

## Some New Information Inequalities Involving $f$ -Divergences

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**Abstract:** *New information inequalities involving  $f$ -divergences have been established using the convexity arguments and some well known inequalities such as the Jensen inequality and the Arithmetic-Geometric Mean (AGM) inequality. Some particular cases have also been discussed.*

**Keywords:**  *$f$ -divergence, convexity, parameterization, arithmetic mean, geometric mean.*

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### 1. The concept of $f$ -divergences

Let  $\mathbb{F}$  be the set of convex functions  $f: [0, \infty) \rightarrow (-\infty, \infty)$  which are finite on  $(0, \infty)$  and continuous at point 0 ( $f(0) = \lim_{u \downarrow 0} f(u)$ ),  $\mathbb{F}_0 = \{f \in \mathbb{F}: f(1) = 0\}$ . Further if  $f \in \mathbb{F}$ , then  $f^*$  is defined by

$$f^*(u) = \begin{cases} u f\left(\frac{1}{u}\right) & \text{for } u \in (0, \infty), \\ \lim_{v \rightarrow \infty} \frac{f(v)}{v} & \text{for } u = 0, \end{cases}$$

is also in  $\mathbb{F}$  and is called the  $*$ -conjugate (convex) function of  $f$ .

**Definition 1.1.** Let

$$(1.1) \quad \Delta_n = \{(p_1, p_2, \dots, p_n): p_i \geq 0, i = 1, 2, \dots, n, \sum_{i=1}^n p_i = 1\}, n = 2, 3, \dots$$

denote the set of all finite discrete ( $n$ -ray) complete probability distributions. For a convex function  $f \in \mathbb{F}$ , the  $f$ -divergence of the probability distributions  $P$  and  $Q$  is given by

$$(1.2) \quad I_f(P, Q) = \sum_{i=1}^n q_i f\left(\frac{p_i}{q_i}\right)$$

where  $P = (p_1, p_2, \dots, p_n) \in \Delta_n$  and  $Q = (q_1, q_2, \dots, q_n) \in \Delta_n$ . In  $\Delta_n$ , we have taken all  $p_i > 0$ . If we take all  $p_i \geq 0$  for  $i = 1, 2, \dots, n$  then we have to suppose that  $0 \ln 0 = 0 \ln\left(\frac{0}{0}\right) = 0$ . It is generally common to take logarithms with base of 2, but here we have taken only natural logarithms.

These divergences were introduced and studied independently by Csizsár [5, 6] and Ali and Silvey [1] and are sometimes known as Csizsár *f-divergences* or Ali-Silvey distances. The *f-divergence* given by (1.1) is a versatile functional form, which with a suitable choice of the function involved, leads to some well known divergence measures. Some examples as  $f(u) = u \ln u$  ( $f^*(u) = -\ln u$ ) provide the Kullback-Leibler's measure [13],  $f(u) = |u - 1|$  ( $f^*(u) = |u - 1|$ ) results in the variational distance [12],  $f(u) = (u - 1)^2$  ( $f^*(u) = \frac{(u-1)^2}{u}$ ) yields the  $\chi^2$  divergence [15] and many more. These measures have been applied in a variety of fields, such as economics and political science [18, 19], biology [16], the analysis of contingency tables [7], approximation of probability distributions [4, 11], signal processing [9, 10] and pattern recognition [2, 3, 8]. The *f-divergence* satisfies a large number of properties which are important from an information theoretic point of view. Österreicher [14] has discussed the basic general properties of *f-divergences* including their axiomatic properties and some important classes.

The *f-divergence* defined by (1.2) is generally asymmetric in  $P$  and  $Q$ . Nevertheless, the convexity of  $f(u)$  implies that of

$$f^*(u) = u f\left(\frac{1}{u}\right)$$

and with this function we have

$$I_f(P, Q) = I_{f^*}(P, Q).$$

Hence, it follows, in particular, that the symmetrised *f-divergence*

$$I_f(P, Q) + I_f(Q, P)$$

is again an *f-divergence*, with respect to the convex function  $f(u) + f^*(u)$ .

In the present work, we have established new information inequalities involving *f-divergences* using the convexity arguments and some well known inequalities, such as the Jensen inequality and the Arithmetic-Geometric Mean (AGM) inequality. Further we have used these inequalities in establishing relationships among some well-known divergence measures. Without essential loss of insight, we restrict ourselves to discrete probability distributions and note that the extension to the general case relies strongly on the Lebesgue–Radon–Nikodym Theorem.

## 2. Information inequalities

**Result 2.1.** If  $\varphi: (0, \infty) \rightarrow \mathbb{R}$  is convex, then the function

$$\psi_1(u, v) = v\varphi\left(\frac{u+v}{2v}\right)$$

of two variables is convex on the domain  $(u, v) \in (0, \infty)^2$ .

*Proof.* Consider  $\lambda \in (0, 1)$  and two points  $x_i = (u_i, v_i)$  from the domain of the function  $\varphi$ . For

$$w = \frac{\lambda v_1}{\lambda v_1 + (1 - \lambda)v_2} \quad \text{and} \quad t_i = \frac{u_i + v_i}{2v_i}$$

we get  $\varphi(wt_1 + (1 - w)t_2) \leq w\varphi(t_1) + (1 - w)\varphi(t_2)$ , so that

$$\begin{aligned} & (\lambda v_1 + (1 - \lambda)v_2)\varphi\left(\frac{\lambda u_1 + (1 - \lambda)u_2 + \lambda v_1 + (1 - \lambda)v_2}{2(\lambda v_1 + (1 - \lambda)v_2)}\right) \leq \\ & \leq \lambda v_1\varphi\left(\frac{u_1 + v_1}{2v_1}\right) + (1 - \lambda)v_2\varphi\left(\frac{u_2 + v_2}{2v_2}\right) \end{aligned}$$

or, equivalently  $\psi(\lambda x_1 + (1 - \lambda)x_2) \leq \lambda\psi(x_1) + (1 - \lambda)\psi(x_2)$  which completes the proof.

**Result 2.2.** If  $\varphi: (0, \infty) \rightarrow \mathbb{R}$  is convex then the function

$$\psi_n(u, v) = v\varphi\left(\frac{u+nv}{(n+1)v}\right), n > 0,$$

of two variables is convex on the domain  $(u, v) \in (0, \infty)^2$ .

*Proof.* The proof follows on similar lines as in the previous result except the choice of  $t_i$  which can be taken as

$$t_i = \frac{u_i + nv_i}{(n + 1)v_i}, \quad n > 0.$$

We, therefore have the following divergence functionals of *f-divergence* type:

$$(2.1) \quad I_{f(n)}(P, Q) = \sum_{i=1}^n q_i f\left(\frac{p_i + nq_i}{(1+n)q_i}\right)$$

where  $P = (p_1, p_2, \dots, p_n) \in \Delta_n$  and  $Q = (q_1, q_2, \dots, q_n) \in \Delta_n$ . For  $n = 0$ , the function (2.1) is reduced to the Csiszár *f-divergence* given by (1.2). Replacing  $n$  by  $1/n$  in (2.1), we obtain

$$(2.2) \quad I_{f\left(\frac{1}{n}\right)}(P, Q) = \sum_{i=1}^n q_i f\left(\frac{np_i + q_i}{(1+n)q_i}\right).$$

**Relationship with Csiszár *f-divergence* follow.**

**Result 2.3.** Let  $f: I \subseteq [0, \infty) \rightarrow \mathbb{R}$  be a differentiable convex function on the interval  $I$ ,  $x_i \in \tilde{I}$  ( $\tilde{I}$  is interior of  $I$ ). Further we assume that  $f(1) = 0$ . Then for all  $P, Q \in \Delta_n$  we have

$$(2.3) \quad I_{f(2n+1)}(P, Q) \leq \frac{1}{2} I_{f(n)}(P, Q),$$

$$(2.4) \quad I_{f\left(\frac{1}{2n+1}\right)}(P, Q) \leq \frac{1}{2} \left( I_{f\left(\frac{1}{n}\right)}(P, Q) + I_f(P, Q) \right)$$

where  $I_f(P, Q)$  and  $I_{f(n)}(P, Q)$  are measures given by (1.2) and (2.1) respectively. The equality holds in the above inequalities if  $p_i = q_i$  for each  $i$ .

*Proof.* Let  $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_n) \in \Delta_n$ . Then it is well known that

$$(2.5) \quad f\left(\sum_{i=1}^n \lambda_i x_i\right) \leq \sum_{i=1}^n \lambda_i f(x_i).$$

If  $f$  is strictly convex, then the equality holds if and only if all  $x_1 = x_2 = \dots = x_n$ .

The above inequality is famous as *Jensen inequality*. If  $f$  is a concave function, then the inequality sign will change. If we assume  $\lambda_1 = \lambda_2 = \frac{1}{2}$  with all other  $\lambda_i$ 's zero, then we obtain

$$(2.6) \quad f\left(\frac{x_1+x_2}{2}\right) \leq \frac{1}{2}[f(x_1) + f(x_2)].$$

Choosing  $x_1 = x$  and  $x_2 = 1$ , we obtain

$$(2.7) \quad f\left(\frac{x+1}{2}\right) \leq \frac{1}{2}[f(x)] \text{ since } f(1) = 0.$$

Substituting  $x = \frac{p_i}{q_i}$  in the above inequality, multiplying by  $q_i$  and then summing over all  $i$ , we obtain

$$(2.8) \quad 2 I_{f(1)}(P, Q) \leq I_f(P, Q).$$

A choice of  $x_1 = \frac{x+1}{2}$  and  $x_2 = 1$  will give  $2I_{f(3)}(P, Q) \leq I_{f(1)}(P, Q)$ .

A choice of  $x_1 = \frac{x+3}{4}$  and  $x_2 = 1$  will give  $2I_{f(7)}(P, Q) \leq I_{f(3)}(P, Q)$ .

Finally a choice of  $x_1 = \frac{x+n}{n+1}$  and  $x_2 = 1$  will yield (2.3).

Combining the above choices of  $x_1$  and  $x_2$ , we obtain

$$2^{n+1} I_{f(2^{n+1}-1)}(P, Q) \leq 2^n I_{f(2^n-1)}(P, Q) \leq \dots \leq 16 I_{f(15)}(P, Q) \leq 8 I_{f(7)}(P, Q) \leq 4 I_{f(3)}(P, Q) \leq 2 I_{f(1)}(P, Q) \leq I_f(P, Q).$$

Also a choice of  $x_1 = \frac{x+\frac{1}{n}}{\frac{1}{n}+1}$  and  $x_2 = x$  will yield (2.4). The inequalities given by (2.3) and (2.4) can be used in establishing relationship among some well known divergence measures. For example, if  $f(u) = -\ln u$  and  $n = 0$  in (2.3), we obtain

$$\sum_{i=1}^n q_i \ln\left(\frac{2q_i}{p_i + q_i}\right) \leq \frac{1}{2} \sum_{i=1}^n q_i \ln\left(\frac{q_i}{p_i}\right), \text{ which gives } F(Q, P) \leq \frac{1}{2} K(Q, P).$$

Here  $F(P, Q)$  and  $K(P, Q)$  denote the Relative Jensen-Shannon divergence measure [17] and the Kullback–Leibler divergence measure [13] respectively.

### 3. Parameterization of $f$ -divergences

Let us consider the set of all those divergence measures for which the associated convex functions  $f$  satisfy the functional equation

$$(3.1) \quad f(u) = u f\left(\frac{1}{u}\right)$$

and for which  $f(1) = 0$  (i. e.,  $f \in \mathbb{F}_0$ ). Now for any such solution  $f$ , set

$$(3.2) \quad g(u) = \frac{u^{1/2}}{(u-1)^2} f(u) \text{ for } u > 1 \text{ and} \\ \varphi(t) = g\left(\left(t + \sqrt{t^2 + 1}\right)^2\right) \text{ for } t > 1$$

(and define  $\varphi(1)$  arbitrarily). One can easily check that

$$\varphi\left(\frac{u+1}{2u^{1/2}}\right) = g\left(\max\left\{u, \frac{1}{u}\right\}\right)$$

therefore, if  $u > 1$ ,

$$f(u) = \frac{(u-1)^2}{u^{1/2}} g(u) = \frac{(u-1)^2}{u^{1/2}} g\left(\max\left\{u, \frac{1}{u}\right\}\right) = \frac{(u-1)^2}{u^{1/2}} \varphi\left(\frac{u+1}{2u^{1/2}}\right)$$

and, if  $u < 1$ ,

$$\begin{aligned} f(u) &= u f\left(\frac{1}{u}\right) = \frac{(u-1)^2}{u^{1/2}} g(u) = \frac{(u-1)^2}{u^{1/2}} g\left(\max\left\{u, \frac{1}{u}\right\}\right) \\ &= \frac{(u-1)^2}{u^{1/2}} \varphi\left(\frac{u+1}{2u^{1/2}}\right). \end{aligned}$$

Thus (3.1) holds (obviously, also for  $u = 0$ ) for the function  $\varphi(\cdot)$  defined by (3.2). Therefore, it is very much clear that every solution of (3.1) satisfying  $f(1) = 0$  can be written in the form

$$f(u) = \frac{(u-1)^2}{u^{1/2}} \varphi\left(\frac{u+1}{2u^{1/2}}\right)$$

for a suitable  $\varphi(\cdot)$ .

We, therefore consider the following symmetric divergence functional

$$(3.3) \quad I_{f(\varphi)}(P, Q) = \sum_{i=1}^n \frac{(p_i - q_i)^2}{(p_i q_i)^{1/2}} f\left(\frac{p_i + q_i}{2(p_i q_i)^{1/2}}\right).$$

It should be noted that (3.3) represents a parameterization of the set of all such divergence measures which satisfy (3.1). But here the function  $\varphi(\cdot)$  can be both convex and concave. Table 1 shows various choices of  $\varphi(\cdot)$  and the corresponding divergence functionals.

Table 1. New symmetric divergence measures

S. No	$\varphi(u)$	$f(u)$	$I_{f(\varphi)}(P, Q)$
1.	$\varphi(u) = k$ (a positive constant)	$k \frac{(u-1)^2}{u^{1/2}}$	$k \sum_{i=1}^n \frac{(p_i - q_i)^2}{(p_i q_i)^{1/2}} = E_k^*(P, Q)$
2.	$\varphi(u) = u^k$ , $k = 1, 2, 3, \dots$	$\frac{(u-1)^2}{u^{1/2}} \left(\frac{u+1}{2u^{1/2}}\right)^k$ , $k = 1, 2, 3, \dots$	$\sum_{i=1}^n \frac{(p_i - q_i)^2}{(p_i q_i)^{1/2}} \left(\frac{p_i + q_i}{2(p_i q_i)^{1/2}}\right)^k = L_k^*(P, Q)$ , $k = 1, 2, 3, \dots$
3.	$\varphi(u) = u^k \ln u$ , $k = 1, 2, 3, \dots$	$\frac{(u-1)^2}{u^{1/2}} \left(\frac{u+1}{2u^{1/2}}\right)^k \ln\left(\frac{u+1}{2u^{1/2}}\right)$ , $k = 1, 2, 3, \dots$	$\sum_{i=1}^n \frac{(p_i - q_i)^2}{(p_i q_i)^{1/2}} \left(\frac{p_i + q_i}{2(p_i q_i)^{1/2}}\right)^k \ln\left(\frac{p_i + q_i}{2(p_i q_i)^{1/2}}\right) =$ $= M_k^*(P, Q)$ , $k = 1, 2, 3, \dots$
4.	$\varphi(u) = \ln u$	$\frac{(u-1)^2}{u^{1/2}} \ln\left(\frac{u+1}{2u^{1/2}}\right)$	$\sum_{i=1}^n \frac{(p_i - q_i)^2}{(p_i q_i)^{1/2}} \ln\left(\frac{p_i + q_i}{2(p_i q_i)^{1/2}}\right) = G(P, Q)$
5.	$\varphi(u) = u^k - 1$ , $k = 1, 2, 3, \dots$	$\frac{(u-1)^2}{u^{1/2}} \left(\left(\frac{u+1}{2u^{1/2}}\right)^k - 1\right)$ , $k = 1, 2, 3, \dots$	$\sum_{i=1}^n \frac{(p_i - q_i)^2}{(p_i q_i)^{1/2}} \left(\left(\frac{p_i + q_i}{2(p_i q_i)^{1/2}}\right)^k - 1\right) = N_k^*(P, Q)$ , $k = 1, 2, 3, \dots$

**Result 3.1.** Consider the measures  $E_1^*(P, Q)$ ,  $L_k^*(P, Q)$ ,  $G(P, Q)$  and  $M_k^*(P, Q)$  as defined in Table 1. Then the following inequalities measures hold

$$(3.4) \quad E_1^*(P, Q) \leq L_1^*(P, Q) \leq L_2^*(P, Q) \leq L_3^*(P, Q) \leq L_4^*(P, Q) \leq \dots$$

and

$$(3.5) \quad G(P, Q) \leq M_1^*(P, Q) \leq M_2^*(P, Q) \leq M_3^*(P, Q) \leq M_4^*(P, Q) \leq \dots$$

The equality holds in the above inequalities if  $p_i = q_i$  for each  $i$ .

*P r o o f.* To start with, let us consider the arithmetic-geometric mean inequality given by

$$\frac{u+1}{2u^{1/2}} \geq 1 \text{ for all } u > 0.$$

The equality holds for  $u = 1$ . In general we have

$$1 \leq \frac{u+1}{2u^{1/2}} \leq \left(\frac{u+1}{2u^{1/2}}\right)^2 \leq \left(\frac{u+1}{2u^{1/2}}\right)^3 \leq \left(\frac{u+1}{2u^{1/2}}\right)^4 \leq \dots$$

which is equivalent to

$$(3.6) \quad \begin{aligned} \frac{(u-1)^2}{u^{1/2}} &\leq \frac{(u-1)^2}{u^{1/2}} \left(\frac{u+1}{2u^{1/2}}\right) \leq \frac{(u-1)^2}{u^{1/2}} \left(\frac{u+1}{2u^{1/2}}\right)^2 \leq \\ &\leq \frac{(u-1)^2}{u^{1/2}} \left(\frac{u+1}{2u^{1/2}}\right)^3 \leq \frac{(u-1)^2}{u^{1/2}} \left(\frac{u+1}{2u^{1/2}}\right)^4 \leq \dots \end{aligned}$$

Substituting  $u = \frac{p_i}{q_i}$  in the above inequality, multiplying by  $q_i$  and then summing over all  $i$ , we obtain (3.4).

Again from (3.6), we have

$$\begin{aligned} \frac{(u-1)^2}{u^{1/2}} \ln \left(\frac{u+1}{2u^{1/2}}\right) &\leq \frac{(u-1)^2}{u^{1/2}} \left(\frac{u+1}{2u^{1/2}}\right) \ln \left(\frac{u+1}{2u^{1/2}}\right) \leq \\ &\leq \frac{(u-1)^2}{u^{1/2}} \left(\frac{u+1}{2u^{1/2}}\right)^2 \ln \left(\frac{u+1}{2u^{1/2}}\right) \leq \\ &\leq \frac{(u-1)^2}{u^{1/2}} \left(\frac{u+1}{2u^{1/2}}\right)^3 \ln \left(\frac{u+1}{2u^{1/2}}\right) \leq \\ &\leq \frac{(u-1)^2}{u^{1/2}} \left(\frac{u+1}{2u^{1/2}}\right)^4 \ln \left(\frac{u+1}{2u^{1/2}}\right) \leq \dots \end{aligned}$$

Substituting  $u = \frac{p_i}{q_i}$  in the above inequality, multiplying by  $q_i$  and then summing over all  $i$ , we obtain (3.5). It is interesting to note that

$$L_1^*(P, Q) = \frac{1}{2} \psi(P, Q) = \frac{1}{2} \{\chi^2(P, Q) + \chi^2(Q, P)\}$$

where  $\chi^2(P, Q)$  is the well known  $\chi^2$  divergence [15]

**Result 3.2.** Consider a differentiable function  $\varphi(\cdot): (0, \infty) \rightarrow \mathbb{R}$  as defined in (3.3). Then the following inequalities hold

$$(3.7) \quad \begin{aligned} \varphi'(1)N_1^*(P, Q) &\leq I_{f(\varphi)}(P, Q) - \varphi(1)E_1^*(P, Q) \leq \\ &\leq \sum_{i=1}^n \frac{(p_i^{1/2} - q_i^{1/2})^2 (p_i - q_i)^2}{2(p_i q_i)} \varphi' \left(\frac{p_i + q_i}{2(p_i q_i)^{1/2}}\right) \end{aligned}$$

if  $\varphi(\cdot)$  is convex, and

$$(3.8) \quad \begin{aligned} \sum_{i=1}^n \frac{(p_i^{1/2} - q_i^{1/2})^2 (p_i - q_i)^2}{2(p_i q_i)} \varphi' \left(\frac{p_i + q_i}{2(p_i q_i)^{1/2}}\right) &\leq \\ &\leq I_{f(\varphi)}(P, Q) - \varphi(1)E_1^*(P, Q) \leq \varphi'(1)N_1^*(P, Q) \end{aligned}$$

if  $\varphi(\cdot)$  is concave.

*Proof.* First we assume that the function  $\varphi(\cdot): (0, \infty) \rightarrow \mathbb{R}$  is differentiable and convex, then we have the following inequality

$$(3.9) \quad \varphi'(x)(y-x) \leq \varphi(y) - \varphi(x) \leq \varphi'(y)(y-x) \text{ for } x, y \in \mathbb{R}.$$

Replacing  $y$  by  $\frac{p_i + q_i}{2(p_i q_i)^{1/2}}$  and  $x$  by 1 in the above inequality, we obtain

$$\begin{aligned} \varphi'(1) \left( \frac{p_i + q_i}{2(p_i q_i)^{1/2}} - 1 \right) &\leq \varphi \left( \frac{p_i + q_i}{2(p_i q_i)^{1/2}} \right) - \varphi(1) \leq \\ &\leq \varphi' \left( \frac{p_i + q_i}{2(p_i q_i)^{1/2}} \right) \left( \frac{p_i + q_i}{2(p_i q_i)^{1/2}} - 1 \right). \end{aligned}$$

Multiplying both sides by and summing over all  $I$  in the above inequality, we obtain (3.7).

In addition, if we have  $\varphi(1) = \varphi'(1) = 0$ , then from (3.7), we have

$$(3.10) \quad 0 \leq I_{f(\varphi)}(P, Q) \leq \sum_{i=1}^n \frac{(p_i^{1/2} - q_i^{1/2})^2 (p_i - q_i)^2}{2(p_i q_i)} \varphi' \left( \frac{p_i + q_i}{2(p_i q_i)^{1/2}} \right).$$

Again if we assume that the function  $\varphi(\cdot): (0, \infty) \rightarrow \mathbb{R}$  to be differentiable and concave, then the inequality given by (3.9) gets reversed and as such the proof of (3.8) follows on similar lines as above.

**Remark.** The measure  $E_1^*(P, Q)$  offers the following extension:

$$I_{f(\alpha)}(P, Q) = \sum_{i=1}^n \frac{|p_i - q_i|^{\alpha+1}}{(p_i q_i)^{\alpha/2}}, \alpha \in (0, \infty),$$

which includes the variation norm for  $\alpha = 1$ . Note that

$$f_\alpha(0) = \begin{cases} 1 & \alpha = 1 \\ \infty & \alpha \in (0, \infty) \end{cases}.$$

By virtue of arithmetic-geometric mean inequality, we have

$$\frac{2}{(u+1)^\alpha} \leq \frac{1}{u^{\alpha/2}} \text{ for all } u > 0, \alpha \in (0, \infty)$$

which is equivalent to

$$\frac{|u-1|^{\alpha+1}}{(u+1)^\alpha} \leq \frac{|u-1|^{\alpha+1}}{u^{\alpha/2}} \text{ for all } u > 0, \alpha \in (0, \infty).$$

Substituting  $u = \frac{p_i}{q_i}$  in the above inequality, multiplying by  $q_i$  and then summing over all  $i$ , we obtain

$$\vartheta_{f(\alpha)}(P, Q) \leq I_{f(\alpha)}(P, Q), \quad \alpha \in (0, \infty).$$

Here  $\vartheta_{f(\alpha)}(P, Q)$  are a class of symmetric divergences studied by Puri and Vincze which includes the triangular discrimination for  $\alpha = 2$ .

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