

On the convex Poincaré inequality

Based on joint work with Radosław Adamczak.

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Prelude: classical setting [Bobkov–Ledoux, '97]

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then $\forall f: \mathbb{R}^n \rightarrow \mathbb{R}$ with $|\nabla f| \leq c < \sqrt{2\lambda}$,

$$\mathbb{E}_\mu f e^f - \ln(\mathbb{E}_\mu e^f) \mathbb{E}_\mu e^f =: \text{Ent}_\mu(e^f) \leq C(c, \lambda) \mathbb{E}_\mu |\nabla f|^2 e^f.$$

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Implies two-level concentration: $f: (\mathbb{R}^n)^N \rightarrow \mathbb{R}$,

$$\left. \begin{array}{l} \sum_{i=1}^N |\nabla_i f|^2 \leq \alpha^2 \\ \max_{1 \leq i \leq N} |\nabla_i f| \leq \beta \end{array} \right\} \implies \mathbb{P}_{\mu^{\otimes N}}(f - \mathbb{E}_{\mu^{\otimes N}} f \geq t) \leq \exp\left(-C_1 \frac{t^2}{\alpha^2} \wedge \frac{t}{\beta}\right)$$

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Example: $n = 1$, $f(x) = f_N(x) = (x_1 + \cdots + x_N)/\sqrt{N}$.

Convex setting

Standing assumption:

μ satisfies the *convex Poincaré inequality*, i.e. \forall **convex** $f: \mathbb{R}^n \rightarrow \mathbb{R}$,

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- Linked to weak transportation inequalities.

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Main result

Theorem (Adamczak-St., '17+)

\forall convex or concave $f: \mathbb{R}^n \rightarrow \mathbb{R}$ with $|\nabla f| \leq c < \sqrt{2\lambda}/e$,

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$$\text{Ent}_\mu(e^f) \leq \mathbb{E}_\mu f e^f - e^f + 1 = \int_0^1 t F(t) dt \leq \frac{1}{2} \max\{F(0), F(1)\}.$$

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$$F(1) = \mathbb{E}_\mu f^2 e^f \lesssim \mathbb{E}_\mu |\nabla f|^2 e^f.$$

Proposition 2

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Proof of Proposition 2

f convex or concave, $\text{Med}_\mu f = 0$, $|\nabla f| \leq c$.

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Proof. $X \sim \mu$; $\tilde{\mathbb{E}} :=$ expectation wrt density $|\nabla f(X)|^2 / \mathbb{E}|\nabla f(X)|^2$.

$$\mathbb{E}|\nabla f(X)|^2 e^{-|f(X)|} = \mathbb{E}|\nabla f(X)|^2 \cdot \tilde{\mathbb{E}} e^{-|f(X)|} \geq \mathbb{E}|\nabla f(X)|^2 \cdot e^{-\tilde{\mathbb{E}}|f(X)|}$$

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$$\begin{aligned} \mathbb{E}|\nabla f(X)|^2 |f(X)| &\leq c \mathbb{E}|\nabla f(X)| |f(X)| \leq c \sqrt{\mathbb{E}|\nabla f(X)|^2} \sqrt{\mathbb{E}f(X)^2} \\ &\leq c \sqrt{2/\lambda} \mathbb{E}|\nabla f(X)|^2 \end{aligned}$$

Proof of Proposition 1 for convex functions

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Proof. $X \sim \mu$;

$\Phi(f)$ is convex with median 0, for $\Phi(x) = \begin{cases} xe^{x/2} & \text{for } x \geq -2, \\ -2/e & \text{for } x < -2. \end{cases}$

$$\mathbb{E}f(X)^2 e^{f(X)} \leq \mathbb{E}\Phi(f(X))^2 =: a^2 \stackrel{?}{\lesssim} b^2 := \mathbb{E}|\nabla f(X)|^2 e^{f(X)}$$

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$$\begin{aligned} a^2 &\leq \frac{2}{\lambda} \mathbb{E}|\nabla f(X)|^2 (1 + f(X)/2)^2 e^{f(X)} 1_{\{f(X) \geq -2\}} \\ &\leq \dots \leq \frac{2}{\lambda} (b + ca/2)^2. \end{aligned}$$

Difficulty for concave functions

Question

If $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is convex and 1-Lipschitz, then, for $t \geq 0$,

$$\mathbb{P}(f(X) \geq \text{Med } f(X) + t) \leq 2 \exp(-C(\lambda)t).$$

Do we also have

$$\mathbb{P}(f(X) \leq \text{Med } f(X) - t) \stackrel{?}{\leq} 2 \exp(-C(\lambda)t) ?$$

Difficulty: for f convex, e^f, f_+^p, \dots are convex,
but e^{-f}, f_-^p, \dots are not always convex/concave.

Lower tail – can you do better?

Lemma

M such that $\mathbb{P}(|X - \mathbb{E}X| \leq M) \geq 3/4$. If $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is convex, then

$$\mathbb{P}(f(X) \leq \text{Med } f(X) - t) \leq 8 \exp\left(-\frac{\sqrt{2\lambda}}{16e\mathbb{E}|\nabla f(X)|} t\right)$$

for $t \geq 32M\mathbb{E}|\nabla f(X)|$.

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Proof. W.l.o.g. $\text{Med } f(X) = 0$.

$$\left. \begin{array}{l} \mathbb{P}(f(X) \geq 0) \geq 1/2 \\ \mathbb{P}(|X - \mathbb{E}X| \leq M) \geq 3/4 \\ \mathbb{P}(|\nabla f(X)| < 8\mathbb{E}|\nabla f(X)|) \geq 7/8 \end{array} \right\} \implies \exists x_0 \begin{cases} f(x_0) \geq 0 \\ |x_0 - \mathbb{E}X| \leq M \\ |\nabla f(x_0)| < 8\mathbb{E}|\nabla f(X)| \end{cases}$$

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But $\mathbb{P}(|X - \mathbb{E}X| \leq M) \geq 3/4$ and

$$\mathbb{P}(|X - \mathbb{E}X| \geq M + t) \leq 8 \exp\left(-\frac{\sqrt{2\lambda}}{e}t\right), \quad t \geq 0,$$

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so for $t/(16\mathbb{E}|\nabla f|) \geq 2M$,

$$\mathbb{P}(f(X) \leq -t) \leq \mathbb{P}(|X - \mathbb{E}X| \geq M + t/(16\mathbb{E}|\nabla f(X)|)) \leq \dots$$

Summary

Assumption: $\mu \sim X$ satisfies convex Poincaré.

Theorem

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$$\text{Ent}_\mu(e^f) \leq C \mathbb{E}_\mu |\nabla f|^2 e^f,$$

where $C = C(\lambda, c, n)$.

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