

Concentration inequalities: Beyond the sub-Gaussian case [Johnson-Lindenstrauss for finite sets]

So far we saw concentration results about sub-Gaussian tails.

Sub-Gaussian variables

For r.v. Z , define the log moment generating fn. (or cumulant)

$$\psi_Z(\lambda) := \log E[\exp(\lambda Z)]$$

Assume $EZ = 0$.

Then, Z is said to be sub-Gaussian with parameter ν ,

denoted $Z \in \mathcal{L}_2(\nu)$ if

$$\psi_Z(\lambda) \leq \frac{\nu \lambda^2}{2} \quad \forall \lambda \in \mathbb{R}.$$

Examples:

(1) Bdd. variables: if $EZ = 0$ & $Z \in [a, b]$ w.p. 1, then

$$Z \in \mathcal{L}_2\left(\frac{(b-a)^2}{4}\right) \quad [\text{Hoeffding's Lemma}]$$

(2) Gaussian: if $Z \sim N(0, \sigma^2)$, then

$$Z \in \mathcal{L}_2(\sigma^2).$$

$$\begin{aligned} \text{Pf: } E[\exp(\lambda Z)] &= \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} \exp(\lambda x - \frac{x^2}{2\sigma^2}) dx = \frac{\exp(\frac{\lambda^2 \sigma^2}{2})}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} \exp(-\frac{(x-\lambda\sigma^2)^2}{2\sigma^2}) dx \\ &= \exp(\frac{\lambda^2 \sigma^2}{2}). \end{aligned}$$

Main property: (1) If X_1, X_2, \dots, X_n are independent, $X_i \in \mathcal{L}_2(\nu_i)$, $E[X_i] = 0$
then $\sum_{i=1}^n X_i \in \mathcal{L}_2\left(\sum_{i=1}^n \nu_i\right)$.

(2) If $X \in \mathcal{L}_2(\nu)$, then $\forall t > 0$,

$$\max(P_r(X > t), P_r(X < -t)) \leq \exp(-\frac{t^2}{2\nu}).$$

This led, for example, to the following

Thm - If $(X_i)_{i=1}^n$ are independent random variables taking values in the intervals $([a_i, b_i])_{i=1}^n$, then

$$\max \left(\Pr [X - E[X] > t], \Pr [X - E[X] < -t] \right) \leq \exp \left(-\frac{2t^2}{\sum (b_i - a_i)^2} \right) \cdot \left[\text{Hoeffding inequality} \right]$$

The dimension reduction problem

Input :- n points in a metric space ($\omega \cdot \log$, in \mathbb{R}^d (why?))

Goal :- Project the points to $O(\log n)$ dimensions so that all pairwise distances are approximately preserved.

The Johnson-Lindenstrauss construction

$A = \frac{1}{\sqrt{d}} (A_{ij})_{d \times n}$, each A_{ij} is an independent random variable with $E[A_{ij}^2] = 1$, $E[A_{ij}] = 0$
 $A_{ij} \in \mathcal{U}(1)$.

Thm :- If $S \subseteq \mathbb{R}^n$ is of size n and $d \geq \frac{100n}{\epsilon^2} \log \left(\frac{n}{\sqrt{d}} \right)$, then

$$1 - \epsilon \leq \frac{\|Ax - Ay\|_2}{\|x - y\|_2} \leq 1 + \epsilon \quad \forall x \neq y \in S.$$

Proof - Let u be any unit vector in \mathbb{R}^n .

Then $\forall i \in [d], (Au)_i = \frac{1}{\sqrt{d}} \sum_j A_{ij} u_j$ satisfies.

$$E[(Au)_i] = 0 \quad E[(Au)_i^2] = \frac{1}{d} \sum_j u_j^2 E[A_{ij}^2] = \frac{1}{d}.$$

$$\Rightarrow E[\|Au\|_2^2] = \sum_{i=1}^d \frac{1}{d} = 1.$$

Further,

$$(Au)_i \in \mathcal{U} \left(\frac{1}{d} \sum_{j=1}^n u_j^2 \right) = \mathcal{U} \left(\frac{1}{d} \right).$$

We are interested in the random variable

$$Z = \|Au\|_2^2 = \sum_{i=1}^d (Au)_i^2$$

But we only know that Au_i is $\mathcal{I}_y\left(\frac{1}{d}\right)$; not $(Au)_i^2$.

Thm:- (Bernstein's inequality) If $Z \sim \mathcal{I}_y(v)$ then

$$\Psi_{Z^2 - E[Z^2]}(\lambda) \leq \frac{\alpha \lambda^2}{2(1 - c\lambda)}, \quad \forall \lambda: |\lambda| < \frac{1}{c}$$

where $\alpha := 16v^2$, $c = 2v$.

Pf:- We first note

$$\Psi_{Z^2 - E[Z^2]}(\lambda) = \log E[\exp(\lambda(Z^2 - E[Z^2]))]$$

$$= \log E[e^{\lambda Z^2}] - E[\lambda Z^2]$$

$$\leq E[e^{\lambda Z^2}] - 1 - E[\lambda Z^2] \quad \left(\because \log x \leq x - 1 \right)$$

$\forall x > 0$

$$= E\left[\sum_{q=2}^{\infty} \frac{\lambda^q Z^{2q}}{q!} \right]$$

$$= \sum_{q=2}^{\infty} \frac{\lambda^q E[Z^{2q}]}{q!} \quad \left[\text{This steps require a limit interchange argument, but can be justified via dominated convergence.} \right]$$

$$\text{Now, } E[Z^{2q}] = \int_0^{\infty} \Pr[Z^{2q} > x] dx = 2q \int_0^{\infty} y^{2q-1} \Pr[|Z| > y] dy$$

$$\leq 4q \int_0^{\infty} y^{2q-1} \exp\left(-\frac{y^2}{2v}\right) dy \quad (\because Z \in \mathcal{I}_y(v))$$

$$\left(t = \frac{y^2}{2v} \right)$$

$$= 2q \cdot (2v)^q \int_0^{\infty} t^{q-1} \exp(-t) dt = 2(q!)(2v)^q$$

$$\Rightarrow \psi_{Z^2 - E[Z^2]}(\lambda) \leq 2 \sum_{q=2}^{\infty} |2\lambda v|^q$$

$$= \frac{8\lambda^2 v^2}{1 - 2|\lambda|v} = \frac{\alpha \lambda^2}{1 - c|\lambda|}, \quad \text{where } \begin{cases} \alpha := 16v^2 \\ c := 2v, \text{ when} \\ |\lambda| < 1/c \end{cases}$$

Note: If r.v. Z satisfies $\psi_Z(\lambda) \leq \frac{\alpha \lambda^2}{1 - c|\lambda|} \quad \forall |\lambda| < 1/c$,
it is known as a sub-Gamma r.v. with params. (α, c) .
(denoted $Z \in \Gamma(\alpha, c)$)

Further, if Z_1, Z_2, \dots, Z_n are independent and $Z_i \in \Gamma(\alpha_i, c)$, then,
 $\sum Z_i \in \Gamma(\sum \alpha_i, c)$.

Concentration for sub-Gamma variables

If $Z \in \Gamma(\alpha, c)$,

$$\Pr(Z > t) \leq \inf_{\lambda \in (0, 1/c)} \exp(-\lambda t + \frac{\alpha \lambda^2}{1 - c\lambda}).$$

After some calculations, we find,

$$\Pr(Z > \sqrt{2\alpha t} + ct) \leq \exp(-t)$$

[Compare sub-Gaussian case: if $Z \in \mathcal{G}(v)$
 $\Pr[Z > \sqrt{2vt}] \leq \exp(-t)$]

Similarly, because $\psi_{-Z}(\lambda) = \psi_Z(-\lambda) \leq \frac{\alpha \lambda^2}{1 - c\lambda}$ for every $\lambda \in (0, 1/c)$,

we get $\Pr(Z < -\sqrt{2\alpha t} - ct) \leq \exp(-t)$

Together, $\Pr(|Z| > \sqrt{2\alpha t} + ct) \leq 2 \exp(-t)$

Thus, in our setting, we have

$$(A_{ij})^2 \in \Gamma\left(\frac{16}{d^2}, \frac{2}{d}\right)$$

$$\|A_{ii}\|^2 \in \Gamma\left(\frac{16}{d}, \frac{2}{d}\right), \text{ and hence}$$

$$\Pr \left[\left| \|A_{ii}\|^2 - 1 \right| > \sqrt{\frac{32t}{d}} + \frac{2t}{d} \right] \leq 2 \exp(-t)$$

Put $t = \log\left(\frac{n^2}{\delta}\right)$. Then,

$$\Pr \left[\left| \|A_{ii}\|^2 - 1 \right| > 4 \sqrt{\frac{2t}{d}} + \frac{2t}{d} \right] \leq \frac{2\delta}{n^2}$$

Let $d = \lceil 2\gamma^2 \varepsilon^{-2} t \rceil$ for some γ to be determined later. Then,

$$\Pr \left[\left| \|A_{ii}\|^2 - 1 \right| > \frac{4\varepsilon}{\gamma} + \frac{\varepsilon^2}{\gamma^2} \right] \leq \frac{2\delta}{n^2} \quad \left[\begin{array}{l} \frac{4}{\gamma} + \frac{\varepsilon}{\gamma^2} < 1 \\ n, \frac{4\gamma + \varepsilon}{\gamma^2} \leq 1 \\ \gamma^2 \geq 4\gamma + 1 \end{array} \right]$$

If $\gamma = 5$, we have

$$\Pr \left[\left| \|A_{ii}\|^2 - 1 \right| > \varepsilon \right] \leq \frac{2\delta}{n^2} \quad \forall \text{ unit vector } v.$$

Applying this to the $\binom{n}{2}$ unit vectors $\left\{ \frac{x-y}{|x-y|} \mid x \neq y \in S \right\}$
and using a union bound gives the result.



Isoperimetry and concentration

Let $X = (X_1, X_2, \dots, X_n) \sim \mathcal{N}(0, I_n)$.

$$\Phi(x) := \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x \exp(-\frac{t^2}{2}) dt ; \quad \phi(x) = \frac{1}{\sqrt{2\pi}} \exp(-x^2/2).$$

$$\Pr[X \leq x] = \Phi(x) \quad \forall x.$$

$$\gamma(x) = \left(\Phi^{-1}(x) \right)' = \phi(\Phi^{-1}(x)).$$

Isoperimetry :- Consider a A and define

$$A_t = \bigcup_{x \in A} B_t(x).$$

$$\text{"Surface area"} := \limsup_{t \downarrow 0} \frac{\text{Vol}(A_t \setminus A)}{t} = \lim_{t \downarrow 0} \frac{P(A_t \setminus A)}{t}$$

Gaussian isoperimetry :- Among all sets A of a given volume, this quantity is minimized by halfspaces.

More precisely,

$$\lim_{t \downarrow 0} \frac{P(A_t \setminus A)}{t} \geq \gamma(P(A))$$

with equality when A is a halfspace.

[We will not prove this.]

Corollary :- "Gaussian concentration"

$$P(A_t) \geq \Phi(\Phi^{-1}(A) + t).$$

Proof Assume $f(t) = \Phi^{-1}(P(A_t))$ is differentiable.

Then

$$f'(t) = \frac{1}{\gamma(P(A_t))} \cdot \frac{dP(A_t)}{dt} \geq 1.$$

by isoperimetry, since

$$\frac{dP(A_t)}{dt} = \lim_{s \downarrow 0} \frac{P(A_{t+s} \setminus A_t)}{s}$$

Thus,

$$\Phi^{-1}(P(A_t)) \geq \Phi^{-1}(A) + t$$

$$\Rightarrow P(A_t) \geq \Phi(\Phi^{-1}(A_t) + t).$$

This is in fact equivalent to isoperimetry, since

$$\begin{aligned} \lim_{t \downarrow 0} \frac{P(A_t) - P(A)}{t} &\geq \lim_{t \downarrow 0} \frac{\Phi(\Phi^{-1}(P(A)) + t) - \Phi(\Phi^{-1}(P(A)))}{t} \\ &= \phi(\Phi^{-1}(P(A))) = \gamma(P(A)). \end{aligned}$$

Corollary!- (Gaussian concentration). If f is 1-Lipschitz on \mathbb{R}^n

$$|f(x) - f(y)| \leq \|x - y\|_2 \text{ then, if } X \sim N(0, I_n)$$

$$P[f(X) - \text{Median}f(X) > t] \leq 1 - \Phi(t), \forall t > 0.$$

Note :- When $t > 0$,

$$\begin{aligned} 1 - \Phi(t) &= \frac{1}{\sqrt{2\pi}} \int_t^{\infty} \exp(-\frac{x^2}{2}) dx \\ &\leq \frac{1}{t\sqrt{2\pi}} \int_t^{\infty} x \exp(-\frac{x^2}{2}) dx \\ &= \frac{\exp(-t^2/2)}{\sqrt{2\pi}t^2}. \end{aligned}$$

In the next few lectures, we shall prove the slightly weaker Borell-Tsirelson-Ibragimov-Sudakov inequality:

$$\text{if } X \sim N(0, I_n)$$

$$\Pr [f(X) - E[f(X)] > t] \leq \exp\left(-\frac{t^2}{2}\right)$$

when f is 1-Lipschitz.

Entropy and the Herbst argument

We now look at some of the above proofs more closely.

Consider for example the Hoeffding lemma.

Assume $E[Z] = 0$, and consider

$$\psi_Z(\lambda) = \log E[\exp(\lambda Z)]$$

Then
$$\psi_Z'(\lambda) = \frac{E[Z \exp(\lambda Z)]}{E[\exp(\lambda Z)]}$$

$$\psi_Z''(\lambda) = \frac{E[Z^2 \exp(\lambda Z)] E[\exp(\lambda Z)] - E[Z \exp(\lambda Z)]^2}{E[\exp(\lambda Z)]^2}$$

= $\text{Var}_{P'}[Z]$, where P' is the probability distribution given by

$$E_{P'}[Y] = \frac{E[Y \exp(\lambda Z)]}{E[\exp(\lambda Z)]} \quad \forall Y.$$