# INTERPOLATION BETWEEN LOGARITHMIC SOBOLEV AND POINCARÉ INEQUALITIES\*

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**Abstract.** This paper is concerned with intermediate inequalities which interpolate between the logarithmic Sobolev (LSI) and the Poincaré inequalities. Assuming that a given probability measure gives rise to a LSI, we derive *generalized Poincaré inequalities*, improving upon the known constants from the literature. We also analyze the special case when these inequalities are restricted to functions with zero components for the first eigenspaces of the corresponding evolution operator.

**Key words.** functional inequalities, Poincaré inequality, logarithmic Sobolev inequality, spectral gap, hypercontractivity

AMS subject classifications. 39B62, 46E35, 35K10, 60J60, 60F10

#### 1. Introduction

In 1989 W. Beckner [7] derived a family of generalized Poincaré inequalities (GPIs) for the Gaussian measure that yield a sharp interpolation between the classical Poincaré inequality and the logarithmic Sobolev inequality (LSI) of L. Gross [10]. For any  $1 \le p < 2$  these GPIs read

$$\frac{1}{2-p} \left[ \int_{\mathbb{R}^d} f^2 d\mu_0 - \left( \int_{\mathbb{R}^d} |f|^p d\mu_0 \right)^{2/p} \right] \le \int_{\mathbb{R}^d} |\nabla f|^2 d\mu_0 \quad \forall f \in H^1(d\mu_0), \quad (1.1)$$

where  $\mu_0(x)$  denotes the normal-centered Gaussian distribution on  $\mathbb{R}^d$ :

$$\mu_0(x) := (2\pi)^{-d/2} e^{-\frac{1}{2}|x|^2}.$$

For p=1, the GPI (1.1) becomes the Poincaré inequality, and in the limit  $p\to 2$  it yields the LSI. Theorem 2.4(b) improves upon (1.1) for functions f that are in the orthogonal complement of the first eigenspaces of the Ornstein-Uhlenbeck operator  $\mathbf{N} := -\Delta + x \cdot \nabla$ . Moreover, we extend this result to more general measures  $d\nu$ .

Generalizations of (1.1) to other probability measures and the quest for "sharpest" constants in such inequalities have attracted much interest in recent years ([2, 5, 6, 11, 15]). In [3] GPIs have been derived for strictly log-concave distribution functions  $\nu(x)$ :

$$\frac{1}{2-p} \left[ \int_{\mathbb{R}^d} f^2 d\nu - \left( \int_{\mathbb{R}^d} |f|^p d\nu \right)^{2/p} \right] \le \frac{1}{\kappa} \int_{\mathbb{R}^d} |\nabla f|^2 d\nu \quad \forall f \in H^1(d\nu), \tag{1.2}$$

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where  $\kappa$  is the uniform convexity bound of  $-\log \nu(x)$ , i.e.,  $\operatorname{Hess}(-\log \nu(x)) \geq \kappa \ \forall x \in \mathbb{R}^d$ . This Bakry-Emery condition [4] also implies a LSI with constant  $\mathcal{C}_{LS} = \frac{1}{\kappa}$ , i.e.,

$$\frac{1}{2} \int_{\mathbb{R}^d} f^2 \log \left( \frac{f^2}{\int_{\mathbb{R}^d} f^2 d\nu} \right) d\nu \le \mathcal{C}_{LS} \int_{\mathbb{R}^d} |\nabla f|^2 d\nu \quad \forall f \in H^1(d\nu), \tag{1.3}$$

which is a special case  $(p \to 2 \text{ limit})$  of (1.2).

Latała and Oleszkiewicz (see [11]; Lemma 1, Corollary 1) derived such GPIs under the weaker assumption that  $\nu(x)$  satisfies a LSI with constant  $0 < \mathcal{C}_{LS} < \infty$ . Under Assumption (1.3) they proved for 1 that

$$\frac{1}{2-p} \left[ \int_{\mathbb{R}^d} f^2 d\nu - \left( \int_{\mathbb{R}^d} |f|^p d\nu \right)^{2/p} \right] \le \mathcal{C}_{LS} \min \left\{ \frac{2}{p}, \frac{1}{2-p} \right\} \int_{\mathbb{R}^d} |\nabla f|^2 d\nu. \tag{1.4}$$

In the limit  $p \to 2$  one recovers again the LSI (1.3). Since this LSI implies a Poincaré inequality (with constant  $C_{LS}$ ), the second constant in the above min just follows from Hölder's inequality  $(\int_{\mathbb{R}^d} f \, d\nu)^2 \le (\int_{\mathbb{R}^d} |f|^p \, d\nu)^{2/p} = ||f||_{L^p(d\nu)}^2$  (cf. §3 in [2] and [11]). For the special case of even distributions on  $\mathbb{R}$  with  $\nu(x) > 0$  and finite second moment, they also proved that the minimum on the right hand side of (1.4) can be replaced by 1 (cf. Lemma 2 in [11]; its proof is related to our Theorem 2.4(a) below).

Theorem 2.4(a) improves upon the p-dependent constant on the right hand side of (1.4).

While (1.2), (1.4), and Theorem 2.4 deal with linear Beckner-type inequalities, §3 is concerned with nonlinear refinements. Such improvements are interesting for  $1 , as there exist no minimal functions that would make (1.2) an equality. As our third result we shall derive in Theorem 3.1 "refined convex Sobolev inequalities" under the assumption that <math>\nu(x)$  satisfies a LSI. These kinds of inequalities were introduced in [2] under the (more restrictive) Bakry-Emery condition. Our new result in Theorem 3.1 is stronger than Inequality (1.2) in the sense of improving the functional dependance of the left hand side of (1.2) on the term  $||f||_{L^2(d\nu)}/||f||_{L^p(d\nu)}$ .

Apart from improving upon known inequalities, an additional motivation of this work stems from studying the large-time behavior of parabolic PDEs (like in [3]). In this context one is interested in best possible decay estimates for the time-dependent solution to the steady state—seeking best rates, sharp constants, and exact decay functions. So, questions like tensorization or additional information on the concentration properties of the measure are *not* our focus here.

### 2. Generalized Poincaré inequalities

Consider a probability measure on  $\mathbb{R}^d$  with density

$$\nu(x) := e^{-V(x)}$$

with respect to Lebesgue's measure, that gives rise to a LSI (1.3) with a positive constant  $\mathcal{C}_{LS}$ . Here and in the sequel we assume  $V \in W^{2,1}_{loc}(\mathbb{R}^d)$ . The corresponding (positive) operator  $\mathbf{N} := -\Delta + \nabla V \cdot \nabla$  then has the non-degenerate eigenvalue  $\lambda_0 = 0$  and a spectral gap  $\lambda_1 > 0$ . This yields the sharp Poincaré constant  $\mathcal{C}_P := 1/\lambda_1$ , which satisfies

$$C_P \leq C_{LS}$$
.

This is easily recovered by taking  $f = 1 + \varepsilon g$  in (1.3) and letting  $\varepsilon \to 0$ . As a special case, we can for instance consider the case of the Gaussian measure  $\nu = \mu_0$ 

corresponding to  $V(x) = |x|^2/2$  up to an additive constant. In this case the eigenvalues of **N** are  $\lambda_k = k$ . For the subsequent analysis we make the following assumption:

(H) The eigenfunctions of the operator N form a basis of  $L^2(d\nu)$ .

We shall denote its (nonnegative) eigenvalues by  $\lambda_k$ ,  $k \in \mathbb{N}_0$ . Eigenvalues with multiplicity larger than 1 are only counted once.

Remark 2.1. We now give two simple conditions for (H) to hold:

- 1. Let N, defined on  $C_0^{\infty}(\mathbb{R}^d)$ , be essentially self-adjoint on  $L^2(d\nu)$  and implying a LSI. Then it has a pure point spectrum without accumulation points, see Theorem 2.1 of [16]. Since  $\lambda_k \nearrow \infty$ , (H) holds, see Theorem XIII.64 in [14].
- 2. With the following transformation, N can be rewritten as a Schrödinger operator as follows: define  $g := f e^{-V/2}$  so that  $\int_{\mathbb{R}^d} |f|^2 d\nu = \int_{\mathbb{R}^d} |g|^2 dx$  and  $\int_{\mathbb{R}^d} |\nabla f|^2 d\nu = \int_{\mathbb{R}^d} (|\nabla g|^2 + V_1 |g|^2) dx$  with  $V_1 := \frac{1}{4} |\nabla V|^2 \frac{1}{2} \Delta V$ . Assume  $V_1 \in L^1_{loc}(\mathbb{R}^d)$ , bounded from below, and  $\lim_{|x| \to \infty} V_1(x) = \infty$ . Then the eigenfunctions of the operator  $-\Delta + V_1$  form a basis of  $L^2(dx)$  and (H) holds (see Theorem XIII.67 of [14]).

Under the assumptions (H) and that **N** is a closed operator, we now make a spectral decomposition of any function  $f \in H^1(d\nu)$  on the eigenspaces associated to  $\lambda_k$ . With  $f = \sum_{k \in \mathbb{N}_0} f_k$ ,  $a_k := \|f_k\|_{L^2(d\nu)}^2$ , one obtains:

$$||f||_{L^2(d\nu)}^2 = \sum_{k \in \mathbb{N}_0} a_k, \quad ||\nabla f||_{L^2(d\nu)}^2 = \sum_{k \in \mathbb{N}_0} \lambda_k a_k, \quad ||e^{-t\mathbf{N}} f||_{L^2(d\nu)}^2 = \sum_{k \in \mathbb{N}_0} e^{-2\lambda_k t} a_k.$$

With these notations, we can now prove the first preliminary result, which generalizes the one stated in [7] for the Gaussian measure in the case  $k_0 = 1$ .

LEMMA 2.2. Let  $f \in H^1(d\nu)$ . If  $f_k = 0$  for  $1 \le k < k_0$  for some  $k_0 \ge 1$ , then

$$\int_{\mathbb{R}^d} |f|^2 \, d\nu - \int_{\mathbb{R}^d} \left| e^{-t \, N} f \right|^2 \, d\nu \le \frac{1 - e^{-2\lambda_{k_0} \, t}}{\lambda_{k_0}} \int_{\mathbb{R}^d} |\nabla f|^2 \, d\nu.$$

Notice that the (constant) component  $f_0$  of f does not contribute to the inequality.

*Proof.* We use the decomposition on the eigenspaces of **N**. For any  $f_k$ ,  $k \geq k_0$ , we have

$$\int_{\mathbb{R}^d} |f_k|^2 \, d\nu - \int_{\mathbb{R}^d} \left| e^{-t \, \mathbf{N}} \, f_k \right|^2 \, d\nu = \left( 1 - e^{-2 \, \lambda_k \, t} \right) a_k.$$

For any fixed t > 0, the function  $\lambda \mapsto (1 - e^{-2\lambda t})/\lambda$  is monotone decreasing: if  $k \ge k_0$ , then

$$1 - e^{-2\lambda_k t} \le \frac{1 - e^{-2\lambda_{k_0} t}}{\lambda_{k_0}} \lambda_k.$$

Thus we get

$$\int_{\mathbb{R}^d} |f_k|^2 \, d\nu - \int_{\mathbb{R}^d} \left| e^{-t \, \mathbf{N}} \, f_k \right|^2 \, d\nu \le \frac{1 - e^{-2 \, \lambda_{k_0} \, t}}{\lambda_{k_0}} \, \int_{\mathbb{R}^d} |\nabla f_k|^2 \, d\nu,$$

which proves the result by summation.

The second ingredient is Nelson's hypercontractive estimate, see [13]:

LEMMA 2.3. For any  $f \in L^p(d\nu)$ ,  $p \in (1,2)$ ,

$$\|e^{-tN}f\|_{L^2(d\nu)} \le \|f\|_{L^p(d\nu)} \quad \forall \ t \ge -\frac{\mathcal{C}_{LS}}{2} \log(p-1).$$

To make this note self-contained we include a sketch of the proof given in [10]. We set  $F(t) := \left(\int_{\mathbb{R}^d} |u(t)|^{q(t)} d\nu\right)^{1/q(t)}$ , with q(t) to be chosen later, and  $u(x,t) := (e^{-t\mathbf{N}}f)(x)$ . A direct computation gives

$$\frac{F'(t)}{F(t)} = \frac{q'(t)}{q^2(t)} \int_{\mathbb{R}^d} \frac{|u|^q}{F^q} \log\left(\frac{|u|^q}{F^q}\right) d\nu - \frac{4}{F^q} \frac{q-1}{q^2} \int_{\mathbb{R}^d} \left|\nabla\left(|u|^{q/2}\right)\right|^2 d\nu.$$

We set  $v := |u|^{q/2}$ , use the LSI (1.3) and choose q such that  $4(q-1) = 2C_{LS}q'$ , q(0) = p and q(t) = 2. This implies that  $F'(t) \leq 0$ , and the result holds with  $2 = q(t) = 1 + (p-1)e^{2t/C_{LS}}$ .

A combination of Lemmas 2.2 and 2.3 gives the following new result.

THEOREM 2.4. Let  $\nu$  satisfy the LSI (1.3) with the positive constant  $\mathcal{C}_{LS}$  (hence having a Poincaré constant  $0 < \mathcal{C}_P \leq \mathcal{C}_{LS}$ ) and assume (H).

(a) Then

$$\frac{1}{2-p} \left[ \int_{\mathbb{R}^d} f^2 d\nu - \left( \int_{\mathbb{R}^d} |f|^p d\nu \right)^{2/p} \right] \le C(p) \int_{\mathbb{R}^d} |\nabla f|^2 d\nu \qquad \forall f \in H^1(d\nu) \quad (2.1)$$

holds for  $1 \le p < 2$ , with

$$C(p) := \frac{1 - (p-1)^{\alpha}}{(2-p)} \mathcal{C}_P, \quad \alpha := \frac{\mathcal{C}_{LS}}{\mathcal{C}_P} \ge 1.$$
 (2.2)

(b) Moreover, if f satisfies  $f_k = 0$  for  $1 \le k < k_0$  for some  $k_0 \ge 2$ , then the constant in (2.1) improves to

$$C(p) := \frac{1 - (p - 1)^{\alpha}}{\lambda_{k_0} (2 - p)}, \quad \alpha := \lambda_{k_0} C_{LS} \ge \frac{\lambda_2}{\lambda_1} > 1.$$
 (2.3)

Remark 2.5. (On case (a).)

- In part (a) of this theorem, the constant C(p) depends on both C<sub>LS</sub> and C<sub>P</sub>, while the estimate (1.4) (obtained in [11]) only depends on C<sub>LS</sub>. The resulting improvement of our Theorem 2.4(a) compared to(1.4) is illustrated in Figure 2.1: It shows the p-dependent constant C(p)/C<sub>LS</sub> for several values of α.
- 2. If the logarithmic Sobolev constant takes its minimal value C<sub>LS</sub> = C<sub>P</sub> (i.e., α = 1), we have C(p) = C<sub>LS</sub>, for all p ∈ [1,2] which is the optimal constant (consider f = 1 + εg with ε → 0 in (2.1)). However, even for the Gaussian measure, Inequality (2.1) does not admit a non-trivial minimal function for any 1

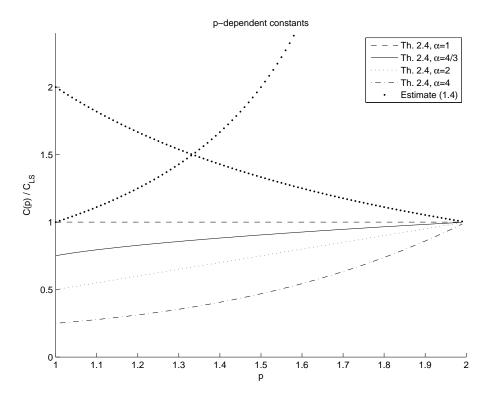


Fig. 2.1. Comparison of the constants in the GPI for the known estimate (1.4) and the new estimates of Theorem 2.4 for various values of  $\alpha$ .

- 3. For fixed  $\alpha \geq 1$ , C(p) takes the sharp limiting values for the Poincaré inequality (p=1) and the LSI (p=2):  $C(1) = \mathcal{C}_P$  and  $\lim_{p\to 2} C(p) = \mathcal{C}_{LS}$  (this also holds for (2.3)).
- 4. For  $\alpha > 1$ , C(p) is monotone increasing in p since it is a difference quotient of the convex function  $p \mapsto (p-1)^{\alpha}$ . Hence,  $C(p) < \mathcal{C}_{LS}$  for p < 2 and  $\alpha > 1$ , and Theorem 2.4 strictly improves upon the constants of estimate (1.4).
- 5. The best constant, c(p), on the right hand side of (2.1) satisfies  $C_P \leq c(p) \leq C(p)$ , for any  $p \in (1,2)$  (consider again  $f = 1 + \varepsilon g$ ,  $\varepsilon \to 0$ ).
- 6. Finally, Inequality (2.1) with (2.2) also gives the correct estimate for a distribution  $\nu$  that only satisfies a Poincaré inequality (with constant  $C_P$ ) but no LSI, which formally corresponds to  $\alpha \to \infty$ : for fixed p we have from (2.2)

$$\lim_{\alpha \to \infty} C(p) = \frac{\mathcal{C}_P}{(2-p)},$$

which corresponds to the second constant in the min of inequality (1.4) (cf. also Theorem 4 in [2] and §2.2 in [9]).

REMARK 2.6. (On case (b).) Even in the Gaussian case  $\nu = \mu_0$ , Theorem 2.4(b) improves on Beckner's result for any  $k_0 \geq 2$ .

Example 2.7.

- 1.  $C_{LS} = C_P$  clearly holds for the Gaussian distribution  $\mu_0$ .
- 2. An example for  $C_{LS} > C_P$  is obtained by the distribution  $\nu(x) := c_{\varepsilon} \exp(-|x| \varepsilon x^2)$ ,  $x \in \mathbb{R}$  with  $\varepsilon \to 0$ , which was kindly suggested to us by Michel Ledoux. While  $C_P$  is bounded for  $\varepsilon \in [0,1]$ ,  $C_{LS}$  blows up like  $\mathcal{O}(1/\varepsilon)$ , which can be estimated with Theorem 1.1 of [8] (also see [6] for a simplified approach and §3 of [12] for a review of applications in geometry).

# 3. A refined interpolation inequality

While (1.2) is a linear inequality between the p-entropy (or p-variance) on the left hand side and the energy on the right hand side, we shall now derive nonlinear improvements of it. An inequality stronger than (1.2) has been shown by the first and the third author in [2]. Under the Bakry-Emery condition on the measure  $d\nu$ , they proved that for all  $p \in [1,2)$ :

$$\frac{1}{(2-p)^2} \left[ \int_{\mathbb{R}^d} f^2 \, d\nu - \left( \int_{\mathbb{R}^d} |f|^p \, d\nu \right)^{2\left(\frac{2}{p}-1\right)} \left( \int_{\mathbb{R}^d} f^2 \, d\nu \right)^{p-1} \right] \le \frac{1}{\kappa} \int_{\mathbb{R}^d} |\nabla f|^2 \, d\nu \tag{3.1}$$

for any  $f \in H^1(d\nu)$ , where  $\kappa$  is the uniform convexity bound of  $-\log \nu(x)$ . The estimate (1.2) is a consequence of this inequality (and hence weaker). This can be shown using Hölder's inequality,  $\left(\int_{\mathbb{R}^d} |f|^p d\nu\right)^{2/p} \leq \int_{\mathbb{R}^d} f^2 d\nu$  and the inequality  $\left(1-t^{2-p}\right)/(2-p) \geq 1-t$  for any  $t \in [0,1]$ ,  $p \in (1,2)$ . With the same notations as in Section 2, we can prove the following new result:

THEOREM 3.1. Let  $\nu$  satisfy the LSI (1.3) with the positive constant  $C_{LS}$  and assume (H). If  $f \in H^1(d\nu)$  is such that  $f_k = 0$  for  $1 \le k < k_0$  for some  $k_0 \ge 1$ , then

$$\lambda_{k_0} \max \left\{ \frac{\|f\|_{L^2(d\nu)}^2 - \|f\|_{L^p(d\nu)}^2}{1 - (p - 1)^{\alpha}}, \frac{\|f\|_{L^2(d\nu)}^2}{|\log(p - 1)^{\alpha}|} \log \left( \frac{\|f\|_{L^2(d\nu)}^2}{\|f\|_{L^p(d\nu)}^2} \right) \right\} \le \|\nabla f\|_{L^2(d\nu)}^2$$
(3.2)

holds for  $1 \leq p < 2$ , with  $\alpha := \lambda_{k_0} C_{LS} \geq 1$ .

*Proof.* We shall proceed in two steps and derive first for all  $\gamma \in (0, 2)$  the following inequality, which is inspired by (3.1):

$$\frac{1}{(2-p)^2} \left[ \int_{\mathbb{R}^d} f^2 \, d\nu - \left( \int_{\mathbb{R}^d} |f|^p \, d\nu \right)^{\frac{\gamma}{p}} \left( \int_{\mathbb{R}^d} f^2 \, d\nu \right)^{\frac{2-\gamma}{2}} \right] \le K_p(\gamma) \int_{\mathbb{R}^d} |\nabla f|^2 \, d\nu, \tag{3.3}$$

with

$$K_p(\gamma) := \frac{1 - (p-1)^{\alpha \gamma/2}}{\lambda_{k_0} (2-p)^2}.$$

**Step 1:** The computations are analogous to the ones of Theorem 2.4. With the same notations as above, the squared bracket of (3.3) can be bounded from above by

$$\mathcal{N} := \|f\|_{L^{2}(d\nu)}^{2} - \|e^{-t\mathbf{N}}f\|_{L^{2}(d\nu)}^{\gamma} \|f\|_{L^{2}(d\nu)}^{2-\gamma}$$

$$= a_{0} + \sum_{k \geq k_{0}} a_{k} - \left(a_{0} + \sum_{k \geq k_{0}} a_{k} e^{-2\lambda_{k}t}\right)^{\frac{\gamma}{2}} \left(a_{0} + \sum_{k \geq k_{0}} a_{k}\right)^{\frac{2-\gamma}{2}}$$

for any  $t \ge -\frac{\mathcal{C}_{LS}}{2} \log(p-1)$  as in Lemma 2.3. By Hölder's inequality, we get

$$a_0 + \sum_{k \ge k_0} a_k e^{-\gamma \lambda_k t} = a_0 + \sum_{k \ge k_0} \left( a_k e^{-2\lambda_k t} \right)^{\frac{\gamma}{2}} \cdot a_k^{\frac{2-\gamma}{2}}$$

$$\le \left( a_0 + \sum_{k \ge k_0} a_k e^{-2\lambda_k t} \right)^{\frac{\gamma}{2}} \left( a_0 + \sum_{k \ge k_0} a_k \right)^{\frac{2-\gamma}{2}}.$$

Then

$$\mathcal{N} \le \sum_{k > k_0} a_k \left( 1 - e^{-\gamma \lambda_k t} \right)$$

can be bounded as in the proof of Theorem 2.4:

$$\mathcal{N} \le \frac{1 - e^{-\gamma \lambda_{k_0} t}}{\lambda_{k_0}} \sum_{k \ge k_0} \lambda_k \, a_k = \frac{1 - e^{-\gamma \lambda_{k_0} t}}{\lambda_{k_0}} \int_{\mathbb{R}^d} |\nabla f|^2 \, d\nu,$$

using the decay of  $\lambda \mapsto (1 - e^{-\gamma \lambda t})/\lambda$ . The result then holds with

$$e^{-\gamma \lambda_{k_0} t} = (p-1)^{\gamma \lambda_{k_0} C_{LS}/2}$$

**Step 2:** Next we shall optimize Inequality (3.3) w.r.t.  $\gamma \in (0, 2)$ . After dividing the left hand side of (3.3) by  $K_p(\gamma)$ , we have to find the maximum of the function

$$\gamma \mapsto h(\gamma) := \frac{1 - a^{\gamma}}{1 - b^{\gamma}}, \quad \text{with} \quad a = \frac{\|f\|_{L^{p}(d\nu)}}{\|f\|_{L^{2}(d\nu)}} \le 1, \quad b = (p - 1)^{\alpha/2} \le 1$$

on  $\gamma \in [0,2]$ . We write  $h(\gamma) = g(b^{\gamma})$  with

$$g(y) := \frac{1 - y^{\frac{\log a}{\log b}}}{1 - y}.$$

For a < b < 1 the function g(y) is monotone increasing (since it is a difference quotient of the convex function  $y^{\log a/\log b}$ ). Hence,  $h(\gamma)$  is monotone decreasing. Analogously, h is monotone increasing for b < a < 1. Hence, the maximum of the function  $h(\gamma)$  on [0,2] is either h(2) (if a > b) or  $\lim_{\gamma \to 0} h(\gamma)$  (in the case a < b). This yields the two terms in the max of (3.2).

## Remark 3.2.

- 1. The limiting cases of (3.2) are the sharp Poincaré inequality  $(p \to 1, for k_0 = 1)$  and the LSI  $(p \to 2)$ .
- 2. Note that the first term in the max of (3.2) exactly corresponds to the linear inequality (2.1). Hence, the statement of Theorem 3.1 is always at least as strong as Theorem 2.4. The second term in this max is dominant iff

$$\frac{\|f\|_{L^p(d\nu)}}{\|f\|_{L^2(d\nu)}} < (p-1)^{\alpha/2},$$

as is seen from the above proof. In this case Inequality (3.2) strictly improves upon (2.1).

3. For the special case when  $\alpha = 1$  and  $k_0 = 1$ , we now compare the new theorem, Theorem 3.1, to the known inequality (3.1). Since the latter was obtained in [2] under the more restrictive Bakry-Emery condition, we assume here  $C_P = C_{LS} = 1/\kappa$ , which makes this comparison very conservative. For  $||f||_{L^p(d\nu)}/||f||_{L^2(d\nu)}$  "large" (i.e., a > b), (3.2) coincides with the linear inequality (1.2), and (3.1) is strictly stronger. On the other hand, for "small"  $||f||_{L^p(d\nu)}/||f||_{L^2(d\nu)}$ , the new estimate (3.2) is stronger than (3.1).

GPI: nonlinear refinements, p=1.5

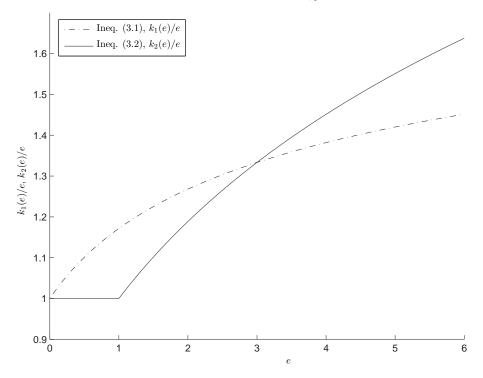


Fig. 3.1. Comparison of the nonlinear refinements of the GPI (1.2) for  $\alpha=1$  and p=1.5: The estimate (3.1) is known from [2] and estimate (3.2) is new.

In Figure 3.1 we illustrate this comparison (still in the case  $\alpha = 1$  and  $C_{LS} = 1/\kappa$ ) between the inequalities (1.2), (3.1), and (3.2). To this end we rewrite them in terms of the non-negative functionals

$$\mathbf{e}_p[f] := \frac{\|f\|_{L^2(d\nu)}^2}{\|f\|_{L^p(d\nu)}^2} - 1, \qquad I_p[f] := \frac{2(2-p)}{\|f\|_{L^p(d\nu)}^2} \|\nabla f\|_{L^2(d\nu)}^2.$$

Note that  $e_p[f]$  is a scaled version of the p-entropy on the left hand side of (1.2). The GPI (1.2) is then the following linear lower bound for  $I_p[f]$ :

$$e_p[f] \le \frac{1}{2\kappa} I_p[f],$$

while (3.1) and (3.2) are the nonlinear refinements:

$$k_1(e_p[f]) \le \frac{1}{2\kappa} I_p[f], \quad k_1(e) := \frac{1}{2-p} [e+1-(e+1)^{p-1}] \ge e,$$

and, respectively,

$$k_2(\mathbf{e}_p[f]) \le \frac{1}{2\kappa} I_p[f], \quad k_2(e) := \max \left\{ e, \, \frac{2-p}{|\log(p-1)|} \, (e+1) \log(e+1) \right\} \ge e.$$

We remark that for the logarithmic entropy similar nonlinear estimates are discussed in  $\S\S1.3, 4.3$  of [12].

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