f, f) \quad \forall f$

(ii) $\text{Var}_{\mu}(P_t f) \leq e^{-\frac{t}{c}} \text{Var}_{\mu}(f) \quad \forall f \quad \forall t \geq 0$

The following are equivalent:

(i) $\text{Ent}_{\mu}(f) \leq c \sum_{\mu, K}(f, f) \quad \forall f > 0$

(ii) $\text{Ent}_{\mu}(P_t f) \leq e^{-\frac{t}{c}} \text{Ent}_{\mu}(f)$

Proof: $\mu(f) = 0$

$$\begin{aligned} \frac{d}{dt} \text{Var}_\mu(P_t f) &= \frac{d}{dt} \mu((P_t f)^2) - 2\mu(P_t f \cdot P_t f) = -2\sum_{j,k} \mu(P_{t,j} P_{t,k}) \\ &\leq -\frac{2}{c} \text{Var}_\mu(P_t f) \quad \text{Hölder Cauchy-Schwarz} \quad \square \end{aligned}$$

$\mu(f) = 1$

$$\begin{aligned} \frac{d}{dt} \text{Ent}_\mu(P_t f) &= \int P_t f \cdot L \log P_t f \, d\mu + \underbrace{\int P_t f \frac{L P_t f}{P_t f} \, d\mu}_{=0} \\ &= -\sum_{j,k} \mu(P_{t,j}, \log P_{t,k}) \\ &\leq -\frac{1}{c} \text{Ent}_\mu(f) \quad \text{Hölder Cauchy-Schwarz} \quad \square \end{aligned}$$

RR: for any $f > 0$, $\text{Ent}_\mu(f) \leq \frac{\text{Var}_\mu(f)}{\mu(f)}$

Indeed $\text{Ent}_\mu(f) = \int f \log(f + 1 - 1) \, d\mu \leq \int f(f-1) \, d\mu = \text{Var}_\mu(f)$

Notably, $\text{Ent}_\mu(P_t f) \leq \frac{\text{Var}_\mu(P_t f)}{\mu(f)} \leq \frac{e^{-\frac{2t}{c}} \text{Var}_\mu(f)}{\mu(f)}$

for the exponential decay of the entropy, this is good.

But if f is ill-behaved, $\text{Var}_\mu(f)$ can be much larger than $\text{Ent}_\mu(f)$ ---

Prop: Assume there exists $C > 0$ such that for all f , there exists C_f such that $\text{Var}_\mu(P_t f) \leq e^{-\frac{2t}{c}} C_f \forall t > 0$.
 Then $C_f \leq C$ and $\text{Var}_\mu(P_t f) \leq e^{-\frac{2t}{c}} \text{Var}_\mu(f)$

This is not true for the entropy (see Cauchy - Dai - Pan - Pasta)

Proof: Let $\phi: (\Sigma_0, +\infty[\rightarrow \mathbb{R}$
 $t \mapsto \log \text{Var}_\mu(P_t \phi)$ with $\mu(\phi) = 0$.

$$\phi'(t) = \frac{2 \mu(\nabla P_t \phi \mid \nabla P_t \phi)}{\mu(P_t \phi)^2}$$

$$\phi''(t) = \frac{4}{\mu(P_t \phi)^2} \left[\mu((\nabla P_t \phi)^2) \mu(P_t \phi)^2 - \mu(\nabla P_t \phi \mid \nabla P_t \phi)^2 \right] \underset{C-S}{\geq}$$

$$\phi''(0) \leq \frac{\phi(t) - \phi(0)}{t} \quad \forall t > 0$$

$$\frac{-2 \varepsilon_\mu(\phi, \phi)}{\text{Var}_\mu(\phi)} \leq \frac{\log \text{Var}_\mu(P_t \phi)}{t} - \frac{\phi(0)}{t} \leq -\frac{2}{t} + \frac{\log C_\phi}{t} - \frac{\phi(0)}{t}$$

$\downarrow t \rightarrow +\infty$
 $-\frac{2}{t}$

II) Ricci in the continuous setting

1) few equivalent formulations of $C(D)(U, \infty)$

M is a smooth compact, finite dimensional, separable, Riemann manifold
 $\phi: M \rightarrow \mathbb{R}$ of class C^2 , $\int e^{-\phi} \text{vol} = 1$

$$\mu = e^{-\phi} \text{vol} \quad L = \Delta - \nabla \phi \cdot \nabla \quad (P_t)_{t \geq 0}$$

$$\Gamma(\phi, \phi) = \frac{1}{2} [L(\phi^2) - \phi L\phi - \phi L\phi]$$

$$\Gamma_2(\phi, \phi) = \frac{1}{2} [L\Gamma(\phi, \phi) - \Gamma(\phi, L\phi) - \Gamma(\phi, L\phi)]$$

$$\Gamma(\phi, \phi) = |\nabla \phi|^2$$

$$\Gamma_2(\phi, \phi) = \|\text{Hess } \phi\|_{HS}^2 + (\nabla \phi)^T \text{Hess } \phi (\nabla \phi) + \text{Ricc}(\nabla \phi, \nabla \phi)$$

Def: For $K \in \mathbb{R}$, Then $CD(K, \infty)$ holds if
 $\Gamma_2(\phi, \phi) \geq K \Gamma(\phi, \phi) \quad \forall \phi \text{ smooth.}$

Ex: $\mathbb{R} = \mathbb{R}^n$, $\phi(x) = \frac{|x|^2}{2} + \frac{y}{2} \phi_n(2\pi)$
 ($|\cdot|$ is Euclidean norm in \mathbb{R}^n)

$$\Gamma_2(\phi, \phi) = \|\text{Hess } \phi\|_{HS}^2 + (\nabla \phi)^T \text{Id}_{\mathbb{R}^n} (\nabla \phi) + 0$$

$$\geq |\nabla \phi|^2 = \Gamma(\phi, \phi)$$

Hence $CD(1, +\infty)$ holds.

Thm: Given $\mu_0, \mu_1 \in \mathcal{P}(\Pi)$, then there exists a continuous curve
 $(\mu_t)_{t \in [0,1]}$ in $(\mathcal{P}(\Pi), W_2)$ interpolating between μ_0 and μ_1
 s.t. $W_2(\mu_s, \mu_t) = (t-s) W_2(\mu_0, \mu_1) \quad \forall 0 \leq t, s \leq 1$
 Such a path is called a constant speed geodesic in $(\mathcal{P}(\Pi), W_2)$
 Furthermore, if μ_0 and $\mu_1 \in \mathcal{P}^{ac}(\Pi)$ then $\mu_t \in \mathcal{P}^{ac}(\Pi) \quad \forall t$.

Proof: Villani's book, Corollary 7.22 and Thm 8.7.

Def: (Displacement K -convexity of $H(\cdot, \mu)$)
 For $K \in \mathbb{R}$, Then $H(\cdot, \mu)$ is said to be K -displacement convexity
 if for any constant speed geodesic $(\mu_t)_{t \in [0,1]}$ in $(\mathcal{P}(\Pi), W_2)$, t
 holds.
 $H(\mu_t, \mu) \leq (1-t) H(\mu_0, \mu) + t H(\mu_1, \mu) - \frac{K}{2} t(1-t) W_2^2(\mu_0, \mu_1)$
 $\forall t \in [0,1]$