SOME INEQUALITIES FOR THE CSISZÁR **Φ**-DIVERGENCE

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ABSTRACT. Some inequalities for the Csiszár Φ -divergence and applications for the Kullback-Leibler, Rényi, Hellinger and Bhattacharyya distances in Information Theory are given.

1. INTRODUCTION

Given a convex function $\Phi : \mathbb{R}_+ \to \mathbb{R}_+$, the Φ -divergence functional

(1.1)
$$I_{\Phi}(p,q) := \sum_{i=1}^{n} q_i \Phi\left(\frac{p_i}{q_i}\right)$$

was introduced in Csiszár [1], [2] as a generalized measure of information, a "distance function" on the set of probability distributions \mathbb{P}^n . The restriction here to discrete distribution is only for convenience, similar results hold for general distributions.

As in Csiszár [2], we interpret undefined expressions by

$$\Phi(0) = \lim_{t \to 0+} \Phi(t), \quad 0\Phi\left(\frac{0}{0}\right) = 0,$$

$$0\Phi\left(\frac{a}{0}\right) = \lim_{\varepsilon \to 0+} \Phi\left(\frac{a}{\varepsilon}\right) = a \lim_{t \to \infty} \frac{\Phi(t)}{t}, \quad a > 0.$$

The following results were essentially given by Csiszár and Körner [3].

Theorem 1. If $\Phi : \mathbb{R}_+ \to \mathbb{R}$ is convex, then $I_{\Phi}(p,q)$ is jointly convex in p and q.

The following lower bound for the Φ -divergence functional also holds.

Theorem 2. Let $\Phi : \mathbb{R}_+ \to \mathbb{R}_+$ be convex. Then for every $p, q \in \mathbb{R}_+^n$, we have the inequality:

(1.2)
$$I_{\Phi}(p,q) \ge \sum_{i=1}^{n} q_i \Phi\left(\frac{\sum_{i=1}^{n} p_i}{\sum_{i=1}^{n} q_i}\right).$$

If Φ is strictly convex, equality holds in (1.2) iff

(1.3)
$$\frac{p_1}{q_1} = \frac{p_2}{q_2} = \dots = \frac{p_n}{q_n}$$

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Corollary 1. Let $\Phi : \mathbb{R}_+ \to \mathbb{R}$ be convex and normalized, i.e.,

$$(1.4) \qquad \Phi(1) = 0.$$

Then for any $p, q \in \mathbb{R}^n_+$ with

(1.5)
$$\sum_{i=1}^{n} p_i = \sum_{i=1}^{n} q_i$$

we have the inequality

(1.6)
$$I_{\Phi}(p,q) \ge 0.$$

If Φ is strictly convex, equality holds in (1.6) iff $p_i = q_i$ for all $i \in \{1, ..., n\}$.

In particular, if p, q are probability vectors, then (1.5) is assured. Corollary 1 then shows, for strictly convex and normalized $\Phi : \mathbb{R}_+ \to \mathbb{R}$, that

(1.7)
$$I_{\Phi}(p,q) \ge 0 \text{ for all } p,q \in \mathbb{P}^n.$$

The equality holds in (1.7) iff p = q.

These are "distance properties". However, I_{Φ} is not a metric: It violates the triangle inequality, and is **asymmetric**, i.e., for general $p, q \in \mathbb{R}^n_+$, $I_{\Phi}(p,q) \neq I_{\Phi}(q,p)$.

In the examples below we obtain, for suitable choices of the kernel Φ , some of the best known distance functions I_{Φ} used in mathematical statistics [4]-[5], information theory [6]-[8] and signal processing [9]-[10].

Example 1. (Kullback-Leibler) For

(1.8)
$$\Phi(t) := t \log t, \ t > 0;$$

the Φ -divergence is

(1.9)
$$I_{\Phi}(p,q) = \sum_{i=1}^{n} p_i \log\left(\frac{p_i}{q_i}\right),$$

the Kullback-Leibler distance [11]-[12].

Example 2. (Hellinger) Let

(1.10)
$$\Phi(t) = \frac{1}{2} \left(1 - \sqrt{t} \right)^2, \ t > 0.$$

Then I_{Φ} gives the **Hellinger distance** [13]

(1.11)
$$I_{\Phi}(p,q) = \frac{1}{2} \sum_{i=1}^{n} \left(\sqrt{p_i} - \sqrt{q_i} \right)^2,$$

which is symmetric.

Example 3. (*Renyi*) For $\alpha > 1$, let

$$(1.12) \qquad \qquad \Phi(t) = t^{\alpha}, \ t > 0$$

Then

(1.13)
$$I_{\Phi}(p,q) = \sum_{i=1}^{n} p_{i}^{\alpha} q_{i}^{1-\alpha},$$

which is the α -order entropy [14].

Example 4. $(\chi^2 - distance)$ Let

(1.14)
$$\Phi(t) = (t-1)^2, \ t > 0.$$

Then

(1.15)
$$I_{\Phi}(p,q) = \sum_{i=1}^{n} \frac{(p_i - q_i)^2}{q_i}$$

is the χ^2 -distance between p and q.

Finally, we have

Example 5. (Variation distance). Let $\Phi(t) = |t - 1|$, t > 0. The corresponding divergence, called the variation distance, is symmetric,

$$I_{\Phi}(p,q) = \sum_{i=1}^{n} |p_i - q_i|.$$

For other examples of divergence measures, see the paper [22] by J.N. Kapur, where further references are given.

2. Other Inequalities for the CSISZÁR Φ -Divergence

We start with the following result.

Theorem 3. Let $\Phi : \mathbb{R}_+ \to \mathbb{R}$ be differentiable convex. Then for all $p, q \in \mathbb{R}^n_+$ we have the inequality

(2.1)
$$\Phi'(1)(P_n - Q_n) \le I_{\Phi}(p,q) - Q_n \Phi(1) \le I_{\Phi'}\left(\frac{p^2}{q}, p\right) - I_{\Phi'}(p,q),$$

where $P_n := \sum_{i=1}^n p_i > 0$, $Q_n := \sum_{i=1}^n q_i > 0$ and $\Phi' : (0, \infty) \to \mathbb{R}$ is the derivative of Φ .

If Φ is strictly convex and $p_i, q_i > 0$ (i = 1, ..., n), then the equality holds in (2.1) iff p = q.

Proof. As Φ is differentiable convex on \mathbb{R}_+ , then we have the inequality

(2.2)
$$\Phi'(y)(y-x) \ge \Phi(y) - \Phi(x) \ge \Phi'(x)(y-x)$$

for all $x, y \in \mathbb{R}_+$.

Choose in (2.2) $y = \frac{p_i}{q_i}$ and x = 1, to obtain

(2.3)
$$\Phi'\left(\frac{p_i}{q_i}\right)\left(\frac{p_i}{q_i}-1\right) \ge \Phi\left(\frac{p_i}{q_i}\right) - \Phi\left(1\right) \ge \Phi'\left(1\right)\left(\frac{p_i}{q_i}-1\right)$$

for all $i \in \{1, ..., n\}$.

Now, if we multiply (2.3) by $q_i \ge 0$ (i = 1, ..., n) and sum over i from 1 to n, we can deduce

$$\sum_{i=1}^{n} (p_i - q_i) \Phi'\left(\frac{p_i}{q_i}\right) \ge I_{\Phi}(p, q) - Q_n \Phi(1) \ge \Phi'(1) (P_n - Q_n)$$

and as

$$\sum_{i=1}^{n} \left(p_i - q_i \right) \Phi'\left(\frac{p_i}{q_i}\right) = I_{\Phi'}\left(\frac{p^2}{q}, p\right) - I_{\Phi'}\left(p, q\right),$$

the inequality in (2.1) is thus obtained.

The case of equality holds in (2.2) for a strictly convex mapping iff x = y and so the equality holds in (2.1) iff $\frac{p_i}{q_i} = 1$ for all $i \in \{1, ..., n\}$, and the theorem is proved.

Remark 1. In the above theorem, if we would like to drop the differentiability condition, we can choose instead of $\Phi'(x)$ any number $l = l(x) \in [\Phi'_{-}(x), \Phi'_{+}(x)]$ and the inequality will still be valid. This follows by the fact that for the convex mapping $\Phi : \mathbb{R}_{+} \to \mathbb{R}_{+}$ we have

$$l_{2}(x)(x-y) \ge \Phi(x) - \Phi(y) \ge l_{1}(y)(x-y), \ x, y \in (0,\infty);$$

where $l_1(y) \in [\Phi'_{-}(y), \Phi'_{+}(y)]$ and $l_2(x) \in [\Phi'_{-}(x), \Phi'_{+}(x)]$, where Φ'_{-} is the left and Φ'_{+} is the right derivative of Φ respectively. We omit the details.

The following corollary is a natural consequence of the above theorem.

Corollary 2. Let $\Phi : \mathbb{R}_+ \to \mathbb{R}_+$ be convex and normalized. If $\Phi'(1)(P_n - Q_n) \ge 0$, then we have the positivity inequality

(2.4)
$$0 \le I_{\Phi}(p,q) \le I_{\Phi'}\left(\frac{p^2}{q},p\right) - I_{\Phi'}(p,q).$$

The equality holds in (2.4) for a strictly convex mapping Φ iff p = q.

Remark 2. Corollary 2 shows that the positivity inequality (1.6) holds for a larger class of $(p,q) \in \mathbb{R}^n_+$ than that one considered in Corollary 1, namely, for $(p,q) \in \{\mathbb{R}^n_+ \times \mathbb{R}^n_+ : P_n = Q_n\}$.

We have the following theorem as well.

Theorem 4. Assume that Φ is differentiable convex on $(0, \infty)$. If $p^{(j)}$, $q^{(j)}$ (j = 1, 2) are probability distributions, then for all $\lambda \in [0, 1]$ we have the inequality

$$(2.5) \quad 0 \leq \lambda I_{\Phi} \left(p^{(1)}, q^{(1)} \right) + (1 - \lambda) I_{\Phi} \left(p^{(2)}, q^{(2)} \right) -I_{\Phi} \left(\lambda p^{(1)} + (1 - \lambda) q^{(1)}, \lambda p^{(2)} + (1 - \lambda) q^{(2)} \right) \leq \lambda (1 - \lambda) \sum_{i=1}^{n} \frac{\left| \begin{array}{c} p_{i}^{(1)} & p_{i}^{(2)} \\ q_{i}^{(1)} & q_{i}^{(2)} \\ \lambda q_{i}^{(1)} + (1 - \lambda) q_{i}^{(2)} \end{array} \right|}{\left(\Phi' \left(\frac{p_{i}^{(1)}}{q_{i}^{(1)}} \right) - \Phi' \left(\frac{p_{i}^{(2)}}{q_{i}^{(2)}} \right) \right],$$

where Φ' is the derivative of Φ .

Proof. Using the inequality (2.2), we may state

$$(2.6) \qquad \Phi'\left(\frac{\lambda p_i^{(1)} + (1-\lambda) p_i^{(2)}}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}}\right) \left(\frac{\lambda p_i^{(1)} + (1-\lambda) p_i^{(2)}}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}} - \frac{p_i^{(1)}}{q_i^{(1)}}\right) \\ \ge \Phi\left(\frac{\lambda p_i^{(1)} + (1-\lambda) p_i^{(2)}}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}}\right) - \Phi\left(\frac{p_i^{(1)}}{q_i^{(1)}}\right) \\ \ge \Phi'\left(\frac{p_i^{(1)}}{q_i^{(1)}}\right) \left(\frac{\lambda p_i^{(1)} + (1-\lambda) p_i^{(2)}}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}} - \frac{p_i^{(1)}}{q_i^{(1)}}\right)$$

and

$$(2.7) \qquad \Phi'\left(\frac{\lambda p_i^{(1)} + (1-\lambda) p_i^{(2)}}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}}\right) \left(\frac{\lambda p_i^{(1)} + (1-\lambda) p_i^{(2)}}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}} - \frac{p_i^{(2)}}{q_i^{(2)}}\right) \\ \ge \Phi\left(\frac{\lambda p_i^{(1)} + (1-\lambda) p_i^{(2)}}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}}\right) - \Phi\left(\frac{p_i^{(2)}}{q_i^{(2)}}\right) \\ \ge \Phi'\left(\frac{p_i^{(2)}}{q_i^{(2)}}\right) \left(\frac{\lambda p_i^{(1)} + (1-\lambda) p_i^{(2)}}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}} - \frac{p_i^{(2)}}{q_i^{(2)}}\right).$$

Multiply (2.6) by $\lambda q_i^{(1)}$ and (2.7) by $(1-\lambda) q_i^{(2)}$ and add the obtained inequalities to get

$$(2.8) \qquad \sum_{i=1}^{n} \Phi' \left(\frac{\lambda p_{i}^{(1)} + (1-\lambda) p_{i}^{(2)}}{\lambda q_{i}^{(1)} + (1-\lambda) q_{i}^{(2)}} \right) \left[\lambda q_{i}^{(1)} \left(\frac{\lambda p_{i}^{(1)} + (1-\lambda) p_{i}^{(2)}}{\lambda q_{i}^{(1)} + (1-\lambda) q_{i}^{(2)}} - \frac{p_{i}^{(1)}}{\eta q_{i}^{(1)}} \right) \\ + (1-\lambda) q_{i}^{(2)} \left(\frac{\lambda p_{i}^{(1)} + (1-\lambda) p_{i}^{(2)}}{\lambda q_{i}^{(1)} + (1-\lambda) q_{i}^{(2)}} - \frac{p_{i}^{(2)}}{q_{i}^{(2)}} \right) \right] \\ \ge I_{\Phi} \left(\lambda p^{(1)} + (1-\lambda) p^{(2)}, \lambda q^{(1)} + (1-\lambda) q^{(2)} \right) \\ -\lambda I_{\Phi} \left(p^{(1)}, q^{(1)} \right) - (1-\lambda) I_{\Phi} \left(p^{(2)}, q^{(2)} \right) \\ \ge \sum_{i=1}^{n} \left[\lambda q_{i}^{(1)} \Phi' \left(\frac{p_{i}^{(1)}}{q_{i}^{(1)}} \right) \left(\frac{\lambda p_{i}^{(1)} + (1-\lambda) p_{i}^{(2)}}{\lambda q_{i}^{(1)} + (1-\lambda) q_{i}^{(2)}} - \frac{p_{i}^{(1)}}{q_{i}^{(1)}} \right) \\ + (1-\lambda) q_{i}^{(2)} \Phi' \left(\frac{p_{i}^{(2)}}{q_{i}^{(2)}} \right) \left(\frac{\lambda p_{i}^{(1)} + (1-\lambda) p_{i}^{(2)}}{\lambda q_{i}^{(1)} + (1-\lambda) q_{i}^{(2)}} - \frac{p_{i}^{(2)}}{q_{i}^{(2)}} \right) \right].$$

However,

$$\begin{split} \lambda q_i^{(1)} & \left(\frac{\lambda p_i^{(1)} + (1-\lambda) p_i^{(2)}}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}} - \frac{p_i^{(1)}}{q_i^{(1)}} \right) \\ & + (1-\lambda) q_i^{(2)} \left(\frac{\lambda p_i^{(1)} + (1-\lambda) p_i^{(2)}}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}} - \frac{p_i^{(2)}}{q_i^{(2)}} \right) \\ & = -\frac{\lambda (1-\lambda) \left| \begin{array}{c} p_i^{(1)} & p_i^{(2)} \\ q_i^{(1)} & q_i^{(2)} \\ q_i^{(1)} & q_i^{(2)} \end{array} \right|}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}} + \frac{\lambda (1-\lambda) \left| \begin{array}{c} p_i^{(1)} & p_i^{(2)} \\ q_i^{(1)} & q_i^{(2)} \\ q_i^{(1)} & q_i^{(2)} \end{array} \right|}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}} = 0, \end{split}$$

which shows that the first membership in (2.8) is zero.

In addition,

$$\lambda q_i^{(1)} \left(\frac{\lambda p_i^{(1)} + (1-\lambda) p_i^{(2)}}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}} - \frac{p_i^{(1)}}{q_i^{(1)}} \right) = -\frac{\lambda (1-\lambda) \left| \begin{array}{c} p_i^{(1)} & p_i^{(2)} \\ q_i^{(1)} & q_i^{(2)} \\ \lambda q_i^{(1)} + (1-\lambda) q_i^{(2)} \end{array} \right|}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}},$$

and

$$(1-\lambda) q_i^{(2)} \left(\frac{\lambda p_i^{(1)} + (1-\lambda) p_i^{(2)}}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}} - \frac{p_i^{(2)}}{q_i^{(2)}} \right) = -\frac{\lambda (1-\lambda) \left| \begin{array}{c} p_i^{(1)} & p_i^{(2)} \\ q_i^{(1)} & q_i^{(2)} \\ \lambda q_i^{(1)} + (1-\lambda) q_i^{(2)} \end{array} \right|}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}},$$

and then, the second membership in (2.4) is

$$-\lambda (1-\lambda) \sum_{i=1}^{n} \frac{\begin{vmatrix} p_i^{(1)} & p_i^{(2)} \\ q_i^{(1)} & q_i^{(2)} \end{vmatrix}}{\lambda q_i^{(1)} + (1-\lambda) q_i^{(2)}} \left[\Phi' \left(\frac{p_i^{(1)}}{q_i^{(1)}} \right) - \Phi' \left(\frac{p_i^{(2)}}{q_i^{(2)}} \right) \right],$$

which proves the theorem. \blacksquare

Remark 3. The first inequality in (2.5) is actually the joint convexity property of $I_{\Phi}(\cdot, \cdot)$ which has been proven here in a different manner than in [3].

3. Applications for Some Particular Φ -Divergences

Let us consider the Kullback-Leibler distance given by (1.9)

(3.1)
$$KL(p,q) := \sum_{i=1}^{n} p_i \log\left(\frac{p_i}{q_i}\right).$$

Consider the convex mapping $\Phi(t) = -\log t, t > 0$. For this mapping we have the Csiszár Φ -divergence

(3.2)
$$I_{\Phi}(p,q) = \sum_{i=1}^{n} q_i \left[-\log\left(\frac{p_i}{q_i}\right) \right]$$
$$= \sum_{i=1}^{n} q_i \log\left(\frac{q_i}{p_i}\right) = KL(q,p).$$

The following inequality holds.

Proposition 1. Let $p, q \in \mathbb{R}^n$. Then we have the inequality

(3.3)
$$Q_n - P_n \le KL(q, p) \le \sum_{i=1}^n \frac{q_i^2}{p_i} - Q_n.$$

The case of equality holds iff p = q.

Proof. Since $\Phi(t) = -\log t$, then $\Phi'(t) = -\frac{1}{t}$, t > 0. We have

$$I_{\Phi'}\left(\frac{p^2}{q},p\right) = \sum_{i=1}^n p_i \cdot \left[-\frac{1}{\left(\frac{p_i^2}{q_i}\right) \cdot \frac{1}{p_i}}\right] = -Q_n,$$
$$I_{\Phi'}\left(p,q\right) = \sum_{i=1}^n q_i \cdot \left[-\frac{1}{\frac{p_i}{q_i}}\right] = -\sum_{i=1}^n \frac{q_i^2}{p_i},$$

and then, from (2.1), we get

$$-(P_n - Q_n) \le KL(q, p) \le -Q_n + \sum_{i=1}^n \frac{q_i^2}{p_i},$$

which is the desired inequality (3.3).

The following result for the Kullback-Leibler distance also holds.

Proposition 2. Let $p, q \in \mathbb{R}^n$. Then we have the inequality

(3.4)
$$P_n - Q_n \le KL(p,q) \le P_n - Q_n + KL(q,p) - KL\left(p,\frac{p^2}{q}\right).$$

The case of equality holds iff p = q.

Proof. As $\Phi(t) = t \log(t)$, then $\Phi'(t) = \log t + 1$. We have

$$I_{\Phi}(p,q) = KL(p,q),$$

$$I_{\Phi'}\left(\frac{p^2}{q},p\right) = I_{\log(\cdot)+1}\left(\frac{p^2}{q},p\right) = P_n + I_{\log(\cdot)}\left(\frac{p^2}{q},p\right).$$

As we know that $I_{-\log(\cdot)}(p,q) = KL(q,p)$ (see (3.2)), then we have that

$$I_{\log(\cdot)}\left(\frac{p^2}{q},p\right) = -KL\left(p,\frac{p^2}{q}\right).$$

In addition, we have

$$I_{\Phi'}(p,q) = I_{\log(\cdot)+1}(p,q) = Q_n + I_{\log(\cdot)}(p,q) = Q_n - KL(q,p)$$

and then, by (2.1), we can state that

$$P_n - Q_n \le KL(p,q) \le P_n - Q_n - KL\left(p,\frac{p^2}{q}\right)Q_n + KL(q,p)$$

and the inequality (3.4) is obtained.

The case of equality holds from the fact that the mapping $\Phi(t) = t \log t$ is strictly convex on $(0, \infty)$.

Now, let us consider the α -order entropy of Rényi (see (1.13))

(3.5)
$$D_{\alpha}(p,q) := \sum_{i=1}^{n} p_{i}^{\alpha} q_{i}^{1-\alpha}, \ \alpha > 1$$

and $p, q \in \mathbb{R}^n_+$.

We know that Rényi's entropy is actually the Csiszár Φ -divergence for the convex mapping $\Phi(t) = t^{\alpha}, \alpha > 1, t > 0$ (see Example 3).

The following proposition holds.

Proposition 3. Let $p, q \in \mathbb{R}^n_+$. Then we have the inequality

(3.6)
$$\alpha \left(P_n - Q_n\right) \le D_\alpha\left(p, q\right) - Q_n \le \alpha \left[D_\alpha\left(p, q\right) - D_\alpha\left(q^{\frac{2-\alpha}{\alpha}}, p^{-1}\right)\right].$$

The case of equality holds iff p = q.

Proof. Since $\Phi(t) = t^{\alpha}$, then $\Phi'(t) = \alpha t^{\alpha-1}$.

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We have

$$I_{\Phi'}\left(\frac{p^2}{q},p\right) = \sum_{i=1}^n p_i \left[\alpha \cdot \left(\frac{p_i^2}{q_i p_i}\right)^{\alpha-1}\right]$$
$$= \alpha \sum_{i=1}^n p_i \left(\frac{p_i}{q_i}\right)^{\alpha-1} = \alpha \sum_{i=1}^n q_i^{1-\alpha} p_i^{\alpha} = \alpha D_{\alpha}\left(p,q\right)$$

and

$$I_{\Phi'}(p,q) = \sum_{i=1}^{n} q_i \left[\alpha \cdot \left(\frac{p_i}{q_i}\right)^{\alpha-1} \right]$$
$$= \alpha \sum_{i=1}^{n} p_i^{\alpha-1} q_i^{2-\alpha} = \alpha D_{\alpha} \left(q^{\frac{2-\alpha}{\alpha}}, \frac{1}{p} \right)$$

Using the inequality (2.1), we have

$$\alpha \left(P_n - Q_n \right) \le D_\alpha \left(p, q \right) - Q_n \le \alpha \left[D_\alpha \left(p, q \right) - D_\alpha \left(q^{\frac{2-\alpha}{\alpha}}, \frac{1}{p} \right) \right]$$

and the inequality (3.6) is proved.

The case of equality holds since the mapping $\Phi(t) = t^{\alpha}$ is strictly convex on $(0,\infty)$ for $\alpha > 1$.

Consider now the Hellinger discrimination (see for example [22])

$$h^{2}(p,q) = \frac{1}{2} \sum_{i=1}^{n} \left(\sqrt{p_{i}} - \sqrt{q_{i}}\right)^{2},$$

where $p, q \in \mathbb{R}^n_+$.

We know that Hellinger discrimination is actually the Csiszár Φ -divergence for the convex mapping $\Phi(t) = \frac{1}{2} (\sqrt{t} - 1)^2$. We may state the following proposition.

Proposition 4. Let $p, q \in \mathbb{R}^n_+$. Then we have the inequality

(3.7)
$$0 \le h^2(p,q) \le \frac{1}{2} \left[P_n - Q_n \right] + \frac{1}{2} \left[\sum_{i=1}^n q_i \left(\sqrt{\frac{q_i}{p_i}} - \sqrt{\frac{p_i}{q_i}} \right) \right].$$

The equality holds iff p = q.

Proof. As $\Phi(t) = \frac{1}{2} \left(\sqrt{t} - 1\right)^2$, we have $\Phi'(t) = \frac{1}{2} - \frac{1}{2\sqrt{t}}$ and $\Phi''(t) = \frac{1}{4} \cdot \frac{1}{\sqrt{t^3}} > 0$ $(t \in (0, \infty))$ which shows that Φ is indeed strictly convex on $(0, \infty)$.

We also have:

$$\begin{split} I_{\Phi}\left(p,q\right) &= h^{2}\left(p,q\right), \\ I_{\Phi'}\left(\frac{p^{2}}{q},p\right) &= \sum_{i=1}^{n} p_{i}\left[\frac{1}{2} - \frac{1}{2\sqrt{\frac{p_{i}^{2}}{q_{i}p_{i}}}}\right] \\ &= \frac{1}{2}P_{n} - \frac{1}{2}\sum_{i=1}^{n}\sqrt{p_{i}q_{i}} = \frac{1}{2}\left[P_{n} - \sum_{i=1}^{n}\sqrt{p_{i}q_{i}}\right] \\ I_{\Phi'}\left(p,q\right) &= \sum_{i=1}^{n} q_{i}\left[\frac{1}{2} - \frac{1}{2\sqrt{\frac{p_{i}}{q_{i}}}}\right] = \frac{1}{2}\left[Q_{n} - \sum_{i=1}^{n} q_{i}\sqrt{\frac{q_{i}}{p_{i}}}\right] \end{split}$$

and as $\Phi'(1) = 0$ and $\Phi(1) = 0$, then, by (2.1) applied for Φ as above, we deduce (3.7). The case of equality is obvious by the strict convexity of Φ .

Consider now the *Bhattacharyya distance* (see for example [22])

$$B(p,q) = \sum_{i=1}^{n} \sqrt{p_i q_i},$$

where $p, q \in \mathbb{R}^n_+$.

We know that for the convex mapping $f(t) = -\sqrt{t}$, we have

$$I_{\Phi}(p,q) = -\sum_{i=1}^{n} q_i \sqrt{\frac{p_i}{q_i}} = -B(p,q).$$

We may state the following proposition.

Proposition 5. Let $p, q \in \mathbb{R}^n_+$. Then we have the inequality

(3.8)
$$\frac{1}{2} (Q_n - P_n) \le Q_n - B(p,q) \le \frac{1}{2} \sum_{i=1}^n q_i \left(\sqrt{\frac{q_i}{p_i}} - \sqrt{\frac{p_i}{q_i}} \right).$$

The case of equality holds iff p = q.

Proof. As $\Phi(1) = -\sqrt{t}$, t > 0, then $\Phi'(t) = -\frac{1}{2\sqrt{t}}$ and $\Phi''(t) = \frac{1}{4\sqrt{t^3}}$, t > 0, which also shows that $\Phi(\cdot)$ is strictly convex on $(0, \infty)$. We also have

$$\begin{split} I_{\Phi'}\left(\frac{p^2}{q},p\right) &= \sum_{i=1}^n p_i \left[-\frac{1}{2\sqrt{\frac{p_i^2}{q_i p_i}}}\right] = -\frac{1}{2} \sum_{i=1}^n \sqrt{p_i q_i} = -\frac{1}{2} B\left(p,q\right),\\ I_{\Phi'}\left(p,q\right) &= -\frac{1}{2} \sum_{i=1}^n q_i \frac{1}{\sqrt{\frac{p_i}{q_i}}} = -\frac{1}{2} \sum_{i=1}^n q_i \sqrt{\frac{q_i}{p_i}} \end{split}$$

and as $\Phi'(1) = -\frac{1}{2}$, $\Phi(1) = -1$, then by (2.1) applied for the mapping Φ as defined above, we deduce (3.8).

The case of equality is obvious by the strict convexity of Φ .

S.S. DRAGOMIR

4. Further Bounds for the Case when $P_n = Q_n$

The following inequality of Grüss type is well known in the literature as the Biernacki, Pidek and Ryll-Nardzewski inequality (see for example [23]).

Lemma 1. Let a_i , b_i (i = 1, ..., n) be real numbers such that

(4.1)
$$a \le a_i \le A, \ b \le b_i \le B \text{ for all } i \in \{1, ..., n\}.$$

Then we have the inequality:

(4.2)
$$\left| \frac{1}{n} \sum_{i=1}^{n} a_i b_i - \frac{1}{n^2} \sum_{i=1}^{n} a_i \sum_{i=1}^{n} b_i \right| \le \frac{1}{n} \left[\frac{n}{2} \right] \left(1 - \frac{1}{n} \left[\frac{n}{2} \right] \right) (A - a) (B - b) ,$$

where [x] denotes the integer part of x.

The following inequality holds.

Theorem 5. Let $\Phi : \mathbb{R}_+ \to \mathbb{R}_+$ be differentiable convex. If $p, q \in \mathbb{R}^n_+$ are such that $P_n = Q_n$ and

(4.3)
$$m \le p_i - q_i \le M, \ i = 1, ..., n$$

(4.4)
$$0 < r \le \frac{p_i}{q_i} \le R < \infty, \ i = 1, ..., n,$$

then we have the inequality

(4.5)
$$0 \le I_{\Phi}(p,q) - Q_n \Phi(1) \le \left[\frac{n}{2}\right] \left(1 - \frac{1}{n} \left[\frac{n}{2}\right]\right) (M-m) \left(\Phi'(R) - \Phi'(r)\right).$$

Proof. From (2.1) we have

(4.6)
$$0 \le I_{\Phi}(p,q) - Q_n \Phi(1) \le \sum_{i=1}^n (p_i - q_i) \Phi'\left(\frac{p_i}{q_i}\right)$$

Applying (4.2) we have

(4.7)
$$\left| \frac{1}{n} \sum_{i=1}^{n} (p_i - q_i) \Phi'\left(\frac{p_i}{q_i}\right) - \frac{1}{n^2} \sum_{i=1}^{n} (p_i - q_i) \sum_{i=1}^{n} \Phi'\left(\frac{p_i}{q_i}\right) \right| \\ \leq \frac{1}{n} \left[\frac{n}{2}\right] \left(1 - \frac{1}{n} \left[\frac{n}{2}\right]\right) (M - m) \left(\Phi'(R) - \Phi'(r)\right)$$

as the mapping Φ' is monotonic nondecreasing, and then

$$\Phi'(r) \le \Phi'\left(\frac{p_i}{q_i}\right) \le \Phi'(R) \text{ for all } i \in \{1, ..., n\}.$$

As $\sum_{i=1}^{n} (p_i - q_i) = 0$, we deduce by (4.6) and (4.7) the desired result (4.5).

The following inequalities for particular distances are valid.

1. If $p, q \in \mathbb{R}_n^+$ are such that the conditions (4.3) and (4.4) hold, then we have the inequalities

(4.8)
$$0 \le KL(q,p) \le \left[\frac{n}{2}\right] \left(1 - \frac{1}{n} \left[\frac{n}{2}\right]\right) (M-m) \frac{R-r}{rR},$$

and

(4.9)
$$0 \le KL(p,q) \le \left[\frac{n}{2}\right] \left(1 - \frac{1}{n} \left[\frac{n}{2}\right]\right) (M-m) \left[\log\left(\frac{R}{r}\right)\right]$$

2. If p, q are as in (4.3) and (4.4), we have the inequality $(\alpha \ge 1)$

$$(4.10) \qquad 0 \le D_{\alpha}\left(p,q\right) - Q_{n} \le \alpha \left[\frac{n}{2}\right] \left(1 - \frac{1}{n}\left[\frac{n}{2}\right]\right) \left(M - m\right) \left(R^{\alpha - 1} - r^{\alpha - 1}\right).$$

3. If p, q are as in (4.3) and (4.4), we have the inequality

(4.11)
$$0 \le h^2(p,q) \le \frac{1}{2} \left[\frac{n}{2}\right] \left(1 - \frac{1}{n} \cdot \left[\frac{n}{2}\right]\right) (M-m) \frac{\sqrt{R} - \sqrt{r}}{\sqrt{rR}}.$$

4. Under the above assumptions for p and q, we have

(4.12)
$$0 \le Q_n - B\left(p,q\right) \le \frac{1}{2} \left[\frac{n}{2}\right] \left(1 - \frac{1}{n} \left[\frac{n}{2}\right]\right) \left(M - m\right) \frac{\sqrt{R} - \sqrt{r}}{\sqrt{rR}}.$$

Using the following Grüss' weighted inequality.

Lemma 2. Assume that a_i , b_i (i = 1, ..., n) are as in Lemma 1. If $q_i \ge 0$, $\sum_{i=1}^n q_i = 1$, then we have the inequality

(4.13)
$$\left| \sum_{i=1}^{n} q_{i} a_{i} b_{i} - \sum_{i=1}^{n} q_{i} a_{i} \sum_{i=1}^{n} q_{i} b_{i} \right| \leq \frac{1}{4} \left(A - a \right) \left(B - b \right).$$

We may prove the following converse inequality as well.

Theorem 6. Let $\Phi : \mathbb{R}_+ \to \mathbb{R}_+$ be differentiable convex. If $p, q \in \mathbb{R}^n_+$ are such that $P_n = Q_n$ and

(4.14)
$$0 < r \le \frac{p_i}{q_i} \le R < \infty, \ i = 1, ..., n,$$

then we have the inequality

(4.15)
$$0 \le I_{\Phi}(p,q) - Q_n \Phi(1) \le \frac{1}{4} (R-r) \left[\Phi'(R) - \Phi'(r) \right].$$

Proof. From (2.1) we have

(4.16)
$$0 \leq I_{\Phi}(p,q) - Q_n \Phi(1) \leq \sum_{i=1}^n (p_i - q_i) \Phi'\left(\frac{p_i}{q_i}\right)$$
$$= \sum_{i=1}^n q_i \left(\frac{p_i}{q_i} - 1\right) \Phi'\left(\frac{p_i}{q_i}\right).$$

As $\Phi'(\cdot)$ is monotonic nondecreasing, then

$$\Phi'(r) \le \Phi'\left(\frac{p_i}{q_i}\right) \le \Phi'(R) \text{ for all } i \in \{1, ..., n\}.$$

Applying (4.13) for $a_i = \frac{p_i}{q_i} - 1$, $b_i = \Phi'\left(\frac{p_i}{q_i}\right)$, we obtain

(4.17)
$$\left| \sum_{i=1}^{n} q_i \left(\frac{p_i}{q_i} - 1 \right) \Phi' \left(\frac{p_i}{q_i} \right) - \sum_{i=1}^{n} q_i \left(\frac{p_i}{q_i} - 1 \right) \sum_{i=1}^{n} q_i \Phi' \left(\frac{p_i}{q_i} \right) \right|$$
$$\leq \frac{1}{4} \left(R - r \right) \left[\Phi' \left(R \right) - \Phi' \left(r \right) \right]$$

and as

$$\sum_{i=1}^{n} q_i \left(\frac{p_i}{q_i} - 1\right) = 0,$$

then, by (4.16) and (4.17) we deduce (4.15). \blacksquare

The following inequalities for particular distances are valid.

1. If p, q are such that $P_n = Q_n$ and (4.14) holds, then

(4.18)
$$0 \le KL(q,p) \le \frac{(R-r)^2}{4rR}$$

and

(4.19)
$$0 \le KL(q,p) \le \frac{1}{4} \left(R-r\right)^2 \ln\left(\frac{R}{r}\right).$$

2. With the same assumptions for p, q, we have

(4.20)
$$0 \leq D_{\alpha}(p,q) - Q_n \leq \frac{\alpha}{4} (R-r) (R^{\alpha-1} - r^{\alpha-1}) \quad (\alpha \geq 1);$$

(4.21)
$$0 \leq h^2(p,q) \leq \frac{1}{8}(R-r)\frac{\sqrt{R}-\sqrt{r}}{\sqrt{Rr}}$$

and

(4.22)
$$0 \le Q_n - B(p,q) \le \frac{1}{8} (R-r) \frac{\sqrt{R} - \sqrt{r}}{\sqrt{Rr}}.$$

Remark 4. Any other Grüss type inequality can be used to provide different bounds for the difference

$$\Delta := \sum_{i=1}^{n} \left(p_i - q_i \right) \Phi' \left(\frac{p_i}{q_i} \right).$$

We omit the details.

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