

Entropy method, log-Sobolev inequalities, Gaussian concentration

Recall: For $Y \geq 0$, $\text{Ent } Y = \mathbb{E} Y \log Y - \mathbb{E} Y \log \mathbb{E} Y$

Entropy method: Exponential tail bounds for $Z = f(X_1, \dots, X_n)$
by bounding entropy of $Y = e^{\lambda Z}$.

Lemma (Herbst argument): Suppose, for some $\sigma^2 > 0$,

$$\text{Ent } e^{\lambda Z} \leq \frac{\lambda^2 \sigma^2}{2} \mathbb{E} e^{\lambda Z} \quad \forall \lambda > 0$$

$$\text{Then } \mathbb{E} e^{\lambda(Z - \mathbb{E} Z)} \leq e^{\frac{\lambda^2 \sigma^2}{2}} \quad \forall \lambda > 0, \text{ and}$$

$$\mathbb{P}[Z - \mathbb{E} Z \geq t] \leq e^{-\frac{t^2}{2\sigma^2}} \quad \forall t \geq 0.$$

Proof: Let $F(\lambda) = \mathbb{E} e^{\lambda Z}$, $F'(\lambda) = \mathbb{E} Z e^{\lambda Z}$. Then

$$\begin{aligned} \text{Ent } e^{\lambda Z} &= \mathbb{E} \lambda Z e^{\lambda Z} - \mathbb{E} e^{\lambda Z} \log \mathbb{E} e^{\lambda Z} \\ &= \lambda F'(\lambda) - F(\lambda) \log F(\lambda) \end{aligned}$$

$$\begin{aligned} \text{Thus } \frac{\sigma^2}{2} &\geq \frac{\text{Ent } e^{\lambda Z}}{\lambda^2 \mathbb{E} e^{\lambda Z}} = \frac{1}{\lambda} \cdot \frac{F'(\lambda)}{F(\lambda)} - \frac{1}{\lambda^2} \log F(\lambda) \\ &= \frac{d}{d\lambda} \left[\frac{1}{\lambda} \log F(\lambda) \right] \quad \forall \lambda > 0. \end{aligned}$$

$$\text{By l'Hôpital, } \lim_{\lambda \rightarrow 0} \frac{\log F(\lambda)}{\lambda} = \lim_{\lambda \rightarrow 0} \frac{d}{d\lambda} \log F(\lambda) = \mathbb{E} Z.$$

So for any $\lambda > 0$,

$$\frac{1}{\lambda} \log F(\lambda) - \mathbb{E} Z = \int_0^\lambda \frac{d}{du} \left[\frac{1}{u} \log F(u) \right] \leq \int_0^\lambda \frac{\sigma^2}{u^2} = \frac{\lambda \sigma^2}{2}$$

$$\Rightarrow F(\lambda) \leq e^{\lambda \mathbb{E} Z + \frac{\lambda^2 \sigma^2}{2}} \Rightarrow \mathbb{E} e^{\lambda(Z - \mathbb{E} Z)} \leq e^{\frac{\lambda^2 \sigma^2}{2}}$$

Log-Sobolev inequalities

By tensorization of entropy, for $Z = f(X_1, \dots, X_n)$ w/ independent X_i 's,

$$\text{Ent } e^{\lambda Z} \leq \sum_{i=1}^n \mathbb{E} \text{Ent}^{(i)} e^{\lambda Z}$$

LSI: For certain distributions X_i and functions f ,

$$\text{Ent}[f(X_i)^2] \leq C \cdot \mathbb{E}[\text{"squared gradient" of } f(X_i)]$$

Thm: Let $X_1, \dots, X_n \stackrel{\text{i.i.d.}}{\sim}$ Rademacher, $f: \{\pm 1\}^n \rightarrow \mathbb{R}$,

$$\text{grad } f(x) = \{D_i f(x)\}_{i=1}^n = \left\{ \frac{f(x_1, \dots, x_{i-1}, +1, x_{i+1}, \dots, x_n) - f(x_1, \dots, x_{i-1}, -1, x_{i+1}, \dots, x_n)}{2} \right\}_{i=1}^n$$

$$\text{Thm } \text{Ent}[f(X_1, \dots, X_n)^2] \leq 2 \mathbb{E} \|\text{grad } f(X_1, \dots, X_n)\|_2^2$$

Proof: In 1-dimension ($n=1$), let $a = f(+1)$, $b = f(-1)$.

$$\text{Ent } f(X)^2 = \mathbb{E} f(X)^2 \log f(X)^2 - \mathbb{E} f(X)^2 \log \mathbb{E} f(X)^2$$

$$= \frac{1}{2} (a^2 \log a^2 + b^2 \log b^2) - \frac{a^2 + b^2}{2} \log \frac{a^2 + b^2}{2}$$

$$\mathbb{E} (\text{grad } f(X))^2 = \frac{1}{4} (a-b)^2$$

Suffices to show $\text{Ent } f(X)^2 \leq 2 \mathbb{E} (\text{grad } f(X))^2$ for $a \geq b \geq 0$.

Fixing $b \geq 0$, can check that

$$h(a) = \frac{1}{2} (a^2 \log a^2 + b^2 \log b^2) - \frac{a^2 + b^2}{2} \log \frac{a^2 + b^2}{2} - \frac{1}{2} (a-b)^2$$

satisfies $h(b) = 0$, $h'(b) = 0$, $h''(a) \leq 0 \quad \forall a \geq b \geq 0$.

$\Rightarrow h(a) \leq 0 \quad \forall a \geq b$, as desired.

For general n , by tensorization,

$$\begin{aligned} \text{Ent } f(X_1, \dots, X_n)^2 &\leq \sum_{i=1}^n \mathbb{E} \underbrace{\text{Ent}^{(i)} f(X_1, \dots, X_n)^2}_{\leq 2 \mathbb{E}^{(i)} D_i f(X_1, \dots, X_n)^2} \leq 2 \mathbb{E} \|\text{grad } f\|_2^2 \end{aligned}$$

Then: Let $X_1, \dots, X_n \stackrel{\text{i.i.d.}}{\sim}$ Rademacher, $Z = f(X_1, \dots, X_n)$.

Suppose $\sum_{i=1}^n \left(D_i f(x_1, \dots, x_n) \right)_+^2 \leq \sigma^2$ for all $x_1, \dots, x_n \in \{\pm 1\}$.

Then $\mathbb{P}[Z - \mathbb{E}Z \geq t] \leq e^{-t^2/4\sigma^2}$.

Proof: Let $g(x_1, x_n) = \mathbb{E} e^{\frac{\lambda}{2} f(x_1, x_n)}$, $\lambda > 0$.

$$\begin{aligned} \mathbb{E} e^{\lambda z} &= \mathbb{E} e^{g(x_1, x_n)} \\ &\leq 2 \cdot \mathbb{E} \|\text{grad } g(x_1, x_n)\|_2^2 \\ &= \frac{1}{2} \cdot \sum_{i=1}^n \mathbb{E} \left(e^{\frac{\lambda}{2} f(x_1, x_n)} - e^{\frac{\lambda}{2} f(x_1, -x_i, x_n)} \right)^2 \\ &= \sum_{i=1}^n \mathbb{E} \left(e^{\frac{\lambda}{2} f(x_1, x_n)} - e^{\frac{\lambda}{2} f(x_1, -x_i, x_n)} \right)_+^2. \end{aligned}$$

By convexity, $e^{\frac{z}{2}} - e^{\frac{y}{2}} \leq \frac{z-y}{2} e^{\frac{z}{2}}$ for $z \geq y$.

$$\Rightarrow \mathbb{E} e^{\lambda z} \leq \sum_{i=1}^n \mathbb{E} \left[\lambda^2 (D_i f(x_1, x_n))_+^2 e^{\lambda z} \right] \leq \lambda^2 \sigma^2 \mathbb{E} e^{\lambda z}$$

By Herbst argument, $P[z - \mathbb{E} z \geq t] \leq e^{-\frac{t^2}{4\sigma^2}}$. □

Cor: Let $x_1, \dots, x_n \stackrel{\text{i.i.d.}}{\sim}$ Rademacher, $z = f(x_1, x_n)$.

If $\|\text{grad } f(x_1, x_n)\|_2^2 \leq \sigma^2$ for all $x_1, x_n \in \{-1, 1\}$,

then $P[|z - \mathbb{E} z| \geq t] \leq 2e^{-\frac{t^2}{4\sigma^2}}$.

Proof: In this case, $\sum_{i=1}^n (D_i f(x_1, x_n))_+^2, \sum_{i=1}^n (D_i f(x_1, x_n))_-^2 \leq \sigma^2$.

Apply previous result to both f and $-f$. 12

Example: $\varepsilon_1, \dots, \varepsilon_n \stackrel{i.i.d.}{\sim} \text{Rademacher}$, $Z = f(\varepsilon) = \sup_{t \in T} \varepsilon^T t$.

Recall $D_i f(\varepsilon)_+ \leq |t_i^*(\varepsilon)|$, so $\sum_{i=1}^n D_i f(\varepsilon)_+^2 \leq \|t^*(\varepsilon)\|_2^2 \leq \underbrace{\sup_{t \in T} \|t\|_2^2}_{= \sigma^2}$.

Then $P[Z \geq \mathbb{E}Z + u] \leq e^{-u^2/4\sigma^2}$.

Then (Gaussian LSI): Let $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \mathcal{N}(0, 1)$,

$f: \mathbb{R}^n \rightarrow \mathbb{R}$ weakly differentiable. Then

$$\mathbb{E} f(X_1, \dots, X_n)^2 \leq 2 \mathbb{E} \|\nabla f(X_1, \dots, X_n)\|_2^2.$$

Proof: In 1-dimension ($n=1$): Assume $f: \mathbb{R} \rightarrow \mathbb{R}$ has compact support, twice continuously differentiable.

Introduce $\varepsilon_1, \dots, \varepsilon_m \stackrel{i.i.d.}{\sim} \text{Rademacher}$, $S_m = \frac{\varepsilon_1 + \dots + \varepsilon_m}{\sqrt{m}}$.

By previous LSI on hypercube:

$$\mathbb{E} f(S_m)^2 \leq 2 \mathbb{E} \|\text{grad } f(S_m)\|_2^2$$

Recall $\lim_{m \rightarrow \infty} \mathbb{E} \|\text{grad } f(S_m)\|_2^2 = \mathbb{E} f'(X)^2$ from

proof of Poincaré inequality, Lecture 4. Then

$$\mathbb{E} \ell(X)^2 = \lim_{m \rightarrow \infty} \mathbb{E} \ell(\zeta_m)^2 \leq 2 \mathbb{E} \ell(X)^2.$$

Approximate general weakly differentiable $\ell: \mathbb{R} \rightarrow \mathbb{R}$ by sequence of smooth, compactly supported functions.

Then in higher dimensions $\ell: \mathbb{R}^n \rightarrow \mathbb{R}$, by tensorization,

$$\begin{aligned} \mathbb{E} \ell(X_1, \dots, X_n)^2 &\leq \sum_{i=1}^n \mathbb{E} \underbrace{\mathbb{E} \ell^{(i)}(X_1, \dots, X_n)^2}_{\leq 2 \mathbb{E}^{(i)}(\partial_i \ell)^2} \leq 2 \mathbb{E} \|\nabla \ell(X_1, \dots, X_n)\|_2^2. \end{aligned}$$

Then (Tsirolson-Ibragimov-Sudakov inequality): If

$X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \mathcal{N}(0, 1)$, $\ell: \mathbb{R}^n \rightarrow \mathbb{R}$ is L -Lipschitz,

(i.e. $|\ell(x) - \ell(y)| \leq L \|x - y\|_2$ for all $x, y \in \mathbb{R}^n$), and

$Z = \ell(X_1, \dots, X_n)$, then $Z - \mathbb{E}Z$ is L^2 -subgaussian and

$$\mathbb{P}[|Z - \mathbb{E}Z| \geq t] \leq 2e^{-\frac{t^2}{2L^2}} \quad \forall t \geq 0.$$

Remark: This result is dimension-free.

Proof: Any L -Lipschitz $\ell: \mathbb{R}^n \rightarrow \mathbb{R}$ is weakly differentiable, with

$\|\nabla \ell(x)\|_2 \leq L$ a.e. Then for any $\lambda \in \mathbb{R}$,

$$\mathbb{E} e^{\lambda Z} = \mathbb{E} e^{\lambda F(x_1, \dots, x_n)}$$

$$\leq \mathbb{E} \|\nabla e^{\frac{\lambda}{2} F(x_1, \dots, x_n)}\|_2^2 \hookrightarrow \text{LSI}$$

$$= \mathbb{E} \left\| e^{\frac{\lambda}{2} F(x_1, \dots, x_n)} \cdot \frac{\lambda}{2} \nabla F(x_1, \dots, x_n) \right\|_2^2$$

$$= \frac{\lambda^2}{2} \mathbb{E} \left[e^{\lambda Z} \cdot \|\nabla F(x_1, \dots, x_n)\|_2^2 \right] \leq \frac{\lambda^2 L^2}{2} \mathbb{E} e^{\lambda Z}$$

By Herbst argument (applied to both F and $-F$),

$$\mathbb{E} e^{\lambda Z} \leq e^{\frac{\lambda^2 L^2}{2}} \quad \forall \lambda \in \mathbb{R},$$

i.e., Z is L^2 -subgaussian. ■

Example: Let $Y \sim \mathcal{N}(0, \Sigma) \in \mathbb{R}^d$. Consider

$$\|Y\|_p = \left(\sum_{i=1}^d |Y_i|^p \right)^{1/p}, \quad p \geq 1.$$

Can write $Y = \Sigma^{1/2} X$, $X \sim \mathcal{N}(0, I)$.

$$\text{Set } f(X) = \|\Sigma^{1/2} X\|_p$$

$$\Rightarrow |f(x) - f(x')| = \left| \|\Sigma^{1/2} x\|_p - \|\Sigma^{1/2} x'\|_p \right|$$

$$\leq \|\Sigma^{1/2}(x - x')\|_p \leq \|\Sigma^{1/2}\|_{\ell_2 \rightarrow \ell_p} \|x - x'\|_2.$$

Let $L = \|\Sigma^{1/2}\|_{\ell_2 \rightarrow \ell_p}$. Then $\mathbb{P}[\|Y\|_p \geq \mathbb{E}\|Y\|_p + t] \leq e^{-\frac{t^2}{2L^2}}.$

Example: Let $x_1, \dots, x_n \stackrel{i.i.d.}{\sim} \mathcal{N}(0, I) \in \mathbb{R}^d$, $\theta_* \in \mathbb{R}^d$ fixed,
 $y_i = x_i^\top \theta_*$ for each $i=1, \dots, n$.

Fix $\theta \in \mathbb{R}^d$, loss function $\ell: \mathbb{R} \rightarrow \mathbb{R}$ with $\|\ell'\|_\infty \leq K$.

$$\begin{aligned} \text{View } F(X) &= \frac{1}{n} \sum_{i=1}^n \ell(y_i - x_i^\top \theta) \\ &= \frac{1}{n} \sum_{i=1}^n \ell(x_i^\top (\theta_* - \theta)) \end{aligned}$$

as function of $X = (x_1, \dots, x_n)$.

$$\begin{aligned} \text{We have } \|\nabla_{x_i} F(X)\|_2^2 &= \left\| \frac{1}{n} \ell'(x_i^\top (\theta_* - \theta)) \cdot (\theta_* - \theta) \right\|_2^2 \\ &\leq \frac{K^2}{n^2} \|\theta_* - \theta\|_2^2 \end{aligned}$$

$$\Rightarrow \|\nabla_X F(X)\|_2^2 = \sum_{i=1}^n \|\nabla_{x_i} F(X)\|_2^2 \leq \frac{K^2}{n} \|\theta_* - \theta\|_2^2$$

So $F(X)$ is $K\|\theta_* - \theta\|_2/\sqrt{n}$ -Lipschitz.

$$\Rightarrow \mathbb{P}[|F(X) - \mathbb{E}F(X)| \geq t] \leq e^{-\frac{nt^2}{2K^2\|\theta_* - \theta\|_2^2}}$$

Remarks: ① Compared w/ Poincaré inequality,

$$\text{Var } f(X) \leq \mathbb{E} \|\nabla f(x_1, \dots, x_n)\|_2^2.$$

TIS inequality requires stronger uniform bound on $\|\nabla f\|_2$

rather than only in expectation, but gives stronger statement of exponential tail decay.

$$\textcircled{2} \text{ LSI } \mathbb{E} \log f(X_1, X_n)^2 \leq \frac{1}{2} \mathbb{E} \|\nabla f(X_1, X_n)\|_2^2$$

implies Poincaré: Set $f = 1 + \varepsilon g$, g bounded. Then

$$\begin{aligned} \mathbb{E} \log f^2 &= \mathbb{E} f^2 \log f^2 - \mathbb{E} f^2 \log \mathbb{E} f^2 \\ &= \frac{1}{2} \varepsilon^2 \text{Var } g + O(\varepsilon^3) \quad (\text{check this!}) \end{aligned}$$

$$\mathbb{E} \|\nabla f\|_2^2 = \varepsilon^2 \mathbb{E} \|\nabla g\|_2^2$$

$$\begin{aligned} \text{LSI} &\Rightarrow \frac{1}{2} \varepsilon^2 \text{Var } g + O(\varepsilon^3) \leq \frac{1}{2} \varepsilon^2 \mathbb{E} \|\nabla g\|_2^2 \\ &\xrightarrow{\varepsilon \rightarrow 0} \Rightarrow \text{Var } g \leq \mathbb{E} \|\nabla g\|_2^2 \text{ which is Poincaré.} \end{aligned}$$

$\textcircled{3}$ Poincaré + LSI for many other distributions via analysis of continuous-time Markov chains:

See van Handel Chapters 2+3.

Further applications of entropy method

Lemma: Let X_1, X_n be independent, $Z = f(X_1, X_n)$,

$Z_i = f^{(i)}(X_1, X_{i-1}, X_{i+1}, X_n)$ for arbitrary functions

$f^{(1)}, \dots, f^{(n)}$. Then

$$E e^{\lambda Z} \leq \sum_{i=1}^n E \left[\frac{\lambda^2}{2} (Z - Z_i)_+^2 e^{\lambda Z} \right] \quad \forall \lambda \geq 0.$$

Proof: By simple calculus, for $Y \geq 0$,

$$E Y = \inf_{u \geq 0} E[Y \log Y - Y \log u - Y u]$$

w/ inf attained at $u^* = E Y$. Apply with $Y = e^{\lambda Z}$, $u = e^{\lambda Z_i}$.

$$E e^{\lambda Z} \leq \sum_{i=1}^n E E^{(i)} e^{\lambda Z}$$

$$\leq \sum_{i=1}^n E E^{(i)} \left[e^{\lambda Z} \log e^{\lambda Z} - e^{\lambda Z} \log e^{\lambda Z_i} - e^{\lambda Z} e^{\lambda Z_i} \right]$$

$$= \sum_{i=1}^n E \left[e^{\lambda Z} \underbrace{(\lambda Z - \lambda Z_i - 1 + e^{\lambda(Z_i - Z)})}_{\text{Apply } t - 1 + e^{-t} \leq \frac{t^2}{2} \quad \forall t \geq 0.} \right]$$

Apply $t - 1 + e^{-t} \leq \frac{t^2}{2} \quad \forall t \geq 0$. □

Thm: Suppose $\sup_{\substack{X_1, \dots, X_n \\ X'_1, \dots, X'_n}} \sum_{i=1}^n (f(X_1, \dots, X_n) - f(X_1, \dots, X'_i, \dots, X_n))^2 \leq \sigma^2$

Let $X_1, \dots, X_n$ be independent, and let $Z = f(X_1, \dots, X_n)$. Then

$$P[Z - E Z \geq t] \leq e^{-\frac{t^2}{2\sigma^2}} \quad \forall t \geq 0.$$

Proof: Take $Z_i = \inf_{x'_i} f(x_1, \dots, x_{i-1}, x'_i, x_{i+1}, \dots, x_n)$

$$\Rightarrow \mathbb{E} e^{\lambda Z} \leq \frac{\lambda^2 \sigma^2}{2} \mathbb{E} e^{\lambda Z} \quad \forall \lambda > 0.$$

Result follows from Herbst argument. □

Compare with Etem-Slein:

$$\text{Var } Z \leq \mathbb{E} \sum_{i=1}^n (f(x_i, x_n) - f(x_i, x'_i, x_n))^2.$$

Then: Let x_i, x_n be independent, $x_i \in [0, 1]$, $f: \mathbb{R}^n \rightarrow \mathbb{R}$ separately convex and L -Lipschitz, $Z = f(x_i, x_n)$. Then

$$\mathbb{P}[Z - \mathbb{E} Z \geq t] \leq e^{-\frac{t^2}{2L^2}} \quad \forall t \geq 0.$$

Proof: Let $x_i^* = \arg\min_{x'_i} f(x_i, x'_i, x_n)$. By convexity,

$$f(x_i, x_n) - f(x_i, x_i^*, x_n) \leq |\partial_i f(x_i, x_n)| \cdot \underbrace{|x_i - x_i^*|}_{\in [0, 1]}.$$

$$\Rightarrow \sup_{\substack{x_i, x_n \\ x'_i, x_n}} \sum_{i=1}^n (f(x_i, x_n) - f(x_i, x'_i, x_n))^2$$

$$\leq \sum_{i=1}^n |\partial_i f(x_i, x_n)|^2 = \|\nabla f(x_i, x_n)\|_2^2 \leq L^2$$

so result follows from previous theorem. □

Compare w/ convex Poincaré: $\forall z \in \mathbb{R} \|\nabla f(x_1, \dots, x_n)\|_2^2$.

Exple: Let $X \in \mathbb{R}^{m \times n}$ have independent entries, $X_{ij} \in [a, b]$.

Recall $\sigma_{\max}(X)$ is convex, $(b-a)$ -Lipschitz function of $\{z_{ij}\} = \{\frac{X_{ij}-a}{b-a}\} \in [0, 1]$.

$$\Rightarrow P[\sigma_{\max}(X) \geq \mathbb{E}\sigma_{\max}(X) + t] \leq e^{-\frac{t^2}{2(b-a)^2}}.$$

Note: This provides only an upper tail bound. If f is jointly convex, we'll see different method for also getting lower tail bound next lecture.

Example: $Z = f(x_1, \dots, x_n)$ is longest subsequence satisfying a hereditary property. Recall from Lecture 4

$$0 \leq f(x_1, \dots, x_n) - f(x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n) \leq 1$$

$$\sum_{i=1}^n f(x_1, \dots, x_n) - f(x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n) \leq f(x_1, \dots, x_n).$$

Set $Z_i = f(x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n)$. Then

$$\mathbb{E} e^{\lambda Z} \leq \sum_{i=1}^n \mathbb{E} \left[\frac{\lambda^2}{2} (Z - Z_i)^2 e^{\lambda Z} \right] \leq \frac{\lambda^2}{2} \mathbb{E} [Z e^{\lambda Z}].$$

[Homework 5: If

$$\mathbb{E} e^{\lambda Z} \leq \lambda^2 \left[b \mathbb{E} Z e^{\lambda Z} + (\sigma^2 - b \mathbb{E} Z) \cdot \mathbb{E} e^{\lambda Z} \right] \quad \forall \lambda \in [0, \frac{1}{b})$$

$$\text{then } \log \mathbb{E} e^{\lambda(Z - \mathbb{E} Z)} \leq \frac{\sigma^2 \lambda^2}{1 - b\lambda} \quad \forall \lambda \in [0, \frac{1}{b}).$$

Setting $b = \frac{1}{2}$, $\sigma^2 = \frac{1}{2} \mathbb{E} Z$, this gives a subexponential tail

$$P[Z - \mathbb{E} Z \geq t] \leq e^{-c \cdot \min\left(\frac{t^2}{\mathbb{E} Z}, t\right)}$$

If $\mathbb{E} Z \rightarrow \infty$ as $n \rightarrow \infty$, this implies $Z \leq \mathbb{E} Z + O_p(\sqrt{\mathbb{E} Z})$.