

# Information-theoretical inequalities for stable densities

Giuseppe Toscani

Department of Mathematics  
University of Pavia, Italy

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# Outline

- 1 Entropy and the central limit theorem
  - A short history
  - The fractional Fisher information
  - Monotonicity of the fractional Fisher information
  
- 2 Inequalities for relative entropy
  - A logarithmic type Sobolev inequality
  - Convergence results in relative entropy
  - References















- The heat equation in the whole space  $\mathbb{R}^n$

$$\frac{\partial u}{\partial t} = \kappa \Delta u, \quad u(x, t = 0) = f(x)$$

relates Shannon's entropy and Fisher information.

- McKean **McKean(1965)**, computed the **evolution** in time of the **subsequent derivatives** of the entropy functional  $H(u(t))$ . At the first two orders, **with  $\kappa = 1$**

$$I(f) = \left. \frac{d}{dt} H(u(t)) \right|_{t=0}; \quad J(f) = -\left. \frac{1}{2} \frac{d}{dt} I(u(t)) \right|_{t=0}.$$



- The functional  $J(X)$  is given by

$$J(X) = J(f) = \sum_{i,j=1}^n \int_{\{f>0\}} [\partial_{ij}(\log f)]^2 f \, dx =$$

$$\sum_{i,j=1}^n \int_{\{f>0\}} \left[ \frac{\partial_{ij} f}{f} - \frac{\partial_i f \partial_j f}{f^2} \right]^2 f \, dx.$$

- The functionals  $J(X)$  and  $I(X)$  are related. It is known that

$$J(X) \geq \frac{I^2(X)}{n}.$$



- Fisher information satisfies the inequality ( $a, b > 0$ )

$$I(X + Y) \leq \frac{a^2}{(a + b)^2} I(X) + \frac{b^2}{(a + b)^2} I(Y)$$

- Optimizing over  $a$  and  $b$  one obtains **Stam's Fisher information inequality**

$$\frac{1}{I(X + Y)} \geq \frac{1}{I(X)} + \frac{1}{I(Y)}.$$

- Note that for the Gaussian random vector  $I(N_\sigma) = n/\sigma$ . Hence, equality holds if and only if  $X$  and  $Y$  are **Gaussian random vectors with proportional covariance matrices**.



- Entropy power inequality implies **isoperimetric inequality for entropies**. If  $N$  is a Gaussian random vector with covariance  $I$ , for  $t > 0$

$$e^{\frac{2}{n}H(X+2tN)} \geq e^{\frac{2}{n}H(X)} + e^{\frac{2}{n}H(2tN)} = e^{\frac{2}{n}H(X)} + 4t\pi e.$$

- This implies

$$\frac{e^{\frac{2}{n}H(X+2tN)} - e^{\frac{2}{n}H(X)}}{t} \geq 4\pi e.$$

- Letting  $t \rightarrow 0$

$$I(X)e^{\frac{2}{n}H(X)} \geq 2\pi en.$$



- The **isoperimetric inequality for entropies** implies **logarithmic Sobolev inequality** with a remainder [G.T. (2013) Rend. Lincei. Mat. Appl.] .
- Same strategy in Dembo(1989), (cf. Villani(2000)). If  $N$  is a Gaussian random vector with covariance  $I$ , for  $t > 0$

$$1/I(X + 2tN) \geq 1/I(X) + 1/I(2tN) = 1/I(X) + \frac{2t}{n}.$$

- This implies

$$\frac{1/I(X + 2tN) - 1/I(X)}{t} \geq \frac{2}{n}.$$

- Letting  $t \rightarrow 0$  gives the inequality

$$\frac{1}{I^2(X)} J(X) \geq \frac{1}{n}.$$



- The inequality part of the proof of the **concavity of entropy power Costa(1985)**. If  $N$  is a Gaussian random vector with covariance  $I$ , the entropy power

$$e^{\frac{2}{n}H(X+tN)}$$

is **concave in  $t$** .

$$\frac{d^2}{dt^2} e^{\frac{2}{n}H(X+tN)} \leq 0.$$

- Concavity of entropy power generalized to Renyi entropies **G.T. and Savaré (2014)**.





- In the classical **central limit theorem** the monotonicity of Shannon's entropy of  $S_n$ ,

$$S_n = \frac{X_1 + X_2 + \cdots + X_n}{n^{1/2}}, \quad n \geq 1.$$

is a **consequence of the monotonicity of Fisher information** of  $S_n$  **Madiman, Barron (2007)**.

- Main idea is to introduce the definition of score (**used in theoretical statistics**). Given an observation  $X$ , with law  $f(x)$ , the **linear score**  $\rho(X)$  is given by

$$\rho(X) = \frac{f'(X)}{f(X)}$$

- The linear score has **zero mean**, and its **variance** is just the **Fisher information**.





- Given  $X$  and  $Y$  with differentiable density functions  $f$  (respectively  $g$ ), the score function of the pair relative to  $X$  is represented by

$$\tilde{\rho}(X) = \frac{f'(X)}{f(X)} - \frac{g'(X)}{g(X)}.$$

- In this case, the **relative to  $X$  Fisher information** between  $X$  and  $Y$  is just the **variance of  $\tilde{\rho}(X)$** .
- A centered Gaussian random variable  $Z_\sigma$  of variance  $\sigma$  is uniquely defined by the score function

$$\rho(Z_\sigma) = -Z_\sigma/\sigma.$$

- The relative (to  $X$ ) score function of  $X$  and  $Z_\sigma$

$$\tilde{\rho}(X) = \frac{f'(X)}{f(X)} + \frac{X}{\sigma}.$$



- The (relative to the Gaussian) Fisher information

$$\tilde{I}(X) = \tilde{I}(f) = \int_{\{f>0\}} \left( \frac{f'(x)}{f(x)} + \frac{x}{\sigma} \right)^2 f(x) dx.$$

- $\tilde{I}(X) \geq 0$ , while  $\tilde{I}(X) = 0$  if (and only if)  $X$  is a **centered Gaussian variable of variance  $\sigma$**
- The concept of linear score can be **naturally extended to cover fractional derivatives**. Given a random variable  $X$  in  $\mathbb{R}$  distributed with a probability density function  $f(x)$  that has a **well-defined fractional derivative of order  $\alpha$** , with  $0 < \alpha < 1$ , the linear fractional score

$$\rho_{\alpha+1}(X) = \frac{\mathcal{D}_\alpha f(X)}{f(X)}.$$



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- We define the **fractional derivative of order  $\alpha$**  of a real function  $f$  as ( $0 < \alpha < 1$ )

$$\frac{d^\alpha f(x)}{dx^\alpha} = \mathcal{D}_\alpha f(x) = \frac{d}{dx} R_{1-\alpha}(f)(x).$$

- In Fourier variables

$$\widehat{\mathcal{D}}_\alpha f(\xi) = i \frac{\xi}{|\xi|} |\xi|^\alpha \widehat{f}(\xi).$$

- Differently from the classical case, the fractional score of  $X$  is **linear** in  $X$  if and only if  $X$  is a **Lévy distribution of order  $\alpha + 1$** .



- For a given positive constant  $C$ , the identity

$$\rho_{\alpha+1}(X) = -CX,$$

verified if and only if, on the set  $\{f > 0\}$

$$\mathcal{D}_\alpha f(x) = -Cxf(x)$$

- Passing to Fourier transform, this identity yields

$$i\xi|\xi|^{\alpha-1}\widehat{f}(\xi) = -iC\frac{\partial\widehat{f}(\xi)}{\partial\xi}.$$

Consequently

$$\widehat{f}(\xi) = \widehat{f}(0)e\left\{-\frac{|\xi|^{\alpha+1}}{C(\alpha+1)}\right\}.$$



- Arranging constants, we show that, if  $Z_\lambda$  is a Lévy distribution of density  $L_\lambda$  ( $1 < \lambda < 2$ )

$$\rho_\lambda(Z_\lambda) = -\frac{Z_\lambda}{\lambda}.$$

- The **relative (to  $X$ )** fractional score function of  $X$  and  $Z_\lambda$  assumes the simple expression

$$\tilde{\rho}_\lambda(X) = \frac{\mathcal{D}_{\lambda-1}f(X)}{f(X)} + \frac{X}{\lambda}.$$

- The **(relative to the Lévy) fractional Fisher information** (in short  $\lambda$ -Fisher relative information) is then defined

$$I_\lambda(X) = I_\lambda(f) = \int_{\{f>0\}} \left( \frac{\mathcal{D}_{\lambda-1}f(x)}{f(x)} + \frac{x}{\lambda} \right)^2 f(x) dx.$$



- The fractional Fisher information is always **greater or equal than zero**, and it is **equal to zero** if and only if  $X$  is a **Lévy symmetric stable distribution** of order  $\lambda$ .
- At difference with the relative standard relative Fisher information,  $I_\lambda$  is **well-defined** any time that the **the random variable  $X$  has a probability density function which is suitably closed** to the Lévy stable law (typically lies in a subset of the domain of attraction). We will define by  $\mathcal{P}_\lambda$  the set of probability density functions such that  $I_\lambda(f) < +\infty$
- The concept of fractional score can be generalized. For  $v > 0$

$$\tilde{\rho}_{\lambda,v}(X) = \frac{\mathcal{D}_{\lambda-1}f(X)}{f(X)} + \frac{X}{\lambda v}.$$

This leads to the relative fractional Fisher information  $I_{\lambda,v}(X)$





- The following Lemma will be useful

### Lemma

*Let  $X_1$  and  $X_2$  be independent random variables with smooth densities, and let  $\rho^{(1)}$  (respectively  $\rho^{(2)}$ ) denote their fractional scores. Then, for each constant  $\lambda$ , with  $1 < \lambda < 2$ , and each positive constant  $\delta$ , with  $0 < \delta < 1$ , the relative fractional score function of the sum  $X_1 + X_2$  can be expressed as*

$$\tilde{\rho}_\lambda(x) = E \left[ \delta \tilde{\rho}_{\lambda,\delta}^{(1)}(X_1) + (1 - \delta) \tilde{\rho}_{\lambda,1-\delta}^{(2)}(X_2) \mid X_1 + X_2 = x \right].$$

- This Lemma has several interesting **consequences**.



- Since the norm of the relative fractional score is not less than that of its projection (i.e. by the Cauchy–Schwarz inequality)

$$I_\lambda(X_1 + X_2) = E [\tilde{\rho}_\lambda^2(X_1 + X_2)] \leq \delta^2 I_{\lambda,\delta}(X_1) + (1 - \delta)^2 I_{\lambda,1-\delta}(X_2).$$

- For  $X$  such that one of the two sides is bounded, and positive constant  $v$ , the following identity holds

$$I_{\lambda,v}(v^{1/\lambda}X) = v^{-2(1-1/\lambda)} I_\lambda(X).$$



- This relation implies the following

### Theorem

Let  $X_j$ ,  $j = 1, 2$  be independent random variables such that their relative fractional Fisher information functions  $I_\lambda(X_j)$ ,  $j = 1, 2$  are bounded for some  $\lambda$ , with  $1 < \lambda < 2$ . Then, for each constant  $\delta$  with  $0 < \delta < 1$ ,  $I_\lambda(\delta^{1/\lambda}X_1 + (1 - \delta)^{1/\lambda}X_2)$  is bounded, and

$$I_\lambda(\delta^{1/\lambda}X_1 + (1 - \delta)^{1/\lambda}X_2) \leq \delta^{2/\lambda}I_\lambda(X_1) + (1 - \delta)^{2/\lambda}I_\lambda(X_2).$$

Moreover, there is *equality* if and only if, up to translation, both  $X_j$ ,  $j = 1, 2$  are Lévy variables of exponent  $\lambda$ .

- The result is the analogous of the **Blachman–Stam inequality** for the standard relative Fisher information.



- The next ingredient in the proof of monotonicity deals with the so-called **variance drop inequality Hoeffding (1948)**.
- Let  $[n]$  denote the index set  $\{1, 2, \dots, n\}$ , and, for any  $\mathbf{s} \subset [n]$ , let  $X_{\mathbf{s}}$  stand for the collection of random variables  $(X_i : i \in \mathbf{s})$ , with the indices taken in their natural increasing order. Then

### Theorem

Let the function  $\Phi : \mathbb{R}^m \rightarrow \mathbb{R}$ , with  $1 \leq m \in \mathbb{N}$ , be symmetric in its arguments, and suppose that  $E[\Phi(X_1, X_2, \dots, X_m)] = 0$ . Define

$$U(X_1, X_2, \dots, X_n) = \frac{m!(n-m)!}{n!} \sum_{\{\mathbf{s} \subset [n] : |\mathbf{s}|=m\}} \Phi(X_{\mathbf{s}}).$$

Then

$$E[U^2] \leq \frac{m}{n} E[\Phi^2].$$

- This quantifies the **reduction**.



- We apply the **variance drop inequality** of Hoeffding to the relative score  $\tilde{\rho}(T_n)$ .
- The following theorem holds true

### Theorem

Let  $T_n$  denote the sum

$$T_n = \frac{X_1 + X_2 + \cdots + X_n}{n^{1/\lambda}},$$

where the random variables  $X_j$  are **independent copies of a centered random variable  $X$  with bounded relative  $\lambda$ -Fisher information**,  $1 < \lambda < 2$ . Then, for each  $n > 1$ , the **relative  $\lambda$ -Fisher information of  $T_n$  is decreasing in  $n$** , and the following bound holds

$$I_\lambda(T_n) \leq \left(\frac{n-1}{n}\right)^{(2-\lambda)/\lambda} I_\lambda(T_{n-1}).$$

- At difference with the classical entropic central limit theorem, this quantifies the **decay**.

$$I_\lambda(T_n) \leq \left(\frac{1}{n}\right)^{(2-\lambda)/\lambda} I_\lambda(X).$$

- There is convergence in relative  $\lambda$ -Fisher information sense at **rate**  $1/n^{(2-\lambda)/\lambda}$ .
- A strong **difference** between the classical central limit theorem and the central limit theorem for stable laws. In the classical central limit theorem, a **very large domain of attraction** with a **very low convergence in relative Fisher** (only monotonicity is guaranteed).
- In this case the **domain of attraction is very restricted** (only distribution which has the same tails at infinity of the Lévy stable law), but the **attraction** in terms of the relative fractional Fisher information is **very strong**.



- The leading example of a function which **belongs to the domain of attraction of the  $\lambda$ -stable law** is the so-called *Linnik distribution*

$$\hat{p}_\lambda(\xi) = \frac{1}{1 + |\xi|^\lambda}.$$

- For all  $0 < \lambda \leq 2$ , this function is the **characteristic function of a symmetric probability distribution**. In addition, when  $\lambda > 1$ ,  $\hat{p}_\lambda \in L^1(\mathbb{R})$ , which, by applying the inversion formula, shows that  $p_\lambda$  is a probability density function.
- Linnik distribution belongs to the **domain of attraction of the fractional Fisher information**. How large is this domain (compared to the domain of attraction of the  $\lambda$ -stable law)?
- As in the classical case **convergence in relative fractional Fisher information** implies **convergence in  $L^1(\mathbb{R})$**  ?

























- We proved the analogous of the **logarithmic Sobolev inequality**, which is obtained when  $\lambda = 2$  (**Gaussian case**).
- In this case, the fractional Fisher information coincides with the classical Fisher information.
- As for the classical logarithmic Sobolev inequality, the inequality is **saturated when the laws of  $X$  and  $Z_\lambda$  coincide**.
- Let us take  $\lambda = 2$ . The **steady state** of the Fokker–Planck equation is the **Gaussian density** and

$$\frac{d}{dt} H(f(t) | \omega) = -I_2(f(t)) = -I(f(t) | \omega_2).$$










































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