

MODIFIED LOGARITHMIC SOBOLEV INEQUALITIES:

[based on Chapter 4 (and 2) of
"Concentration of Measure and
Logarithmic Sobolev Inequalities"
by Michel Ledoux, 1997]

① Motivation:

Consider the product measure ν^n on $(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n))$ such that ν is the (two-sided exponential)
Laplace distribution: $\forall x \in \mathbb{R}, \nu(x) = \frac{1}{2}e^{-|x|}$. \uparrow Borel σ -algebra
 \uparrow pdf (with abuse of notation)

Question: Does ν^n satisfy a log-Sobolev inequality (LSI) with respect to "standard" Dirichlet form?

Suppose it does...

LSI: $\exists C > 0, \forall f \in A, \text{Ent}_{\nu^n}(f^2) \leq 2C \mathbb{E}_{\nu^n}[|\nabla f|^2]$

$A =$ subset of measurable functions
 $f: \mathbb{R}^n \rightarrow \mathbb{R}$ such that the
gradient $\nabla f: \mathbb{R}^n \rightarrow \mathbb{R}^n$ exists and
 $\mathbb{E}_{\nu^n}[|\nabla f|^2] < \infty$

Entropy: $\text{Ent}_{\nu^n}(f^2) \triangleq \mathbb{E}_{\nu^n}[f^2 \log(f^2)] - \mathbb{E}_{\nu^n}[f^2] \log(\mathbb{E}_{\nu^n}[f^2])$

Dirichlet form: $\mathbb{E}_{\nu^n}[|\nabla f|^2] = \sum_{i=1}^n \mathbb{E}_{\nu^n}[(\partial_i f)^2]$
 \uparrow partial derivative with respect to i th coordinate

Then, for any $F: \mathbb{R}^n \rightarrow \mathbb{R}$ smooth with $\|F\|_{\text{Lip}} \leq 1$, setting $f^2 = e^{\lambda F}$ for $\lambda \in \mathbb{R}$ and employing the Herbst argument gives the following concentration of measure inequality:
 $\forall r \geq 0, \nu^n(F \geq \mathbb{E}_{\nu^n}[F] + r) \leq e^{-r^2/2C}$. \leftarrow after optimizing over $\lambda \in \mathbb{R}$

Contradiction: Since F linear satisfies the required conditions, we see that a linear function has a Gaussian tail. However, the tail for a linear function must be exponential!

② Exponential LSI via Gaussian LSI:

Recall the Gaussian LSI: For all $f: \mathbb{R}^n \rightarrow \mathbb{R}$ with $\mathbb{E}_\gamma[|\nabla f|^2] < \infty$,

$$\text{Ent}_\gamma(f^2) \leq 2 \mathbb{E}_\gamma[|\nabla f|^2],$$

where $\gamma \sim \mathcal{N}(0, I_n)$ is the canonical Gaussian measure on $(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n))$.
 \uparrow $n \times n$ identity matrix

Consider (one-sided) exponential measure $\hat{\nu}$ on $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ with pdf $\hat{\nu}(x) = \begin{cases} e^{-x}, & x \geq 0 \\ 0, & x < 0 \end{cases}$.

It is well-known that if $Z_1, Z_2 \stackrel{\text{iid}}{\sim} \mathcal{N}(0, 1)$, then $X = \frac{Z_1^2 + Z_2^2}{2}$ has distribution $\hat{\nu}$.

[Check: $f_{Z_1, Z_2}(z_1, z_2) = \frac{1}{2\pi} \exp(-\frac{1}{2}(z_1^2 + z_2^2)) = \frac{1}{2\pi} e^{-x} = \underbrace{f_\theta(\theta)}_{\text{Unif}[0, 2\pi]} \underbrace{f_X(x)}_{\nu(x)}$]

Consider $f(x, y) = g(\frac{x^2 + y^2}{2})$. Then, $|\nabla f|^2 = (\frac{\partial f}{\partial x})^2 + (\frac{\partial f}{\partial y})^2 = (x g'(\frac{x^2 + y^2}{2}))^2 + (y g'(\frac{x^2 + y^2}{2}))^2$

$$\Rightarrow |\nabla f|^2 = 2 \left(\frac{x^2 + y^2}{2} \right) g'(\frac{x^2 + y^2}{2})^2$$

$$\Rightarrow \mathbb{E}_{Z_1, Z_2}[|\nabla f|^2] = 2 \mathbb{E}_X[X g'(X)^2]$$

$$= \text{Ent}_{\hat{\nu}}(g^2)$$

Hence, we have: $\text{Ent}_{\hat{\nu}}(g^2) \leq 4 \mathbb{E}_X[X g'(X)^2]$ for every $g: \mathbb{R}_+ \rightarrow \mathbb{R}$ such that the right-hand side is finite.

\uparrow Consequence of Gaussian LSI product measure

\therefore For every sufficiently smooth $f: \mathbb{R}_+^n \rightarrow \mathbb{R}$, $\text{Ent}_{\hat{\nu}^n}(f^2) \leq 4 \int \sum_{i=1}^n x_i |\partial_i f(x)|^2 d\hat{\nu}^n(x)$, via tensorization of entropy - see next section.

Unfortunately, this LSI does not give concentration inequality via Herbst argument.

③ Tensorization of Entropy:

Given probability spaces $(X_i, \mathcal{B}(X_i), \mu_i)$, $1 \leq i \leq n$, let $P = \mu_1 \otimes \dots \otimes \mu_n$ denote the product measure on the product measurable space $(X_1 \times \dots \times X_n, \mathcal{B}(X_1) \otimes \dots \otimes \mathcal{B}(X_n))$.
 \uparrow product σ -algebra

Given $f: X_1 \times \dots \times X_n \rightarrow \mathbb{R}_+$ (measurable), for each $1 \leq i \leq n$, define $f_i: X_i \rightarrow \mathbb{R}_+$ to be:

$$f_i(x_i) = f(x_1, \dots, x_{i-1}, x_i, x_{i+1}, \dots, x_n)$$

where $x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n$ are fixed. \uparrow only this varies

Prop: Under appropriate integrability conditions,

$$\underline{\underline{\text{Ent}_P(f) \leq \sum_{i=1}^n \mathbb{E}_P[\text{Ent}_{\mu_i}(f_i)]}}. \quad \leftarrow \text{Variance has similar tensorization.}$$

Proof: We first prove that $f: X \rightarrow \mathbb{R}_+$, where $(X, \mathcal{B}(X), \mu)$ is a probability space, has entropy satisfying:

$$[\star] \quad \text{Ent}_\mu(f) = \sup \{ \mathbb{E}_\mu[f g] : \mathbb{E}_\mu[e^g] \leq 1 \}, \quad \leftarrow \text{variational characterization of entropy}$$

where the supremum is over all measurable functions $g: X \rightarrow \mathbb{R}$ with $\mathbb{E}_\mu[e^g] \leq 1$.

By homogeneity, assume $\mathbb{E}_\mu[f] = 1$. Recall from Young's inequality that:

$$\rightarrow \text{Ent}_\mu(a f) = a \text{Ent}_\mu(f) \text{ for } a \geq 0$$

$$\forall u \geq 0, \forall v \in \mathbb{R}, \quad uv \leq u \log(u) - u + e^v.$$

For any g with $\mathbb{E}_\mu[e^g] \leq 1$, we have from above:

$$\begin{aligned} \mathbb{E}_\mu[f g] &\leq \mathbb{E}_\mu[f \log(f)] - 1 + \mathbb{E}[e^g] \\ &\leq \text{Ent}_\mu(f). \end{aligned}$$

Setting $g = \log(f)$ [note that $\mathbb{E}_\mu[e^g] = \mathbb{E}_\mu[f] = 1$], we get the desired result $[\star]$.

Pf: Let $f(v) = e^v$ for $v \in \mathbb{R}$.

$$\Rightarrow f^*(u) = \sup_{v \in \mathbb{R}} uv - f(v) \quad [\text{convex conjugate}]$$

$$\text{Let } \phi(v) = uv - e^v, \quad \phi'(v) = u - e^v \stackrel{\text{set}}{=} 0$$

$$\Leftrightarrow u = e^v (\geq 0).$$

$$\Rightarrow f^*(u) = u \log(u) - u \text{ for } u \geq 0$$

$$\text{So, } uv \leq f(v) + f^*(u) \text{ for all } u \geq 0, v \in \mathbb{R}. \\ = e^v + u \log(u) - u$$

Next, consider $g: X_1 \times \dots \times X_n \rightarrow \mathbb{R}$ such that $\mathbb{E}_P[e^g] \leq 1$, and define for each $1 \leq i \leq n$:

$$g^i(x_i, \dots, x_n) = \log \left(\frac{\int e^{g(x_1, \dots, x_n)} d\mu_1(x_1) \dots d\mu_{i-1}(x_{i-1})}{\int e^{g(x_1, \dots, x_n)} d\mu_1(x_1) \dots d\mu_i(x_i)} \right).$$

$$\text{Then, } \sum_{i=1}^n g^i = g - \log(\mathbb{E}_P[e^g]) \geq g, \text{ and } \mathbb{E}_{\mu_i}[e^{(g^i)_i}] = 1.$$

$$\Rightarrow \mathbb{E}_P[f g] \leq \sum_{i=1}^n \mathbb{E}_P[f g^i] = \sum_{i=1}^n \mathbb{E}_P[\mathbb{E}_{\mu_i}[f (g^i)_i]] \leq \sum_{i=1}^n \mathbb{E}_P[\text{Ent}_{\mu_i}(f_i)] \quad \text{for } f: X_1 \times \dots \times X_n \rightarrow \mathbb{R}^+$$

$$\therefore \text{Ent}_P(f) \leq \sum_{i=1}^n \mathbb{E}_P[\text{Ent}_{\mu_i}(f_i)], \text{ as desired.}$$

Remark: This result allows us to prove LSI for $n=1$ (single-letter) case and translate to general n . Moreover, the LSI constants are translated in a dimension-free manner, which makes this a useful tool for co-dimensional analysis.

Example: From previous section,

$$\text{Ent}_{\mathcal{D}^n}(f^2) \leq \sum_{i=1}^n \mathbb{E}_{\mathcal{D}^n}[\text{Ent}_{\mathcal{D}}(f_i^2)] \leq \sum_{i=1}^n \mathbb{E}_{\mathcal{D}^n} \left[4 \int x_i \left(\frac{\partial f}{\partial x_i} \right)^2 d\hat{\nu}(x_i) \right] = 4 \int \sum_{i=1}^n x_i |\partial_i f(x)|^2 d\hat{\nu}(x).$$

\uparrow tensorization \uparrow single-letter proof \uparrow dimension-free constant

④ Talagrand's Poincaré Inequality:

Talagrand proved a certain Poincaré inequality for the Laplace distribution ν on $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$.

The proof of this inequality offers insight on how to prove a different type of LSI for ν .
Let $S^n \triangleq \{f: \mathbb{R}^n \rightarrow \mathbb{R} \mid f \text{ continuous, differentiable a.e., } \int |f| d\nu < \infty, \int |f'|^2 d\nu < \infty, \lim_{x_i \rightarrow \pm\infty} e^{-|x|} |f(x_1, \dots, x_n)| = 0, \forall i, \forall x_j, j \neq i\}$.

Lemma: If $\phi \in S^1$, then:

$$\int \phi d\nu = \phi(0) + \int \text{sign}(x) \phi'(x) d\nu(x).$$

signum function: $\text{sign}(x) = \begin{cases} 1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases}$

Proof: (non-rigorous)

By integration by parts,

$$\begin{aligned} \int_{-\infty}^{\infty} \phi(x) \frac{1}{2} e^{-|x|} dx &= \left[\underbrace{\phi(x)}_u \underbrace{\left(\frac{1}{2} + \frac{1}{2} \text{sign}(x)(1 - e^{-|x|}) \right)}_{v = \text{CDF of } \nu(x)} \right]_{-\infty}^{\infty} - \int_{-\infty}^{\infty} \underbrace{\phi'(x)}_{u'} \underbrace{\left(\frac{1}{2} + \frac{1}{2} \text{sign}(x)(1 - e^{-|x|}) \right)}_v dx \\ &= \phi(\infty) - \int_{-\infty}^{\infty} \frac{\phi'(x)}{2} dx - \int_{-\infty}^{\infty} \frac{\phi'(x) \text{sign}(x)}{2} dx + \int_{-\infty}^{\infty} \phi'(x) \text{sign}(x) \frac{1}{2} e^{-|x|} dx \\ &= \frac{\phi(\infty) + \phi(-\infty)}{2} - \int_0^{\infty} \frac{\phi'(x)}{2} dx + \int_{-\infty}^0 \frac{\phi'(x)}{2} dx + \int_{-\infty}^{\infty} \phi'(x) \text{sign}(x) \frac{1}{2} e^{-|x|} dx \\ &= \phi(0) + \int_{-\infty}^{\infty} \phi'(x) \text{sign}(x) \frac{1}{2} e^{-|x|} dx. \end{aligned}$$

Prop: (Poincaré inequality for ν) For every $f \in S^1$,

$$\text{VAR}_{\nu}(f) \triangleq \mathbb{E}_{\nu}[f^2] - \mathbb{E}_{\nu}[f]^2 \leq 4 \mathbb{E}_{\nu}[f'^2].$$

Proof: Set $g(x) = f(x) - f(0)$. Then, we have:

$$\mathbb{E}_{\nu}[g^2] = \cancel{g(0)^2} + \int \text{sign}(x) \cdot 2g(x)g'(x) d\nu(x) \quad [\text{using Lemma}]$$

$$\leq 2 \mathbb{E}_{\nu}[g^2]^{\frac{1}{2}} \mathbb{E}_{\nu}[g'^2]^{\frac{1}{2}} \quad [\text{Cauchy-Schwarz inequality}]$$

$$\Rightarrow \mathbb{E}_{\nu}[g^2]^{\frac{1}{2}} \leq 2 \mathbb{E}_{\nu}[g'^2]^{\frac{1}{2}}$$

$$\Rightarrow \mathbb{E}_{\nu}[g^2] \leq 4 \mathbb{E}_{\nu}[g'^2].$$

Hence, since $f' = g'$, $\text{VAR}_{\nu}(f) = \text{VAR}_{\nu}(g) \leq \mathbb{E}_{\nu}[g^2] \leq 4 \mathbb{E}_{\nu}[g'^2] = 4 \mathbb{E}_{\nu}[f'^2]$. \blacksquare

⑤ Modified LSI for Exponential Measure:

Thm: (Modified LSI for ν) For every $0 < c < 1$ and every Lipschitz continuous function $f: \mathbb{R} \rightarrow \mathbb{R}$ such that $|f'| \leq c$ a.e.,

$$\text{Ent}_{\nu}(e^f) \leq \frac{2}{1-c} \mathbb{E}_{\nu}[f'^2 e^f].$$

Proof: It is straightforward to check that the modified LSI is invariant to adding constants. Assume without loss of generality that $f(0) = 0$. [continued.]

Proof continued:

Since $\forall u \geq 0$, $u \log(u) \geq u - 1$, we have:

$$\text{Ent}_\nu(e^f) = \mathbb{E}_\nu[f e^f] - \underbrace{\mathbb{E}_\nu[e^f]}_{=1} \log(\mathbb{E}_\nu[e^f]) \leq \mathbb{E}_\nu[f e^f] - \mathbb{E}_\nu[e^f] + 1 = \mathbb{E}_\nu[f e^f - e^f + 1].$$

Moreover, as $|f'| \leq c$ a.e., $e^f, f e^f, f^2 e^f$ are all in S' . \leftarrow straightforward to check.

$$\begin{aligned} \mathbb{E}_\nu[f e^f - e^f + 1] &= \underbrace{f(0)e^{f(0)} - e^{f(0)} + 1}_{=0} + \int \text{sign}(x) \left[f'(x)f(x)e^{f(x)} + \cancel{f(x)e^{f(x)}} - \cancel{f(x)e^{f(x)}} \right] d\nu(x) \\ &\stackrel{[*]}{=} \int \text{sign}(x) f'(x)f(x)e^{f(x)} d\nu(x) \quad [\text{using Lemma}] \end{aligned}$$

$$\begin{aligned} \mathbb{E}_\nu[f^2 e^f] &= \underbrace{f(0)^2 e^{f(0)}}_{=0} + \int \text{sign}(x) \left[f'(x)f(x)^2 e^{f(x)} + 2f'(x)f(x)e^{f(x)} \right] d\nu(x) \\ &= 2 \int \underbrace{\text{sign}(x) f'(x)f(x)e^{f(x)}}_{\text{sign}(x)f'(x)e^{f(x)/2} \cdot f(x)e^{f(x)/2}} d\nu(x) + \int \underbrace{\text{sign}(x) f'(x)f(x)^2 e^{f(x)}}_{\leq c f(x)^2 e^{f(x)}} d\nu(x) \quad [\text{using Lemma}] \end{aligned}$$

By Cauchy-Schwarz inequality,

$$\begin{aligned} \mathbb{E}_\nu[f^2 e^f] &\leq 2 \mathbb{E}_\nu[f'^2 e^f]^{\frac{1}{2}} \mathbb{E}_\nu[f^2 e^f]^{\frac{1}{2}} + c \mathbb{E}_\nu[f^2 e^f] \\ \Rightarrow (1-c) \mathbb{E}_\nu[f^2 e^f]^{\frac{1}{2}} &\leq 2 \mathbb{E}_\nu[f'^2 e^f]^{\frac{1}{2}} \\ \Rightarrow \mathbb{E}_\nu[f^2 e^f]^{\frac{1}{2}} &\stackrel{[*]}{\leq} \left(\frac{2}{1-c} \right) \mathbb{E}_\nu[f'^2 e^f]^{\frac{1}{2}} \end{aligned}$$

Finally, we have:

$$\begin{aligned} \text{Ent}_\nu(e^f) &\leq \mathbb{E}_\nu[f e^f - e^f + 1] \leq \int |f'(x)e^{f(x)/2}| |f(x)e^{f(x)/2}| d\nu(x) \quad [\text{triangle inequality on } [*]] \\ &\leq \mathbb{E}_\nu[f'^2 e^f]^{\frac{1}{2}} \mathbb{E}_\nu[f^2 e^f]^{\frac{1}{2}} \quad [\text{Cauchy-Schwarz inequality}] \\ &\leq \left(\frac{2}{1-c} \right) \mathbb{E}_\nu[f'^2 e^f]. \quad [\text{using } [*]] \end{aligned}$$

▀

Modified LSI for product measure ν^n :

Using the tensorization of entropy, for every smooth enough $F: \mathbb{R}^n \rightarrow \mathbb{R}$ such that $\max_{1 \leq i \leq n} |\partial_i F| \leq 1$ a.e. and every $\lambda \in \mathbb{R}$ with $|\lambda| \leq c < 1$, we have:

$$\underline{\underline{\text{Ent}_{\nu^n}(e^{\lambda F}) \leq \frac{2\lambda^2}{1-c} \mathbb{E}_{\nu^n} \left[\sum_{i=1}^n (\partial_i F)^2 e^{\lambda F} \right] = \frac{2\lambda^2}{1-c} \mathbb{E}_{\nu^n} [|\nabla F|^2 e^{\lambda F}]}.$$

\swarrow
comes from
 $\partial_i(\lambda F) = \lambda(\partial_i F)$

In particular, setting $c = \frac{1}{2}$ gives:

$$\text{Ent}_{\nu^n}(e^{\lambda F}) \leq 4\lambda^2 \mathbb{E}_{\nu^n} [|\nabla F|^2 e^{\lambda F}].$$

We may use this to prove Talagrand's concentration inequality for ν^n .

⑥ Talagrand's Concentration Inequality for Exponential Measure:

Assume that we have $F: \mathbb{B}^n \rightarrow \mathbb{R}$ smooth enough so that $\max_{1 \leq i \leq n} |\partial_i F| \leq 1$ a.e. and $|\nabla F|^2 = \sum_{i=1}^n (\partial_i F)^2 \leq \alpha^2$ a.e. For every λ with $|\lambda| \leq \frac{1}{2}$, we have:

$$(*) \quad \text{Ent}_{\mathbb{B}^n}(e^{\lambda F}) \leq 4\lambda^2 \mathbb{E}_{\mathbb{B}^n}[|\nabla F|^2 e^{\lambda F}] \leq 4\lambda^2 \alpha^2 \mathbb{E}_{\mathbb{B}^n}[e^{\lambda F}]. \quad [\text{using modified LSI}]$$

We can now use the Herbst argument. Define $H(\lambda) \triangleq \mathbb{E}_{\mathbb{B}^n}[e^{\lambda F}]$ and $K(\lambda) \triangleq \frac{\log(H(\lambda))}{\lambda}$.
 \uparrow natural log

$$\begin{aligned} \text{Ent}_{\mathbb{B}^n}(e^{\lambda F}) &= \mathbb{E}_{\mathbb{B}^n}[\lambda F e^{\lambda F}] - \mathbb{E}_{\mathbb{B}^n}[e^{\lambda F}] \log(\mathbb{E}_{\mathbb{B}^n}[e^{\lambda F}]) \\ &= \lambda H'(\lambda) - H(\lambda) \log(H(\lambda)) \quad [\text{swap } \mathbb{E}[\cdot] \text{ \& derivative using DCT}] \end{aligned}$$

$$\Rightarrow \lambda H'(\lambda) - H(\lambda) \log(H(\lambda)) \leq 4\lambda^2 \alpha^2 H(\lambda) \quad [\text{using } (*)]$$

$$\Rightarrow \frac{H'(\lambda)}{\lambda H(\lambda)} - \frac{\log(H(\lambda))}{\lambda^2} \leq 4\alpha^2$$

$$\Rightarrow K'(\lambda) \leq 4\alpha^2$$

$$\Rightarrow K(\lambda) = \underbrace{K(0)}_{= \mathbb{E}_{\mathbb{B}^n}[F]} + \int_0^\lambda K'(t) dt \leq \mathbb{E}_{\mathbb{B}^n}[F] + \int_0^\lambda 4\alpha^2 dt = \mathbb{E}_{\mathbb{B}^n}[F] + 4\alpha^2 \lambda$$

$$\Rightarrow H(\lambda) = \mathbb{E}_{\mathbb{B}^n}[e^{\lambda F}] \leq \exp(\mathbb{E}_{\mathbb{B}^n}[F]\lambda + 4\alpha^2 \lambda^2) \quad \text{for } 0 \leq \lambda \leq \frac{1}{2}.$$

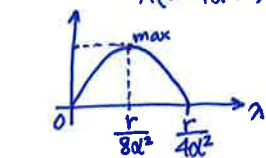
By Chernoff bound,

$$\nu^n(F \geq \mathbb{E}_{\mathbb{B}^n}[F] + r) \leq \frac{\mathbb{E}_{\mathbb{B}^n}[e^{\lambda F}]}{\exp(\mathbb{E}_{\mathbb{B}^n}[F]\lambda + r\lambda)} \leq \exp(-r\lambda + 4\alpha^2 \lambda^2), \quad \forall r \geq 0$$

same as Gaussian concentration proof until here

for $0 \leq \lambda \leq \frac{1}{2}$. Optimizing this bound over λ gives two cases:

$$\max_{0 \leq \lambda \leq \frac{1}{2}} r\lambda - 4\alpha^2 \lambda^2 = \begin{cases} r\left(\frac{r}{8\alpha^2}\right) - 4\alpha^2\left(\frac{r}{8\alpha^2}\right)^2, & \text{if } \frac{r}{8\alpha^2} \leq \frac{1}{2} \\ r\left(\frac{1}{2}\right) - 4\alpha^2\left(\frac{1}{2}\right)^2, & \text{if } \frac{r}{8\alpha^2} > \frac{1}{2} \end{cases} = \begin{cases} \frac{r^2}{16\alpha^2}, & \text{if } r \leq 4\alpha^2 \\ \frac{r}{2} - \alpha^2, & \text{if } r > 4\alpha^2 \end{cases}$$



$$\geq \frac{r}{4} \quad (\text{because } \frac{r}{4} \leq \frac{r}{2} - \alpha^2 \Leftrightarrow r \leq 2r - 4\alpha^2 \Leftrightarrow r \geq 4\alpha^2)$$

$$\Rightarrow \nu^n(F \geq \mathbb{E}_{\mathbb{B}^n}[F] + r) \leq \begin{cases} \exp(-\frac{r^2}{16\alpha^2}), & \text{if } r \leq 4\alpha^2 \quad \leftarrow \text{Gaussian bound for small } r \\ \exp(-\frac{r}{4}), & \text{if } r > 4\alpha^2 \quad \leftarrow \text{Exponential bound for large } r \end{cases}$$

$$\therefore \nu^n(F \geq \mathbb{E}_{\mathbb{B}^n}[F] + r) \leq \exp\left(-\frac{1}{4} \min\left(r, \frac{r^2}{4\alpha^2}\right)\right) \quad \text{for every } r \geq 0.$$

By homogeneity, we get for every $F: \mathbb{B}^n \rightarrow \mathbb{R}$ smooth enough so that $|\nabla F|^2 \leq \alpha^2$ a.e. and $\max_{1 \leq i \leq n} |\partial_i F| \leq \beta$ a.e.

$$\forall r \geq 0, \quad \nu^n(F \geq \mathbb{E}_{\mathbb{B}^n}[F] + r) \leq \exp\left(-\frac{1}{16} \min\left(\frac{r}{\beta}, \frac{r^2}{\alpha^2}\right)\right).$$

\uparrow Talagrand concentration inequality

⑦ General Modified LSI:

Let $(X, \mathcal{B}(X), \mu)$ be a probability space, and let \mathcal{A} be a set of functions from X to \mathbb{R} such that the ensuing objects are well-defined.

Let T be a "gradient" operator on \mathcal{A} such that $T(f) \geq 0$ and $T(\lambda f) = \lambda^2 T(f)$ for all $f \in \mathcal{A}, \lambda \in \mathbb{R}$.
 \hookrightarrow like $|\nabla f|^2$

Def: We say that μ satisfies a modified LSI with respect to T if there is a function $B: \mathbb{R}_+ \rightarrow \mathbb{R}_+$ such that for all $f \in \mathcal{A}$ with $\|T(f)\|_\infty^{\frac{1}{2}} \leq \lambda$,
 \uparrow sup-norm

$$\text{Ent}_\mu(e^f) \leq B(\lambda) \mathbb{E}_\mu[T(f)e^f].$$

Examples:

1. (Exponential measure ν) $T(f) = f'^2$, $B(\lambda) = \frac{2}{1-c}$ for $0 \leq \lambda \leq c$ for some $c < 1$.
 \uparrow on \mathbb{R} \nwarrow constant for small λ

2. (Gaussian measure $\gamma = \mathcal{N}(0, 1)$) $T(f) = f'^2$, $B(\lambda) = \frac{1}{2}$ for $\lambda \geq 0$.
 \uparrow on \mathbb{R}

Gaussian LSI: $\forall f: \mathbb{R} \rightarrow \mathbb{R}$ with $\mathbb{E}_\gamma[f'^2] < \infty$, $\text{Ent}_\gamma(f^2) \leq 2 \mathbb{E}_\gamma[f'^2]$
 \Rightarrow For $F: \mathbb{R} \rightarrow \mathbb{R}$ smooth, set $f^2 = e^F$: $\text{Ent}_\gamma(e^F) \leq \frac{1}{2} \mathbb{E}_\gamma[F'^2 e^F]$.

New Feature:

LSI tensorizes in terms of the Lipschitz bound, but modified LSI tensorizes in terms of two parameters!

Given probability spaces $(X_i, \mathcal{B}(X_i), \mu_i)$, $1 \leq i \leq n$, let $P = \mu_1 \otimes \dots \otimes \mu_n$ denote the product measure on $(X_1 \times \dots \times X_n, \mathcal{B}(X_1) \otimes \dots \otimes \mathcal{B}(X_n))$. Let T_i be the "gradient" operators on the corresponding spaces of functions \mathcal{A}_i from X_i to \mathbb{R} . Finally, let \mathcal{A} be the space of functions from $X_1 \times \dots \times X_n$ to \mathbb{R} such that for any $f \in \mathcal{A}$, $f_i \in \mathcal{A}_i$.

The tensorization of entropy yields:

Prop: Assume for every $f \in \mathcal{A}_i$ such that $\|T_i(f)\|_\infty^{\frac{1}{2}} \leq \lambda$,

$$\text{Ent}_{\mu_i}(e^f) \leq B(\lambda) \mathbb{E}_{\mu_i}[T_i(f)e^f] \quad [\text{modified LSI in each space}]$$

for $i = 1, \dots, n$. Then, for every $f \in \mathcal{A}$ such that $\max_{1 \leq i \leq n} \|T_i(f_i)\|_\infty^{\frac{1}{2}} \leq \lambda$,

$$\text{Ent}_P(e^f) \leq B(\lambda) \mathbb{E}_P\left[\sum_{i=1}^n T_i(f_i)e^f\right] \left(\leq B(\lambda) \left\|\sum_{i=1}^n T_i(f_i)\right\|_\infty \mathbb{E}_P[e^f]\right)$$

So, this modified LSI tensorizes in terms of two parameters:

$$\max_{1 \leq i \leq n} \|T_i(f_i)\|_\infty^{\frac{1}{2}} \quad \text{and} \quad \left\|\sum_{i=1}^n T_i(f_i)\right\|_\infty.$$

\uparrow like $\max_{1 \leq i \leq n} |\partial_i f|$ \uparrow like $|\nabla f|^2$

Depending on the structure of $B(\lambda)$, the corresponding concentration inequality can have one or two "behaviours" (eg: min). If B is bounded for small λ , then we get inequalities like that of ν , and if B is bounded for all $\lambda \geq 0$, then we get inequalities like that of the Gaussian measure.