

Phenomena in high dimensions in geometric analysis,  
random matrices, and computational geometry  
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**BOUNDS AND ASYMPTOTICS  
FOR FISHER INFORMATION  
IN THE CENTRAL LIMIT THEOREM**

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## 1 Fisher's quantity of information

$X$  a random variable with values in  $\mathbf{R}$

**Definition.** If  $X$  has an absolutely continuous density  $p$ , its Fisher information is defined by

$$I(X) = I(p) = \int_{-\infty}^{+\infty} \frac{p'(x)^2}{p(x)} dx,$$

where  $p'$  is a Radon-Nikodym derivative of  $p$ .

In all other cases,  $I(X) = +\infty$ .

Equivalently,

$$I(X) = \mathbf{E} \left[ \frac{p'(X)}{p(X)} \right]^2.$$

### Remarks.

1)  $\mathbf{P}\{p(X) > 0\} = 1$ , so the definition makes sense.

Integration is over  $\{x : p(x) > 0\}$ .

2) Assume  $I(X) < +\infty$ . Then  $p(x) = 0 \Rightarrow p'(x) = 0$ .

3) Translation invariance and homogeneity:  $I(a+bX) = \frac{1}{b^2} I(X)$   
( $a \in \mathbf{R}, b \neq 0$ ).

## 2 When the Fisher information appears naturally

- Statistics: Estimation of the shift parameter in  $p(x - \theta)$ .
- Probability: Shifts of product measures, distinguishing a sequence of iid random variables from a translate of itself.

$\mu$  a probability measure on  $\mathbf{R}$ ,  $\mu_\theta^\infty(A) = \mu^\infty(A + \theta)$ ,  $\theta \in \mathbf{R}^\infty$ ,  $A \subset \mathbf{R}^\infty$

**Theorem** (Feldman 1961, Shepp 1965)

$$(\forall \theta \in \ell^2 \quad \mu_\theta^\infty \ll \mu^\infty) \iff I(\mu) < +\infty \quad \text{and} \quad \frac{d\mu(x)}{dx} > 0 \text{ a.e.}$$

- Information Theory: de Bruijn's identity  
Differential entropy

$$h(X) = - \int_{-\infty}^{+\infty} p(x) \log p(x) dx.$$

**Theorem.** If a random variable  $X$  has finite variance, then for all  $\tau > 0$ ,

$$\frac{d}{d\tau} h(X + \sqrt{\tau}Z) = \frac{1}{2} I(X + \sqrt{\tau}Z),$$

where  $Z \sim N(0, 1)$  is independent of  $X$ .

### 3 Distances to normality

$X$  a r.v., with density  $p(x)$ , and  $a = \mathbf{E}X$ ,  $\sigma^2 = \text{Var}(X) < +\infty$   
 $Z \sim N(a, \sigma^2)$  with density

$$q(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-a)^2/2\sigma^2}.$$

**Relative entropy** of  $X$  with respect to  $Z$   
(informational divergence, Kullback-Leibler distance):

$$\begin{aligned} D(X) &= D(X||Z) \\ &= h(Z) - h(X) = \int p \log \frac{p}{q} dx. \end{aligned}$$

**Relative Fisher information** of  $X$  with respect to  $Z$

$$I(X||Z) = I(X) - I(Z) = \int \left( \frac{p'}{p} - \frac{q'}{q} \right)^2 p dx.$$

#### Properties

- $0 \leq D(X) \leq +\infty$
- $D(a + bX) = D(X)$
- Same for the standardized Fisher information

$$\sigma^2 I(X||Z) = \sigma^2 I(X) - 1$$

- $D(X) = 0 \iff I(X||Z) = 0 \iff X$  is normal

## 4 Relations between distances

- Csiszár-Kullback-Pinsker inequality for total variation (1967):  
For all random variables  $X$  and  $Z$ ,

$$\frac{1}{2} \|P_X - P_Z\|_{\text{TV}}^2 \leq D(X||Z).$$

- Stam's inequality (1959)  $\sim$  Logarithmic Sobolev inequality:  
If  $Z \sim N(0, 1)$ ,

$$D(X||Z) \leq \frac{1}{2} I(X||Z).$$

Sharpening (still equivalent): If  $Z \sim N(a, \sigma^2)$ ,  $\mathbf{E}X = \mathbf{E}Z = a$ ,  $\text{Var}(X) = \text{Var}(Z) = \sigma^2$ , then

$$D(X) \leq \frac{1}{2} \log [1 + \sigma^2 I(X||Z)] = \frac{1}{2} \log [\sigma^2 I(X)].$$

- Let  $\mathbf{E}X = 0$ ,  $\text{Var}(X) = 1$ ,  $X \sim p$ ,  $Z \sim N(0, 1)$ :

$$\|P_X - P_Z\|_{\text{TV}} = \int_{-\infty}^{+\infty} |p(x) - \varphi(x)| dx \leq \sqrt{2 I(X||Z)}.$$

- Shimizu (1975):

$$\sup_x |p(x) - \varphi(x)| \leq C \sqrt{I(X||Z)}.$$

- Sharpening: One can show that

$$\|p - \varphi\|_{\text{TV}} = \int_{-\infty}^{+\infty} |p'(x) - \varphi'(x)| dx \leq C \sqrt{I(X||Z)}.$$

## 5 Central limit theorem

$(X_n)_{n \geq 1}$  independent identically distributed random variables,  
 $\mathbf{E}X_1 = 0$ ,  $\text{Var}(X_1) = 1$

**CLT:** Weakly in distribution

$$Z_n = \frac{X_1 + \dots + X_n}{\sqrt{n}} \Rightarrow Z \sim N(0, 1) \quad (n \rightarrow \infty)$$

**Theorem** (Barron-Johnson 2004)

$$\begin{aligned} I(Z_n || Z) \rightarrow 0, \quad \text{as } n \rightarrow \infty &\iff \\ I(Z_{n_0} || Z) < +\infty &\quad \text{for some } n_0. \end{aligned}$$

Equivalently:  $I(Z_{n_0}) < +\infty$  for some  $n_0$ .

Sufficient:  $I(X_1) < +\infty$ .

Necessary:  $\forall n \geq n_1$ ,  $Z_n$  have bounded densities  $p_n$  and

$$\sup_x |p_n(x) - \varphi(x)| \rightarrow 0 \quad (n \rightarrow \infty).$$

### Problems

1. How to determine in terms of  $X_1$  ? (range of applicability)
2. What is rate for  $I(Z_n || Z)$ , and under what conditions?

## 6 Uniform local limit theorem

**Theorem** (Gnedenko 1950's)

The following properties are equivalent:

a) For all sufficiently large  $n$ ,  $Z_n$  have (continuous) bounded densities  $p_n$  satisfying

$$\sup_x |p_n(x) - \varphi(x)| \rightarrow 0 \quad (n \rightarrow \infty);$$

b) For some  $n$ ,  $Z_n$  has a (continuous) bounded density  $p_n$ ;

c) The characteristic function  $f_1(t) = \mathbf{E} e^{itX_1}$  of  $X_1$  satisfies a "smoothness" condition

$$\int_{-\infty}^{+\infty} |f_1(t)|^\nu dt < +\infty, \quad \text{for some } \nu > 0.$$

## 7 CLT for Fisher information distance

$(X_n)_{n \geq 1}$  independent identically distributed random variables,  $\mathbf{E}X_1 = 0$ ,  $\text{Var}(X_1) = 1$ .

**Theorem 1.** The following assertions are equivalent:

- a) For some  $n$ ,  $Z_n$  has finite Fisher information;
- b) For some  $n$ ,  $Z_n$  has density of bounded total variation;
- c) For some  $n$ ,  $Z_n$  has a continuously differentiable density  $p_n$  such that

$$\int_{-\infty}^{+\infty} |p'_n(x)| dx < +\infty;$$

- d) For some  $\varepsilon > 0$ , the characteristic function  $f_1(t) = \mathbf{E} e^{itX_1}$  satisfies

$$|f_1(t)| = O(t^{-\varepsilon}), \quad \text{as } t \rightarrow +\infty;$$

- e) For some  $\nu > 0$ ,

$$\int_{-\infty}^{+\infty} |f_1(t)|^\nu |t| dt < +\infty.$$

- In this and only in this case,

$$I(Z_n || Z) \rightarrow 0 \quad (n \rightarrow \infty).$$



## 8 $1/n$ – bounds

Barron, Johnson (2004)

Artstein, Ball, Barthe, Naor (2004)

**Theorem.** Assume that  $\mathbf{E}X_1 = 0$ ,  $\text{Var}(X_1) = 1$ , and that  $X_1$  satisfies a Poincaré-type inequality

$$\lambda_1 \text{Var}(u(X_1)) \leq \mathbf{E} u'(X_1)^2 \quad (0 < \lambda_1 \leq 1).$$

Then

$$I(Z_n||Z) \leq \frac{1}{1 + \frac{\lambda_1}{2}(n-1)} I(X_1||Z).$$

Thus,  $I(Z_n||Z) = O(1/n)$ .

**Extension** to  $Z_n = a_1X_1 + \dots + a_nX_n$  ( $a_1^2 + \dots + a_n^2 = 1$ )  
A-B-B-N (2004):

$$I(Z_n||Z) \leq \frac{L_4}{\frac{\lambda_1}{2} + (1 - \frac{\lambda_1}{2}) L_4} I(X_1||Z),$$

where

$$L_4 = a_1^4 + \dots + a_n^4.$$

## 9 Rate of convergence under moment conditions

$(X_n)_{n \geq 1}$  independent identically distributed random variables.  
Let  $\mathbf{E}X_1 = 0$ ,  $\text{Var}(X_1) = 1$ , and  $I(Z_{n_0}) < +\infty$ , for some  $n_0$ .

**Theorem 2.** If  $\mathbf{E}|X_1|^s < +\infty$ , for some  $s > 2$ , then

$$I(Z_n||Z) = \sum_{j=1}^{[(s-2)/2]} \frac{c_j}{n^j} + o\left(\frac{1}{n^{(s-2)/2} (\log n)^{(s-3)/2}}\right),$$

where each  $c_j$  is a certain polynomial in cumulants  $\gamma_3, \dots, \gamma_{2j+1}$  of  $X_1$ , or moments  $\mathbf{E}X_1^3, \dots, \mathbf{E}X_1^{2j+1}$ .

•  $s = 4$ :  $\mathbf{E}X_1^4 < +\infty \Rightarrow$

$$I(Z_n||Z) = \frac{c_1}{n} + o\left(\frac{1}{n (\log n)^{1/2}}\right), \quad c_1 = \frac{1}{2!} \gamma_3^2 = \frac{1}{2} (\mathbf{E}X_1^3)^2.$$

•  $s = 6$ :  $\mathbf{E}X_1^6 < +\infty$ ,  $\mathbf{E}X_1^3 = 0 \Rightarrow$

$$I(Z_n||Z) = \frac{c_2}{n^2} + o\left(\frac{1}{n^2 (\log n)^{3/2}}\right), \quad c_2 = \frac{1}{3!} \gamma_4^2 = \frac{1}{6} (\mathbf{E}X_1^4 - 3)^2.$$

## 10 Case $2 < s < 4$ . Lower bounds

In case  $\mathbf{E}|X_1|^s < +\infty$  with  $2 < s < 4$ , Theorem 2 only yields

$$I(Z_n||Z) = o\left(\frac{1}{n^{(s-2)/2}(\log n)^{(s-3)/2}}\right).$$

This is worse than  $1/n$ -rate.

Let  $\eta > \frac{s}{2}$ ,  $2 < s < 4$ .

**Theorem 3.** There exists a sequence  $(X_n)_{n \geq 1}$  of independent i.i.d. random variables with symmetric distributions, with

$$\mathbf{E}X_1^2 = 1, \quad \mathbf{E}|X_1|^s < +\infty, \quad I(X_1) < +\infty,$$

and such that with some constant  $c = c(\eta, s)$

$$I(Z_n||Z) \geq \frac{c}{n^{(s-2)/2}(\log n)^\eta}, \quad n \geq n_1(X_1).$$

**Remark.** The distribution of  $X_1$  may be a mixture of mean zero normal laws.

## 11 When is Fisher information finite?

**Question:** What should one assume about  $X$  with density  $p$  to ensure that

$$I(X) = \int_{-\infty}^{+\infty} \frac{p'(x)^2}{p(x)} dx < +\infty ?$$

And if so, how to bound  $I(X)$  from above?

- Stam's inequality: If  $X_1$  and  $X_2$  are independent, then

$$I(X_1 + X_2) \leq \frac{1}{\frac{1}{I(X_1)} + \frac{1}{I(X_2)}}.$$

- Monotonicity:  $I(X_1 + X_2) \leq I(X_1)$ .

- Example:  $X_j \sim$  Uniform on intervals of length  $a_j \Rightarrow$

$$\begin{aligned} I(X_1) &= +\infty && \text{(uniform distribution)} \\ I(X_1 + X_2) &= +\infty && \text{(triangle distribution)} \\ I(X_1 + X_2 + X_3) &< +\infty && \text{(like beta with } \alpha = \beta = 2\text{)}. \end{aligned}$$

## 12 Necessary conditions

From the definition

$$I(X) = \mathbf{E} \left[ \frac{p'(X)}{p(X)} \right]^2 \geq \left[ \mathbf{E} \frac{|p'(X)|}{p(X)} \right]^2 = \left[ \int_{-\infty}^{+\infty} |p'(x)| dx \right]^2.$$

Hence,  $p$  is a function of bounded variation with

$$\|p\|_{\text{TV}} \leq \sqrt{I(X)}.$$

In general, the characteristic function  $f(t) = \mathbf{E} e^{itX}$  satisfies

$$|f(t)| \leq \frac{1}{|t|} \|p\|_{\text{TV}} \quad (t \in \mathbf{R}).$$

**Conclusion.**

$$|f(t)| \leq \frac{1}{|t|} \sqrt{I(X)} \quad (t \in \mathbf{R}).$$

### 13 Convolution of densities of bounded variation

Let  $S = X_1 + X_2 + X_3$  be the sum of three independent random variables with densities  $p_1, p_2, p_3$  having bounded total variation.

**Proposition 1.** One has

$$2I(S) \leq \|p_1\|_{\text{TV}} \|p_2\|_{\text{TV}} + \|p_1\|_{\text{TV}} \|p_3\|_{\text{TV}} + \|p_2\|_{\text{TV}} \|p_3\|_{\text{TV}}.$$

In particular, if  $p_1 = p_2 = p_3 = p$ ,

$$I(X_1 + X_2 + X_3) \leq \frac{3}{2} \|p\|_{\text{TV}}^2.$$

**Definition.**

$$\|p\|_{\text{TV}} = \sup \sum_{k=1}^n |p(x_k) - p(x_{k-1})|,$$

where the sup is over all  $x_0 < x_1 < \dots < x_n$ , and where we may assume that  $p(x)$  is in between  $p(x-)$  and  $p(x+)$ , for all  $x$ .

**Particular case:** If  $X_j \sim \text{Uniform}$  on intervals of length  $a_j$ , then

$$\frac{1}{2} I(X_1 + X_2 + X_3) \leq \frac{1}{a_1 a_2} + \frac{1}{a_1 a_3} + \frac{1}{a_2 a_3}.$$

However,  $I(X_1 + X_2) = +\infty$ .

## 14 Proof of Proposition 1

Let  $\mathcal{P}$  denote the collection of all densities of bounded variation.

Let  $\mathcal{U}$  denote the collection of all uniform densities

$$q(x) = \frac{1}{b-a}, \quad \text{for } a < x < b.$$

Note that

$$\|q\|_{\text{TV}} = \frac{2}{b-a}.$$

Proposition 1 follows from the case of uniform densities and the following:

**Lemma.** Any density  $p \in \mathcal{P}$  can be represented as a convex mixture of uniform densities

$$p(x) = \int_{\mathcal{U}} q(x) d\pi(q) \quad \text{a.e.}$$

and with the property that

$$\|p\|_{\text{TV}} = \int_{\mathcal{U}} \|q\|_{\text{TV}} d\pi(q).$$

**Remark.** The mixing probability measure  $\pi$  on  $\mathcal{U}$  seems to be unique, but no explicit construction is available.

When  $p$  is piece-wise constant, the lemma can be proved by induction on the number of supporting intervals.

## 15 Proof of Theorem 1

Let  $S_n = X_1 + \dots + X_n$  with i.i.d. summands and characteristic function

$$f_n(t) = \mathbf{E} e^{itS_n} = f_1(t)^n.$$

- If  $I_n = I(S_n) < +\infty$ , then, as noted,

$$|f_1(t)|^n = |f_n(t)| \leq \frac{1}{|t|} \sqrt{I_n} \Rightarrow |f_1(t)| = O(t^{-1/n}).$$

- Now, assume that, for some (fixed)  $n$ ,

$$\int_{-\infty}^{+\infty} |f_1(t)|^n |t| dt < +\infty.$$

Then  $S_n$  has density

$$p_n(x) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} e^{-itx} f_1(t)^n dt,$$

which has a continuous derivative satisfying

$$(1 + x^2) p'_n(x) = \frac{i}{2\pi} \int_{-\infty}^{+\infty} e^{-itx} (t f_n''(t) + 2f_n'(t) - t f_n(t)) dt.$$

Hence,  $|p'_n(x)| \leq \frac{C}{1+x^2}$  and  $\|p_n\|_{\text{TV}} < +\infty$ . By Proposition 1,

$$I_{3n} < +\infty.$$



## 16 Towards Theorem 2

Let  $(X_n)_{n \geq 1}$  be i.i.d.,  $\mathbf{E}X_1 = 0$ ,  $\text{Var}(X_1) = 1$ ,

$$Z_n = \frac{X_1 + \dots + X_n}{\sqrt{n}}, \quad I(Z_n) < +\infty \quad (n \geq n_0),$$

with densities  $p_n$  so that

$$I(Z_n || Z) = \int_{-\infty}^{+\infty} \frac{(p'_n(x) + xp_n(x))^2}{p_n(x)} dx = I_0 + I_1,$$

$$I_0 = \int_{-T_n}^{T_n} \frac{(p'_n(x) + xp_n(x))^2}{p_n(x)} dx, \quad I_1 = \int_{|x| \geq T_n} \dots$$

Good choice:

$$T_n = \sqrt{(s-2) \log n + s \log \log n + \rho_n} \quad (s > 2),$$

where  $\rho_n \rightarrow +\infty$  sufficiently slowly to guarantee that

$$\sup_{|x| \leq T_n} \left| \frac{p_n(x)}{\varphi(x)} - 1 \right| \rightarrow 0.$$

Case  $s = 4$ :  $T_n^2 \sim 2 \log n + 4 \log \log n + \rho_n$ .

## 17 Edgeworth-type expansion for densities

Let  $\mathbf{E}X_1^s < +\infty$  ( $s \geq 3$  integer).

For  $|x| \leq T_n$ , one may use a suitable approximation of  $p_n$ .

Not enough:

$$(1 + |x|^s) (p_n(x) - \varphi(x)) = O\left(\frac{1}{\sqrt{n}}\right).$$

Edgeworth approximation of  $p_n$ :

$$\varphi_s(x) = \varphi(x) + \sum_{k=1}^{s-2} q_k(x) n^{-k/2}$$

with

$$q_k(x) = \varphi(x) \sum \frac{H_{k+2j}(x)}{r_1! \dots r_k!} \left(\frac{\gamma_3}{3!}\right)^{r_1} \dots \left(\frac{\gamma_{k+2}}{(k+2)!}\right)^{r_k}.$$

Here  $r_1 + 2r_2 + \dots + kr_k = k$ ,  $j = r_1 + \dots + r_k$  and

$$\gamma_r = i^{-r} \frac{d^r}{dt^r} \log \mathbf{E} e^{itX_1} \Big|_{t=0} \quad (3 \leq r \leq s).$$

**Lemma 1.** Let  $I(Z_{n_0}) < +\infty$ , for some  $n_0$ . Fix  $l = 0, 1, \dots$

Then, for all sufficiently large  $n$ , for all  $x$ ,

$$|p_n^{(l)}(x) - \varphi_s^{(l)}(x)| \leq \frac{\psi_{l,n}(x)}{1 + |x|^s} \frac{\varepsilon_n}{n^{(s-2)/2}},$$

where  $\varepsilon_n \rightarrow 0$ , as  $n \rightarrow \infty$ , and

$$\sup_x |\psi_{l,n}(x)| \leq 1, \quad \int_{-\infty}^{+\infty} \psi_{l,n}(x)^2 dx \leq 1.$$

## 18 Moderate deviations

Second step:

$$I_1 = \int_{|x| \geq T_n} \frac{(p'_n(x) + xp_n(x))^2}{p_n(x)} dx = o\left(\frac{1}{n^{(s-2)/2} (\log n)^{(s-3)/2}}\right).$$

We have

$$I_1 \leq 2I_{1,1} + 2I_{1,2},$$

where

$$I_{1,1} = \int_{|x| \geq T_n} \frac{p'_n(x)^2}{p_n(x)} dx,$$

$$I_{1,2} = \int_{|x| \geq T_n} x^2 p_n(x) dx \quad \text{easy.}$$

Integration by parts:

$$\begin{aligned} I_{1,1}^+ &= \int_{T_n}^{+\infty} \frac{p'_n(x)^2}{p_n(x)} dx \\ &= -p'_n(T_n) \log p_n(T_n) - \int_{T_n}^{+\infty} p''_n(x) \log p_n(x) dx. \end{aligned}$$

**Lemma 2.** Assume  $p$  is representable as convolution of three densities with Fisher information  $\leq I$ . Then, for all  $x$ ,

$$|p'(x)| \leq I^{3/4} \sqrt{p(x)},$$

$$|p''(x)| \leq I^{5/4} \sqrt{p(x)}.$$