

# Entropy jumps in the presence of a spectral gap

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## Abstract

It is shown that if  $X$  is a random variable whose density satisfies a Poincaré inequality, and  $Y$  is an independent copy of  $X$ , then the entropy of  $(X + Y)/\sqrt{2}$  is greater than that of  $X$  by a fixed fraction of the entropy gap between  $X$  and the Gaussian of the same variance. The argument uses a new formula for the Fisher information of a marginal, which can be viewed as a local, reverse form of the Brunn-Minkowski inequality (in its functional form due to Prékopa and Leindler).

## 1 Introduction

The information-theoretic entropy of a real random variable  $X$  with density  $f : \mathbb{R} \rightarrow [0, \infty)$  is defined as

$$\text{Ent}(X) = - \int_{\mathbb{R}} f \log f$$

provided that the integral makes sense. For many random systems, entropy plays a fundamental role in the analysis of how they evolve towards an equilibrium. In this article we are interested in the convergence of the normalised sums

$$\frac{1}{\sqrt{n}} \sum_1^n X_i$$

of independent copies of  $X$  to the Gaussian limit: the convergence in the central limit theorem for IID copies of  $X$ .

Among random variables with a given variance, the Gaussian has the largest entropy. For any random variable,  $X$ , the gap between its entropy and that of a Gaussian  $G$  with the same variance, is a strong measure of how close  $X$  is to being Gaussian. In particular, if  $X$  has mean 0, variance 1 and density  $f$ , and  $G$  is the standard Gaussian with density  $g$ , then the Pinsker-Csiszar-Kullback inequality ([17], [9], [13]) implies that

$$\frac{1}{2} \left( \int_{\mathbb{R}} |f - g| \right)^2 \leq \text{Ent}(G) - \text{Ent}(X).$$

It is a consequence of the Shannon-Stam inequality ([19], [21]) that if  $X$  and  $Y$  are IID, then the normalised sum  $(X + Y)/\sqrt{2}$  has entropy at least as large as that of  $X$  and  $Y$ . Thus, along the sequence of powers of 2, the normalised sums

$$\frac{1}{\sqrt{2^k}} \sum_1^{2^k} X_i$$

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have increasing entropy. Under fairly weak assumptions it can be shown that this increasing entropy converges to that of the Gaussian limit. The idea of tracking the central limit theorem using entropy goes back to Linnik [15] who used it to give a particularly attractive proof of the central limit theorem. Barron [2] was the first to prove a central limit theorem with convergence in the entropy sense. A stronger result in this direction was obtained by Carlen and Soffer [8] (see also the works of Brown and Shimizu [7] [20]). The crucial point is that if  $X$  is not itself a Gaussian random variable, and  $X$  and  $Y$  are IID, then the entropy of  $(X + Y)/\sqrt{2}$  is strictly larger than that of  $X$ .

Carlen and Soffer obtained a uniform result of this type, showing that for any decreasing function  $K$  converging to zero at infinity and any real number  $\varepsilon > 0$ , there is a constant  $\delta > 0$  so that if  $X$  is a random variable with variance 1 whose entropy is at least  $\varepsilon$  away from that of the standard Gaussian  $G$ , and if  $X$  satisfies the tail estimate

$$\int_{|x|>t} x^2 f(x) dx \leq K(t), \quad t > 0$$

then the entropy of the sum  $(X + Y)/\sqrt{2}$  of IID copies of  $X$  is greater than that of  $X$  by at least  $\delta$ . Thus, the entropy experiences a definite jump, as long as it starts off some way below the Gaussian value. Carlen and Soffer used this result to give a very clear entropy proof of the central limit theorem and to study various quantum systems. Their approach uses a compactness argument at one point, and for this reason does not give any quantitative estimates of  $\delta$  in terms of  $\varepsilon$  and  $K$ . The main purpose of this article is to obtain such quantitative estimates, at least for certain special classes of random variables.

The starting point for the article is a method already used to good effect by (almost all) the authors mentioned earlier. Instead of considering the entropy directly, they study the Fisher information

$$4 \int_{\mathbb{R}} ((\sqrt{f})')^2 = \int_{\mathbb{R}} f((\log f)')^2.$$

For random variables with a given variance, the Gaussian has the *smallest* Fisher information, and according to the Blachman-Stam inequality ([4], [21]), the Fisher information of a general density, decreases with repeated convolution. It was discovered by Bakry and Emery [1] and again by Barron [2] that there is a remarkable connection between entropy and information provided by the adjoint Ornstein-Uhlenbeck semigroup. This is the semigroup  $\{P_t\}_{t \geq 0}$  of convolution operators on  $L_1$  which act on densities in the following way. If  $f$  is the density of  $X$  then  $P_t f$  is the density of the random variable  $X_t = \sqrt{e^{-t}}X + \sqrt{1 - e^{-t}}G$  where  $G$  is a standard Gaussian, independent of  $X$ . The time derivative of the entropy gap  $-\text{Ent}(X_t) + \text{Ent}(G)$  is precisely the gap between the Fisher information of  $X_t$  and that of  $G$ . Since the semigroup commutes with self-convolution, any linear inequality for the information gap can be integrated up to give the “same” inequality for the entropy gap. This argument is explained in more detail in Section 2.

Quantitative estimates for information jumps, in a very similar spirit to ours, have recently been obtained also by Barron and Johnson, [3]. Their result will be explained more precisely at the end of this introduction.

Our original plan was to try to get estimates for so-called log-concave random variables: those for which the density  $f$  has a concave logarithm. Since the Ornstein-Uhlenbeck evolutes of such a random variable are also log-concave, the Fisher information approach makes sense for these random variables. Now the Fisher information can be written as

$$\int_{\mathbb{R}} \frac{(f')^2}{f}.$$

Motivated by the desire to understand log-concave random variables one may observe that if the derivative of  $f$  decays at infinity, the integral is equal to

$$\int_{\mathbb{R}} \frac{(f')^2}{f} - f'' = \int_{\mathbb{R}} f(-\log f)''$$

The log-concave random variables are precisely those for which the latter integrand is pointwise non-negative.

Now, if  $X$  and  $Y$  are IID random variables with density  $f$ , the normalised sum  $(X + Y)/\sqrt{2}$  has density

$$u \mapsto \int_{\mathbb{R}} f\left(\frac{u+v}{\sqrt{2}}\right) f\left(\frac{u-v}{\sqrt{2}}\right) dv$$

which is a marginal of the joint density on  $\mathbb{R}^2$  of the pair  $(X, Y)$ . It is a consequence of the Brunn-Minkowski inequality (in its functional form due to Prékopa and Leindler, see e.g. [18]) that log-concave random variables have log-concave marginals and hence that if  $X$  and  $Y$  are log-concave, then so is  $X + Y$ . So, in principle, the Prékopa-Leindler inequality tells us something about the positivity of

$$(-\log(f * f))''$$

in terms of the positivity of

$$(-\log f)''.$$

The crucial first idea in this article is to rewrite a proof of the Brunn-Minkowski inequality so that it provides an explicit relation between these two functions which can be used to estimate the Fisher information of the convolution in terms of the information of the original  $f$ .

Most proofs of the Brunn-Minkowski inequality are not very well adapted for this purpose, since they involve combining values of the functions at points which are far apart: but since we want to end up just with derivatives, we need a “local” proof. Such a proof is the so-called “transportation” proof explained in Section 3 below. This is a variation of an argument by Henstock and Macbeath [11], see also [12]. In Section 4, we differentiate the transportation proof to obtain the following identity which relates  $(-\log h)''$  to the Hessian of  $-\log w$  where  $w : \mathbb{R}^2 \rightarrow (0, \infty)$  is a positive function on the plane and  $h$  is its marginal given by

$$h(x) = \int w(x, y) dy.$$

**The basic formula** *Let  $w : \mathbb{R}^2 \rightarrow (0, \infty)$  be integrable and let  $h$  be the marginal given by,*

$$h(x) = \int w(x, y) dy.$$

*Then, under appropriate regularity conditions, for each  $x$*

$$\begin{aligned} \frac{h'(x)^2}{h(x)} - h''(x) &= \int w \cdot (\partial_y p)^2 dy + \\ &+ \int w \cdot (1, p) \text{Hess}(-\log w) (1, p)^* dy \end{aligned} \quad (1)$$

*where  $p$  is given by*

$$p(x, y) = \frac{1}{w(x, y)} \left( \frac{h'(x)}{h(x)} \int_{-\infty}^y w(x, v) dv - \int_{-\infty}^y \partial_x w(x, v) dv \right).$$

The particular function  $p$  in the preceding formula arises as the derivative of a transportation map. The righthand side of the above formula, is a quadratic form in the function  $p$  and it makes sense to ask whether the particular choice of  $p$  that yields the information of the marginal is the choice that minimises the quadratic form. It is not hard to check that this particular  $p$  does indeed satisfy the Euler-Lagrange equation for the minimisation problem. So under appropriate conditions we arrive at a second version of the formula.

**Variational inequality for the marginal**

Let  $w : \mathbb{R}^2 \rightarrow (0, \infty)$  be integrable and let  $h$  be the marginal given by,

$$h(x) = \int w(x, y) dy.$$

Then under appropriate regularity conditions, for each  $x$ ,

$$\begin{aligned} \frac{h'(x)^2}{h(x)} - h''(x) &\leq \int w \cdot (\partial_y p)^2 dy + \\ &+ \int w \cdot (1, p) \text{Hess}(-\log w) (1, p)^* dy. \end{aligned}$$

By integrating over all  $x$  we obtain the estimate for information that we really want.

**Theorem 1 (Variational inequality for the information)**

Let  $w : \mathbb{R}^2 \rightarrow (0, \infty)$  be a density with

$$\int \frac{|\nabla w|^2}{w}, \int |\partial_{xx} w| < \infty.$$

Let  $h$  be the marginal density given by,

$$h(x) = \int w(x, y) dy$$

and let  $J(h)$  be its Fisher information. Then

$$\begin{aligned} J(h) &\leq \int w \cdot (\partial_y p)^2 dx dy + \\ &+ \int w \cdot (1, p) \text{Hess}(-\log w) (1, p)^* dx dy \end{aligned}$$

where  $p : \mathbb{R}^2 \rightarrow \mathbb{R}$  is any differentiable function for which the terms  $\frac{p \partial_x w \partial_y w}{w}$ ,  $p \partial_{xy} w$  and  $p^2 \partial_{yy} w$  are integrable.

We have also obtained higher dimensional analogues of these variational inequalities (i.e. similar inequalities for the  $\mathbb{R}^m$ -marginal of a density on  $\mathbb{R}^m \times \mathbb{R}^n$ ). In this sense, it is possible to obtain a local, reverse form of the Prékopa Leindler inequality in its full. We defer the statement and proof of these facts to a future article in which we will focus on their geometric applications.

As one might expect, once Theorem 1 is written down, it can easily be proved directly without any reference to transportation or the calculus of variations. This is done in Section 5. The aim will be to choose a function  $p$  which is *not* optimal, but which is simple enough to calculate with, so as to obtain good estimates of the left side. Section 6 of the article explains how a suitable function  $p$  may be chosen in the case in which the marginal comes from a convolution. The problem of estimating an entropy jump is quite subtle and, presumably because of this, we were unable to write down an explicit  $p$  in any simple way. Our solution to this problem was to make the best possible choice of  $p$  from within a restricted family of functions of a certain type for which the formulae are simpler. So, this particular  $p$  is chosen to be the solution to the Euler-Lagrange equation for a restricted minimisation problem. Using standard Sturm-Liouville techniques, we then show that this choice of  $p$  guarantees a significant information jump, provided that the density  $f$  of the random variable  $X$  satisfies a spectral gap (or Poincaré) inequality:

$$c \int_{\mathbb{R}} f s^2 \leq \int_{\mathbb{R}} f (s')^2$$

for any function  $s$  satisfying

$$\int_{\mathbb{R}} f s = 0.$$

The estimate is given by the following theorem.

**Theorem 2** *Let  $X$  be a random variable with variance 1 and finite Fisher information  $J$ , whose density  $f$  satisfies the Poincaré inequality above, and  $Y$  an independent copy of  $X$ . If the Fisher information of  $(X + Y)/\sqrt{2}$  is  $J_2$  then*

$$J - J_2 \geq \frac{c}{2 + 2c}(J - 1).$$

The result states that for a density with a spectral gap inequality, the information decreases by a fixed proportion of its distance to the Gaussian, each time the random variable is added to itself. Using the Ornstein-Uhlenbeck semigroup, this inequality can be integrated up to give the “same” result for entropy.

**Theorem 3** *Let  $X$  be a random variable with variance 1 and finite entropy, whose density  $f$  satisfies the Poincaré inequality above, and  $Y$  an independent copy of  $X$ . Then*

$$\text{Ent}\left(\frac{X + Y}{\sqrt{2}}\right) - \text{Ent}(X) \geq \frac{c}{2 + 2c}(\text{Ent}(G) - \text{Ent}(X)).$$

As mentioned earlier, in a recent article, [3], Barron and Johnson have obtained an inequality very much in the same spirit as that of Theorem 2. Their method is completely different (at least in detail) but they also prove an information jump in the presence of a spectral gap. The main difference is that they have an extra factor  $1/J$  on the right side. This non-linearity means that an entropy jump inequality cannot immediately be recovered but the inequality yields good large-time estimates for the rate of information decrease.

As we mentioned earlier, our original aim had been to obtain jump estimates for log-concave random variables. Although the really relevant property seems to be a spectral gap, log-concave random variables on the line, *do* satisfy a spectral gap inequality with a uniform constant (see the paper [5] by Bobkov, and also [16], in which Muckenhoupt gives a complete characterisation of densities on the line with a spectral gap). Moreover, the Gaussian random variable satisfies the best possible spectral gap inequality (see e.g. [6]), so one expects the constant to improve as the random variable is repeatedly convolved with itself. There may be scope here for understanding long-term entropy behaviour, even for random variables that do not themselves satisfy a Poincaré inequality. Before we begin the analysis of the information of marginals we collect some of the standard facts alluded to above.

## 2 Preliminaries concerning information

Throughout this article,  $X$  will be a random variable with mean 0, variance 1 and density  $f$  and  $G$  will be a standard Gaussian with density  $g : x \mapsto (1/\sqrt{2\pi})e^{-x^2/2}$ . The Fisher information of  $G$  is

$$\int \frac{(g')^2}{g} = \frac{1}{\sqrt{2\pi}} \int x^2 e^{-x^2/2} dx = 1.$$

Now as long as  $f$  has finite Fisher information

$$\begin{aligned} 0 &\leq \int \left( \frac{f'(x)}{f(x)} + x \right)^2 f(x) dx \\ &= \int \frac{(f')^2}{f} + 2 \int x f'(x) + \int x^2 f(x) \\ &= J(X) - 2 \int f + 1 = J(X) - 1 \end{aligned}$$

where  $J(X)$  is the Fisher information of  $X$ . Thus among random variables with variance 1, the Gaussian has the least information.

Given a random variable  $X$  with density  $f$  and variance 1, we may run an Ornstein-Uhlenbeck process starting with  $X$  and the ordinate at time  $t$  having the same distribution as  $\sqrt{e^{-t}}X + \sqrt{1 - e^{-t}}G$  where  $G$  is a Gaussian with variance 1. Call the density of this random variable,  $f_t$ . For each  $t > 0$ ,  $f_t$  will be strictly positive, smooth, and with the information

$$J_t = \int \frac{(f_t')^2}{f_t}$$

finite.

Moreover  $f_t$  satisfies the modified diffusion equation

$$\frac{\partial}{\partial t} f_t = f_t'' + (x f_t)'$$

Let the spatial differential operator on the right be denoted  $L$ . Then the time derivative of the entropy is

$$\begin{aligned} -\frac{\partial}{\partial t} \int f_t \log f_t &= -\int L f_t \cdot \log f_t - \int L f_t \\ &= -\int L f_t \cdot \log f_t \\ &= -\int f_t'' \log f_t - \int (x f_t)' \log f_t \\ &= \int \frac{(f_t')^2}{f_t} + \int x f_t' \\ &= \int \frac{(f_t')^2}{f_t} - 1 = J_t - 1 \end{aligned}$$

where  $J_t$  is the Fisher information of the random variable at time  $t$ .

Thus the derivative of the entropy is the gap between the information of the ordinate and that of the Gaussian limit. To obtain the result of Bakry-Emery and Barron, that the entropy gap is the integral of the information gap

$$\text{Ent}(G) - \text{Ent}(X) = \int_0^\infty (J_v - 1) dv$$

therefore boils down to a continuity result about the semigroup. A streamlined proof of this, under the assumption just that  $X$  has finite entropy can be found in [8] (in particular, Lemma 1.1 there implies that for every  $t > 0$ ,  $J_t$  is finite). Since we want to apply Theorem 2 along the semigroup, we need to know that the Poincaré constant does not deteriorate. (As we shall see below, it strictly improves along the semigroup). This observation seems to be well known, but we include a proof for the sake of completeness.

**Proposition 1** *Let  $X, Y$  be independent random variables such that for every smooth function  $s$ ,  $\text{Var}[s(X)] \leq A \mathbb{E}s'(X)^2$  and  $\text{Var}[s(Y)] \leq B \mathbb{E}s'(Y)^2$ . Then for every  $\lambda \in (0, 1)$  one has*

$$\text{Var}[s(\sqrt{\lambda}X + \sqrt{1 - \lambda}Y)] \leq (\lambda A + (1 - \lambda)B) \mathbb{E}s'(\sqrt{\lambda}X + \sqrt{1 - \lambda}Y)^2.$$

**Proof:** Let  $P, Q$  denote the laws of  $X, Y$  respectively. Then

$$\begin{aligned} &\text{Var}[s(\sqrt{\lambda}X + \sqrt{1 - \lambda}Y)] \\ &= \int s^2(\sqrt{\lambda}x + \sqrt{1 - \lambda}y) dP(x)dQ(y) - \left( \int s(\sqrt{\lambda}x + \sqrt{1 - \lambda}y) dP(x)dQ(y) \right)^2 \end{aligned}$$

$$\begin{aligned}
&= \int \left[ \int s^2(\sqrt{\lambda}x + \sqrt{1-\lambda}y) dQ(y) - \left( \int s(\sqrt{\lambda}x + \sqrt{1-\lambda}y) dQ(y) \right)^2 \right] dP(x) \\
&\quad + \int \left( \int s(\sqrt{\lambda}x + \sqrt{1-\lambda}y) dQ(y) \right)^2 dP(x) - \left( \int s(\sqrt{\lambda}x + \sqrt{1-\lambda}y) dP(x) dQ(y) \right)^2 \\
&\leq B(1-\lambda) \int s'(\sqrt{\lambda}x + \sqrt{1-\lambda}y)^2 dP(x) dQ(y) \\
&\quad + A \int \left( \frac{\partial}{\partial x} \int s(\sqrt{\lambda}x + \sqrt{1-\lambda}y) dQ(y) \right)^2 dP(x) \\
&\leq (\lambda A + (1-\lambda)B) \mathbb{E} s'(\sqrt{\lambda}X + \sqrt{1-\lambda}Y)^2.
\end{aligned}$$

■

From these remarks we immediately see that Theorem 3 above follows from Theorem 2.

### 3 The transportation argument

The aim of this section is to explain the transportation proof of the Brunn-Minkowski-Prékopa-Leindler inequality and why it is a “local” argument. We start with a function  $w : \mathbb{R}^2 \rightarrow [0, \infty)$  which is log-concave and for each  $x$  we set

$$h(x) = \int w(x, y) dy.$$

We want to show that  $h$  is log-concave. For our purposes this means that for each  $a$  and  $b$ ,

$$h\left(\frac{a+b}{2}\right) \geq h(a)^{1/2} h(b)^{1/2}. \quad (2)$$

Now define new functions as follows: for each  $y$  let

$$\begin{aligned}
f(y) &= w(a, y) \\
g(y) &= w(b, y) \\
m(y) &= w\left(\frac{a+b}{2}, y\right)
\end{aligned}$$

We want to show that

$$\int m \geq \left( \int f \right)^{1/2} \left( \int g \right)^{1/2}$$

and from the log-concavity of  $w$  we know that for any  $y$  and  $z$ ,

$$\begin{aligned}
m\left(\frac{y+z}{2}\right) &= w\left(\frac{a+b}{2}, \frac{y+z}{2}\right) \\
&\geq w(a, y)^{1/2} w(b, z)^{1/2} \\
&= f(y)^{1/2} g(z)^{1/2}.
\end{aligned} \quad (3)$$

By homogeneity, we may assume that  $\int f = \int g = 1$  and we may also assume that  $f$  and  $g$  are smooth and strictly positive. Choose a fixed smooth density on the line, say  $k : \mathbb{R} \rightarrow [0, \infty)$ . We *transport* the measure defined by  $k$  to that defined by  $f$  and  $g$  in the following sense. We let  $T, S : \mathbb{R} \rightarrow \mathbb{R}$  be the monotone increasing functions with the property that for each  $z$ ,

$$\int_{-\infty}^z k(u) du = \int_{-\infty}^{S(z)} f(u) du$$

and

$$\int_{-\infty}^z k(u) du = \int_{-\infty}^{T(z)} g(u) du.$$

Equivalently, for each  $z$ ,

$$k(z) = S'(z)f(S(z)) = T'(z)g(T(z)).$$

Then

$$\begin{aligned} 1 = \int k &= \int S'(z)^{1/2}T'(z)^{1/2}f(S(z))^{1/2}g(T(z))^{1/2} \\ &\leq \int S'(z)^{1/2}T'(z)^{1/2}m \left( \frac{S(z) + T(z)}{2} \right) \\ &\leq \int \left( \frac{S'(z) + T'(z)}{2} \right) m \left( \frac{S(z) + T(z)}{2} \right) \\ &= \int m \end{aligned}$$

where the first of the two inequalities is from (3) and the second is the arithmetic/geometric mean inequality. So  $\int m \geq 1$  as required.

Our first aim in this article is to replace the inequality (2) with an identity relating the second derivative of  $\log h$  to the Hessian of  $\log w$ . So we wish to examine the inequality when  $a$  and  $b$  are close together. In that case the functions  $f$ ,  $g$  and  $m$  used in the proof are all close together. Thus, if we choose the density  $k$  to be the appropriate multiple of  $m$ , the transportation functions  $S$  and  $T$  will both be close to the identity function on  $\mathbb{R}$ :

$$S(z) \approx T(z) \approx z.$$

Therefore, the inequality

$$m \left( \frac{S(z) + T(z)}{2} \right) \geq f(S(z))^{1/2}g(T(z))^{1/2}$$

used in the proof, which depends upon the log-concavity of  $w$ , involves only values of  $w$  at points near to one another. So, in the limit, it will convert into an expression involving the Hessian of  $\log w$ . The resulting identity is the subject of the next section.

## 4 The basic formula

The aim in this section is to derive (informally) a formula for the Fisher information of a marginal in terms of the original density. We are given a density  $w : \mathbb{R}^2 \rightarrow (0, \infty)$  and for each  $x$  we set

$$h(x) = \int_{\mathbb{R}} w(x, y) dy.$$

We want an expression for

$$\frac{h'^2}{h} - h'' = h(-\log h)''$$

at each point. To simplify the notation, let's fix this point at 0. For each value of  $x$  the function

$$y \mapsto \frac{w(x, y)}{h(x)}$$

is a density. Now for each value of  $x$  other than 0, transport the density at 0 to the one at  $x$  by a map  $y \mapsto T(x, y)$ . Thus, for each  $x$  and  $y$  we have

$$\frac{w(x, T(x, y)) \cdot \partial_y T(x, y)}{h(x)} = \frac{w(0, y)}{h(0)}. \quad (4)$$

Next we take logarithms and differentiate twice with respect to  $x$ . Setting  $x = 0$ , and using the fact that  $T(0, y) = y$  (and hence  $\partial_y T(0, y) = 1$ ), we obtain a simpler relationship which can be rearranged to give

$$\begin{aligned} \frac{h'(0)^2}{h(0)^2} - \frac{h''(0)}{h(0)} &= (\partial_x \partial_y T|_{x=0})^2 + \\ &+ (1, \partial_x T|_{x=0}) \cdot \text{Hess}(-\log w)|_{x=0} (1, \partial_x T|_{x=0})^* \\ &- \frac{1}{w(0, y)} \partial_y [w(0, y) \cdot \partial_{xx} T|_{x=0}] \\ &= p'(y)^2 + (1, p(y)) \text{Hess}(-\log w)|_{x=0} (1, p(y))^* \\ &- \frac{1}{w(0, y)} \partial_y [w(0, y) \partial_{xx} T|_{x=0}] \end{aligned}$$

where  $p : \mathbb{R} \rightarrow \mathbb{R}$  is given by

$$p(y) = \partial_x T(x, y)|_{x=0}. \quad (5)$$

Now multiply by  $w(0, y)$  and integrate with respect to  $y$ . The last term in the above makes no contribution because we integrate a derivative. Since  $\int w(0, y) = h(0)$  we end up with

$$\begin{aligned} \frac{h'(0)^2}{h(0)} - h''(0) &= \int w \cdot (p')^2 dy + \\ &+ \int w \cdot (1, p) \text{Hess}(-\log w)|_{x=0} (1, p)^* dy. \end{aligned} \quad (6)$$

The connection with the Prékopa-Leindler inequality is now clear, since if  $w$  is log-concave then  $\text{Hess}(-\log w)$  is positive semi-definite and the right side of (6) is non-negative while the left side is  $h(0)(-\log h)''(0)$ .

The function  $p$  can be written directly in terms of  $w$  by differentiating equation (4) just once with respect to  $x$ . We get

$$\frac{d}{dy} (w(0, y)p(y)) = w(0, y) \frac{h'(0)}{h(0)} - \partial_x w(x, y)|_{x=0}. \quad (7)$$

The solution satisfying appropriate boundary conditions at  $\pm\infty$  is

$$p(y) = \frac{1}{w(0, y)} \left( \frac{h'(0)}{h(0)} \int_{-\infty}^y w(0, v) dv - \int_{-\infty}^y \partial_x w(x, v)|_{x=0} dv \right).$$

Now, replacing the point 0 by a general one  $x$  we obtain formula (1).

**The basic formula** Let  $w : \mathbb{R}^2 \rightarrow (0, \infty)$  be integrable and let  $h$  be the marginal given by,

$$h(x) = \int w(x, y) dy.$$

Then, under appropriate regularity conditions, for each  $x$

$$\begin{aligned} \frac{h'(x)^2}{h(x)} - h''(x) &= \int w \cdot (\partial_y p)^2 dy + \\ &+ \int w \cdot (1, p) \text{Hess}(-\log w) (1, p)^* dy \end{aligned} \quad (8)$$

where  $p$  is given by

$$p(x, y) = \frac{1}{w(x, y)} \left( \frac{h'(x)}{h(x)} \int_{-\infty}^y w(x, v) dv - \int_{-\infty}^y \partial_x w(x, v) dv \right). \quad (9)$$

The right side of (8) is a quadratic form in  $p$ . As explained in the introduction, it is natural to ask whether its minimum occurs at the particular function  $p$  given by (9). The Euler-Lagrange equation for the minimum is

$$-\partial_y(w\partial_y p) + \partial_{xy}(-\log w) + p\partial_{yy}(-\log w) = 0,$$

which simplifies to

$$\frac{\partial}{\partial y} \frac{1}{w(x,y)} \left( \frac{\partial}{\partial y} w(x,y)p(x,y) + \partial_x w(x,y) \right) = 0$$

and this is satisfied by the function  $p$ . Hence the inequality in (1).

## 5 The inequality for information

The aim in this section is to give a proof of the inequality for information contained in Theorem 1.

**Theorem (Variational inequality for the information)** *Let  $w : \mathbb{R}^2 \rightarrow (0, \infty)$  be a continuously twice differentiable density with*

$$\int \frac{|\nabla w|^2}{w}, \int |\partial_{xx} w| < \infty.$$

*Let  $h$  be the marginal density given by,*

$$h(x) = \int w(x,y) dy$$

*and let  $J(h)$  be its Fisher information. Then,*

$$\begin{aligned} J(h) &\leq \int w \cdot (\partial_y p)^2 dx dy + \\ &+ \int w \cdot (1,p) \text{Hess}(-\log w) (1,p)^* dx dy \end{aligned}$$

*where  $p : \mathbb{R}^2 \rightarrow \mathbb{R}$  is any differentiable function for which the terms  $\frac{p\partial_x w \partial_y w}{w}$ ,  $p\partial_{xy} w$  and  $p^2 \partial_{yy} w$  are integrable.*

**Proof:** Plainly we may assume that

$$\int w(\partial_y p)^2, \int \frac{(\partial_y w)^2}{w} p^2 < \infty.$$

For such  $p$  we have that for almost every  $x$ ,

$$\int \partial_y [w(x,y) \cdot p(x,y)] dy = 0.$$

The conditions on  $w$  ensure that for every  $x$

$$h'(x) = \int \partial_x w(x,y) dy.$$

Hence

$$\begin{aligned} \int \frac{h'(x)^2}{h(x)} dx &= \int \frac{(\int \partial_x w dy)^2}{\int w dy} \\ &= \int \frac{(\int [\partial_x w + \partial_y (w \cdot p)] dy)^2}{\int w dy} \\ &\leq \int \int \frac{1}{w} (\partial_x w + \partial_y [w \cdot p])^2 dy dx \end{aligned}$$

by the Cauchy-Schwarz inequality. The integrand on the right and the expression

$$\partial_{xx}w + w(\partial_y p)^2 + w \cdot (1, p) \text{Hess}(-\log w)(1, p)^* + \partial_y (p^2 \partial_y w + 2p \partial_x w)$$

are equal, as follows from direct expansion and rearrangement of both terms. The conditions on  $w$  ensure that  $\int \int \partial_{xx}w = 0$ . The conditions on  $p$  ensure that the last term also integrates to zero. ■

## 6 The variational construction of a test function

In this section we shall turn our attention to convolutions and estimate the jump in Fisher information for sums of random variables satisfying a spectral gap inequality. Let  $X$  be a random variable on the line with mean 0 and variance 1. Assume that  $X$  has a positive, continuously twice differentiable density  $f$ , for which

$$\int \frac{(f')^2}{f}, \int |f''| < \infty.$$

Let  $Y$  be an independent copy of  $X$  and  $w : \mathbb{R}^2 \rightarrow (0, \infty)$  be the joint density given by  $(u, v) \mapsto f((u+v)/\sqrt{2})f((u-v)/\sqrt{2})$  so that the density of  $(X+Y)/\sqrt{2}$  is

$$h : u \mapsto \int w(u, v) dv.$$

By the preceding theorem, the Fisher information of  $(X+Y)/\sqrt{2}$  is at most

$$\int w \cdot (\partial_v p)^2 dvdu + \int w \cdot (1, p) \text{Hess}(-\log w)(1, p)^* dvdu.$$

for any suitable  $p$ . If we make the change of variables  $x = (u+v)/\sqrt{2}$ ,  $y = (u-v)/\sqrt{2}$ , and rewrite  $p(u, v)$  as  $q(x, y)$  we get

$$\begin{aligned} & \frac{1}{2} \int f(x)f(y) (\partial_x q - \partial_y q)^2 dx dy + \\ & + \frac{1}{2} \int f(x)f(y) [\phi''(x) + \phi''(y) + 2(\phi''(x) - \phi''(y))q(x, y) + (\phi''(x) + \phi''(y))q(x, y)^2] dx dy, \end{aligned} \quad (10)$$

where here, and in what follows, we denote  $\phi = -\log f$ .

Our task is to find a function  $q$  for which we can obtain a good estimate on this expression. The choice  $q = 0$  leaves us with  $\int f(-\log f)''$  which is the information for the original random variable  $X$ . So we need to choose a function  $q$  which improves upon this. We were led to the method which follows by studying a particular convolution semigroup: the Gamma semigroup. This semigroup consists of positive random variables  $X_t$ , indexed by a positive real parameter  $t$ , where  $X_t$  has density

$$x \mapsto \frac{e^{-x} x^{t-1}}{\Gamma(t)}.$$

For every  $s$  and  $t$ , independent copies of  $X_s$  and  $X_t$  have a sum whose distribution is the same as  $X_{s+t}$ . In particular, for each  $t$  it is easy to describe the distribution of the sum of 2 independent copies of  $X_t$ . It turns out that for these random variables, the optimal function  $q$  is always given by

$$q(x, y) = \frac{x-y}{x+y}.$$

As  $t$  increases and the random variables look more and more Gaussian, the mass of the random variables concentrates in regions where  $x$  and  $y$  are large, so the denominator of  $q$  is essentially constant in the

places where the action occurs. This suggested that it might be possible to replace  $q$  by an appropriate multiple of  $x - y$  and this turns out to work well.

This in turn suggested that in the general situation, it might be sufficient to consider a function  $q$  of the form  $q(x, y) = r(x) - r(y)$  for some function  $r$  of one variable. For such functions, the formula (10) simplifies considerably and it becomes clear that one loses very little by simplifying further and choosing  $q$  of the form  $q(x, y) = r(x)$ . In this case, continuing with the notation  $\phi = -\log f$ , the upper estimate for the Fisher information of the convolution, (10), becomes

$$J + \frac{1}{2} \int f(r')^2 + \frac{1}{2} \int f\phi''r^2 + \frac{J}{2} \int fr^2 + \int f\phi''r - J \int fr$$

where  $J$  is the information of the original random variable

$$J = \int f\phi''$$

and the regularity conditions on  $q$  will be satisfied as long as  $fr^2$ ,  $f(\phi')^2r^2$  and  $f\phi''r^2$  are integrable. The information *change* as a result of convolution is thus at most

$$T(r) = \frac{1}{2} \int f(r')^2 + \frac{1}{2} \int f\phi''r^2 + \frac{J}{2} \int fr^2 + \int f\phi''r - J \int fr$$

and our aim is to choose the function  $r$  so as to make this quantity as negative as possible. The argument given below ignores questions of existence, regularity and integrability of solutions to the Sturm-Liouville problems that arise. All these issues are dealt with in the appendix.

At first sight this may look slightly odd if  $\phi''$  can take negative values but under the assumptions, we may integrate by parts to get

$$\int f(r')^2 + \int f\phi''r^2 = \int f(r' - \phi'r)^2 \tag{11}$$

so the objective functional cannot be too small.

The Euler-Lagrange equation for this minimisation problem is

$$-(fr')' + f(J + \phi'')r = f(J - \phi'') \tag{12}$$

Integrating this Sturm-Liouville equation respectively against  $r$  and 1 we obtain

$$\int f(r')^2 + \int f\phi''r^2 + J \int fr^2 = J \int fr - \int f\phi''r$$

and

$$J \int fr + \int f\phi''r = 0.$$

Adding up these two relations shows that for an appropriately integrable solution of equation (12)

$$T(r) = -J \int fr.$$

In order to estimate this quantity it is more convenient to obtain a differential equation for a new function  $s$  whose derivative is  $r$ . By writing  $f' = -f\phi'$ , and dividing by  $f$ , we can rewrite equation (12) as

$$-r'' + \phi'r' + \phi''r + Jr = J - \phi''.$$

If  $r = s'$  then we can integrate the equation to get

$$-s'' + \phi's' + Js = Jx - \phi' \tag{13}$$

(apart from a constant of integration).

It remains to show that  $T = -J \int f s'$  is bounded well away from 0. Multiplying (13) by  $f$  we get

$$-(f s')' + J f s = J f x + f' \quad (14)$$

Now equation (14) is the Euler-Lagrange equation for a different minimisation problem in which the objective function is

$$Q(s) = \frac{1}{2} \int f (s')^2 + \frac{J}{2} \int f \left( s - x + \frac{\phi'}{J} \right)^2. \quad (15)$$

Set  $A = \int f s'$  and  $B = \int f s x$ . Integrating equation (14) against  $s$  and  $x$  respectively we get

$$\int f s'^2 + J \int f s^2 = J \int f s x - \int f s' = J B - A \quad (16)$$

and

$$\int f s' + J \int f s x = J \int f x^2 - \int f = J - 1$$

since  $f$  is the density of a random variable with variance 1. The latter inequality reads as

$$A + J B = J - 1. \quad (17)$$

Now, using equations (16) and (17) we get that the objective (15) is precisely  $A$ . Indeed

$$\begin{aligned} \inf Q = Q(s) &= \frac{1}{2} \int f (s')^2 + \frac{J}{2} \int f s^2 + \frac{J}{2} \int f x^2 + \frac{1}{2J} \int f (\phi')^2 \\ &\quad + J \left( - \int f s x + \int f s \frac{\phi'}{J} - \int f x \frac{\phi'}{J} \right) \\ &= \frac{J B - A}{2} + \frac{J}{2} + \frac{1}{2} + J \left( -B + \frac{A}{J} - \frac{1}{J} \right) = A. \end{aligned}$$

The aim is to obtain a good lower bound for (15). Now suppose that  $f$  satisfies a Poincaré inequality with constant  $c$ . The constant of integration was chosen above so that the condition  $\int f(x)x = 0$  (on the mean of the random variable) ensures that  $\int f s = 0$ . This means that the Poincaré inequality applies to  $s$  and

$$c \int f s^2 \leq \int f (s')^2.$$

Thus we get

$$\begin{aligned} A &= \frac{1}{2} \int f (s')^2 + \frac{J}{2} \int f \left( s - x + \frac{\phi'}{J} \right)^2 \\ &\geq \frac{1}{2} \int f \left( c s^2 + J \left( s - x + \frac{\phi'}{J} \right)^2 \right) \\ &\geq \frac{1}{2} \frac{cJ}{c+J} \int f \left( -x + \frac{\phi'}{J} \right)^2 = \frac{cJ}{2(c+J)} \frac{J-1}{J}. \end{aligned}$$

This in turn gives, using  $J \geq 1$

$$T = -J A \leq -\frac{cJ}{2(c+J)} (J-1) \leq -\frac{c}{2+2c} (J-1).$$

## 7 Appendix

Here we give detailed proofs for the arguments in the preceding section involving the calculus of variations.

First we notice that for the purpose of proving Theorem 2, we may restrict attention to densities  $f$  with the following properties:  $f$  is  $C^\infty$  and everywhere strictly positive, and  $f, f', f''$  have a strong decay at infinity (like  $1/t^2$  or even  $e^{-Kt}$  for some constant  $K > 0$ ). To achieve this we replace  $f$  by the density  $f_t$  of  $\sqrt{t}X + \sqrt{1-t}G$ , for  $t$  very small. We have seen that  $f_t$  also satisfies a Poincaré inequality with constant  $c$ . Letting  $t$  tend to zero in the result for  $f_t$ , will provide the required inequality for  $f$ . It is plain that  $f_t$  is smooth and strictly positive. Its decay at zero is related to the tails of the density  $f$ . Indeed, up to a scaling factor,  $f_t$  is the convolution of  $f$  with a Gaussian function. More generally, let  $h$  be a function on  $\mathbb{R}$  with  $\int |h| = M$  and  $|h(x)| \leq Ce^{-Bx^2}$ . One has

$$\begin{aligned} \left| \int f(x-y)h(y)dy \right| &\leq \int_{|y| \leq |x|/2} f(x-y)|h(y)|dy + \int_{|y| > |x|/2} f(x-y)|h(y)|dy \\ &\leq M \int_{|y| > |x|/2} f + Ce^{-Bx^2/4}. \end{aligned}$$

So we obtain a bound for  $f$  determined by the tails of its distribution. The fact that  $\int fx^2 = 1$  ensures a bound of the form  $A/|x|^2$ , but the spectral gap inequality is known to guarantee sub-exponential tails (see e.g. [14]). Therefore  $|f * h(x)| \leq A_1 e^{-A_2|x|}$  where the constants depend on  $B, C, M$  and the spectral gap  $c$ . Applying this in turn for  $h$  equal to  $g, g'$  and  $g''$  (where  $g(x) = e^{-Kx^2}$ ) shows that  $f_t$  and its first and second derivatives are bounded by exponential functions. This in turns justifies the use of relations like  $\int f'' = 0$ .

From now on we assume that  $f$  has the above properties. Next we observe a consequence of the spectral gap inequality satisfied by  $f$ . Recall that for every smooth function  $s$ , we have assumed  $\int fs^2 \leq C \int fs'^2 + (\int fs)^2$ . This makes sense as soon as  $\int fs^2$  and  $\int fs'^2$  are finite. We shall work in  $H^1(f)$ , the Sobolev space with weight  $f$  of locally integrable functions  $s$  for which  $\int fs^2 < \infty$  ( $s \in L_2(f)$ ) and  $\int fs'^2 < \infty$  where  $s'$  is the distributional derivative of  $s$ . This is a Hilbert space, equipped with the norm  $\|s\|_{H^1(f)}^2 = \int fs^2 + \int fs'^2$ . By the density of smooth functions, the Poincaré inequality is valid for  $s \in H^1(f)$ . We point out a useful fact: if  $s$  is smooth and  $s' \in L_2(f)$ , then the assumption on  $f$  ensures that  $s \in L_2(f)$  as well, and that the inequality holds for  $s$ . We give a proof of this. For each  $n \geq 1$  let  $s_n = \xi_n - \int f \xi_n$ , where  $\xi_n(t) = s(t)$  if  $t \in [-n, n]$ ,  $\xi_n(t) = s(n)$  if  $t > n$  and  $\xi_n(t) = s(-n)$  if  $t < -n$ . Clearly  $s_n$  is in  $H^1(f)$ ,  $\int fs_n'^2 \leq \int fs'^2$  and by the spectral gap inequality,  $\int fs_n^2 \leq C \int fs'^2$ . Therefore the sequence  $(s_n)$  is in a ball of  $H^1(f)$ , which is compact for the weak topology. So the on subsequence has a weak limit  $s_\infty$  in  $H^1(f)$ . However by construction, the limit of  $s'_n$  in the  $L_2(f)$  sense is  $s'$ . Thus  $s' = s'_\infty$  in the distributional sense. This implies that  $s$  is equal to  $s_\infty \in H^1(f)$  plus a constant function (also in  $H^1(f)$ ). So  $s \in H^1(f)$  and the Poincaré inequality is valid for  $s$ .

We are now ready to give details of the argument in Section 6. We recall some classical facts from the calculus of variations:

**Proposition 2** *Let  $w$  be a strictly positive smooth function on  $\mathbb{R}$ . Let  $\varphi_0 \in L_2(w)$  be also smooth. For  $\varphi \in H^1(w)$ , let*

$$F(\varphi) = \int w\varphi'^2 + J \int w(\varphi - \varphi_0)^2$$

- 1) *The infimum  $\inf_{\varphi \in H^1(w)} F(\varphi)$  is achieved by a function  $\rho \in H^1(w)$ .*
- 2) *For every function  $\varphi \in H^1(f)$ , one has*

$$\int w\rho'\varphi' + J \int w(\rho - \varphi_0)\varphi = 0.$$

3) The minimum of the functional is equal to

$$F(\rho) = J \int w\varphi_0^2 - J \int w\varphi_0\rho.$$

4) The function  $\rho$  is in  $C^\infty$  and satisfies the Euler-Lagrange equation

$$(-w\rho')' + Jw(\rho - \varphi_0) = 0.$$

**Proof:** Let  $m \geq 0$  be the infimum of the functional and  $(\varphi_n)_{n \geq 1}$  be a minimising sequence with  $F(\varphi_n) \leq m+1/n$ . Clearly  $\int w\varphi_n^2 \leq m+1$  and  $\|\varphi_n\|_{L_2(w)} \leq \|\varphi_0\|_{L_2(w)} + \|\varphi_n - \varphi_0\|_{L_2(w)} \leq \|\varphi_0\|_{L_2(w)} + \sqrt{(m+1)/J}$ . So the sequence is in a bounded subset of  $H^1(w)$ , which is weakly relatively compact. Therefore there is a subsequence with a weak limit  $\rho \in H^1(w)$ . The functional  $F$  is clearly norm-continuous in  $H^1(w)$ . Since it is also convex, it is weakly continuous and  $F(\rho) = m$  is the minimum. To prove the second part of the proposition, one looks at the behaviour around the minimum. For every  $\varphi \in H^1(w)$  and  $t \in \mathbb{R}$ ,  $F(\rho) \leq F(\rho + t\varphi)$ . As  $t \rightarrow 0$  this yields the relation stated in 2). This applied for  $\varphi = \rho$  gives the formula for  $F(\rho)$  given in 3). The relation given in 2) applied for smooth compactly supported functions shows that  $\rho$  satisfies the equation  $(-w\rho')' + Jw(\rho - \varphi_0) = 0$  in the distributional sense. This equation can be rearranged as

$$\rho'' + \frac{w'}{w}\rho' - J\rho = -J\varphi_0.$$

The theory of regularity for uniformly elliptic second order linear equations can be used to show that  $\rho$  is a strong solution (see e.g. [10]). We first apply  $L_p$  regularity theory on open segments  $I$ : the second term in the equation is bounded by continuity so it is in  $L_2(I)$  (with Lebesgue measure). It follows from the theory that  $\rho$  has two derivatives in  $L_2(I')$  for every smaller open interval  $I'$ . In particular  $\rho \in H^1(I')$ , so by the Sobolev injection,  $\rho$  is Hölder continuous. It is therefore locally bounded, and Schauder theory then applies (see [10, Theorem 6.2 page 85]). Thus  $\rho$  is infinitely differentiable, and the Euler-Lagrange equation is satisfied in the strong sense. ■

This proposition applies directly to the minimisation of the quantity (15). It ensures that the minimum is achieved for a smooth  $s$  satisfying equation (14), and is equal to  $A$ . More effort is needed for the quantity

$$T(r) = \frac{1}{2} \int f(r')^2 + \frac{1}{2} \int f\phi''r^2 + \frac{J}{2} \int fr^2 + \int f\phi''r - J \int fr.$$

Our aim is to show that the infimum of  $T$  on, (say) smooth compactly supported functions, is well below zero. For such functions, we may rewrite  $T(r)$  as:

$$T(r) = -J + \frac{1}{2} \int f(r+1)^2 + \frac{1}{2} \int f\phi''(r+1)^2 + \frac{J}{2} \int f(r-1)^2.$$

Integrating by parts as in (11), which is justified for functions that are eventually constant, we get

$$T(r) = -J + \frac{1}{2} \left( \int \frac{1}{f}(f(r+1))^2 + J \int \frac{1}{f}(f(r+1) - 2f)^2 \right).$$

So by the density of functions of the form  $f(r+1)$  we are reduced to the study of the infimum problem

$$\inf_{\varphi \in H^1(1/f)} \int \frac{1}{f}(\varphi')^2 + J \int \frac{1}{f}(\varphi - 2f)^2.$$

By the proposition above, there is a smooth minimiser  $\rho \in H^1(1/f)$ . Let  $r$  be such that  $\rho = f(r+1)$ . The minimum of the functional  $T$  is given in terms of  $\rho$  by statement 3). In terms of  $r$  it is equal to  $-J \int fr$ . Moreover, the Euler-Lagrange equation satisfied by  $\rho$  translates into equation (12) for  $r$ . Now choose the primitive  $\sigma$  of  $r$  for which there is no additional constant in equation (13). We are done if we

can prove that this  $\sigma$  is the function  $s$  obtained as a minimiser and satisfying the same equation. To do so, note that  $\int f\sigma'^2 = \int fr^2 < \infty$ , so by the previous remarks on the Poincaré inequality,  $\sigma \in H^1(f)$ . Finally,  $s$  and  $\sigma$  are two critical points of the same strictly convex functional on  $H^1(f)$ : so they coincide and the argument is complete

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