

NEW DEVELOPMENTS OF INFORMATION INEQUALITIES

RAM NARESH SARASWAT

Department of Mathematics and Statistics, Manipal University Jaipur
Jaipur (Rajasthan), India, E-mail: sarswatrn@gmail.com

Abstract-Information and divergence measure are very useful and play an important role in many areas like as Sensor Networks [11], Testing the order in a Markov chain [12], Risk for binary experiments[13], Region segmentation and estimation [14] etc. In this paper we establish an upper and lower bounds of Relative arithmetic-geometric divergence, Relative J-divergence, Jenson-Shannon's divergence, Triangular discrimination, Unified Relative Jensen-Shannon and arithmetic-geometric divergence of types etc. in terms of Chi-square divergence using a new f-divergence measure and inequalities.

Key Word- Chi-square divergence, Jenson-Shannon's divergence, Triangular discrimination etc.

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1. INTRODUCTION

Let

$$\Gamma_n = \left\{ P = (p_1, p_2, \dots, p_n) \mid p_i \geq 0, \sum_{i=1}^n p_i = 1 \right\}, n \geq 2 \quad (1.1)$$

be the set of all complete finite discrete probability distributions. There are many information and divergence measures exists in the literature of information theory and statistics. Csiszar [2] & [3] introduced a generalized measure of information using f-divergence measure given by

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

where $f: \mathbf{R}_+ \rightarrow \mathbf{R}_+$ is a convex function and $P, Q \in \Gamma_n$.

As in Csiszar [3], The Csiszar's f-divergence is a general class of divergence measures that includes several divergences used in measuring the distance or affinity between two probability distributions. This class is introduced by using a convex function f, defined on $(0, \infty)$. An important property of this divergence is that many known divergences can be obtained from this measure by appropriately defining the convex function f.

There are some examples of divergence measures in the category of Csiszar's f-divergence measure. Bhattacharya divergence [1], Triangular discrimination [5], Relative J-divergence [7], Hellinger discrimination [8], Chi-square divergence [15], Relative Jensen-shannon divergence [16], Relative arithmetic-geometric divergence [17], Unified relative Jensen-Shannon and arithmetic-geometric divergence of type s [18]

2. NEW f-DIVERGENCE MEASURE AND ITS PARTICULAR CASES

In this section we shall consider some properties of a new f-divergence measure [Jain and Saraswat, 10] and its particular cases which are may be interesting in areas of information theory is given by

$$S_f(P, Q) = \sum_{i=1}^n q_i f\left(\frac{p_i + q_i}{2q_i}\right) \quad (2.1)$$

Where $f: \mathbf{R}_+ \rightarrow \mathbf{R}_+$ is a convex function and $P, Q \in \Gamma_n$.

It is shown that using new f-divergence measure we derive some well-known divergence measures such as Chi-square divergence, Relative J-divergence, Jenson-Shannon's divergence, Triangular discrimination, Hellinger discrimination, Bhattacharya divergence, Unified relative Jensen-Shannon and arithmetic-geometric divergence of type's etc. in this section. An inequality of f-divergence in terms of Chi-square divergence measure is established in section 3. Using the inequality of section 3, bounds of various particular measures are found in terms of Chi-square divergence measure in section 4.

The following results are on similar lines the result presented by Csiszar & Kerner [4] and Dragomir [6].

2.1 PROPOSITION

Let $f : [0, \infty) \rightarrow \mathbf{R}$ be convex and $P, Q \in \Gamma_n$ then we have the following inequality

$$S_f(P, Q) \geq f(1)$$

(2.2)

Equality holds in (2.2) iff

$$p_i = q_i \quad \forall i = 1, 2, \dots, n \quad (2.3)$$

Proof: If f is a convex function then using well known Jensen's discrete inequality, we get

$$\sum_{i=1}^n q_i f(x_i) \geq f\left(\sum_{i=1}^n q_i x_i\right)$$

$$\text{Put } x_i = \frac{p_i + q_i}{2q_i}$$

$$\sum_{i=1}^n q_i f\left(\frac{p_i + q_i}{2q_i}\right) \geq f\left(\sum_{i=1}^n q_i \left(\frac{p_i + q_i}{2q_i}\right)\right)$$

$$\sum_{i=1}^n q_i f\left(\frac{p_i + q_i}{2q_i}\right) \geq f\left(\frac{\sum_{i=1}^n p_i + \sum_{i=1}^n q_i}{2\sum_{i=1}^n q_i}\right) \geq 0$$

$$\sum_{i=1}^n q_i f\left(\frac{p_i + q_i}{2q_i}\right) \geq f(1)$$

$$\sum_{i=1}^n q_i f\left(\frac{p_i + q_i}{2q_i}\right) = S_f(P, Q) \geq f(1)$$

$$S_f(P, Q) \geq f(1)$$

Equality holds if

$$p_i = q_i, \quad \forall i = 1, 2, \dots, n$$

2.1.1 COROLLARY (Non-negativity of new f-divergence measure)

Let $f : [0, \infty) \rightarrow \mathbf{R}$ be convex and normalized, i.e.

$$f(1) = 0 \quad (2.4)$$

Then for any $P, Q \in \Gamma_n$ from (2.2) of proposition 2.1 and (2.4), we have the inequality

$$S_f(P, Q) \geq 0 \quad (2.5)$$

If f is strictly convex, equality holds in (2.5) iff

$$p_i = q_i \quad \forall i \in [1, 2, \dots, n] \quad (2.6)$$

and

$$S_f(P, Q) \geq 0 \quad \text{and} \quad S_f(P, Q) = 0 \quad \text{iff} \quad P = Q \quad (2.7)$$

2.2 PROPOSITION

Let f_1 & f_2 are two convex functions and $g = a f_1 + b f_2$ then $S_g(P, Q) = a S_{f_1}(P, Q) + b S_{f_2}(P, Q)$, where a & b are constants and $P, Q \in \Gamma_n$

Proof: Let $f : [0, \infty) \rightarrow \mathbf{R}$ be convex mapping. Let f_1 & f_2 are two convex functions and $g = a f_1 + b f_2$ then we get

$$S_g(P, Q) = \sum_{i=1}^n q_i g\left(\frac{p_i + q_i}{2q_i}\right) = a \sum_{i=1}^n q_i f_1\left(\frac{p_i + q_i}{2q_i}\right) + b \sum_{i=1}^n q_i f_2\left(\frac{p_i + q_i}{2q_i}\right)$$

$$S_g(P, Q) = \sum_{i=1}^n q_i g\left(\frac{p_i + q_i}{2q_i}\right) = a S_{f_1} + b S_{f_2}$$

We now give some examples of well- known information divergence measures which are obtained from new f-divergence measure.

- If $f(t) = (t-1)^2$ then Chi-square divergence measure is given by

$$S_f(P, Q) = \frac{1}{4} \left[\sum_{i=1}^n \frac{p_i^2}{q_i} - 1 \right] = \frac{1}{4} \chi^2(P, Q) \quad (2.8)$$

- If $f(t) = -\log t$ then relative Jensen-Shannon divergence measure is given by

$$S_f(P, Q) = \sum_{i=1}^n q_i \log\left(\frac{2q_i}{p_i + q_i}\right) = F(Q, P) \quad (2.9)$$

- If $f(t) = t \log t$ then relative arithmetic-geometric divergence measure is given by

$$S_f(P, Q) = \sum_{i=1}^n \left(\frac{p_i + q_i}{2}\right) \log\left(\frac{p_i + q_i}{2q_i}\right) = G(Q, P) \quad (2.10)$$

- If $f(t) = \frac{(t-1)^2}{t}$, $\forall t > 0$ then Triangular discrimination is given by

$$S_f(P, Q) = \sum_{i=1}^n \frac{(p_i - q_i)^2}{2(p_i + q_i)} = \frac{1}{2} \Delta(P, Q) \quad (2.11)$$

- If $f(t) = (t-1) \log t$ then Relative J-divergence measure is given by

$$S_f(P, Q) = \sum_{i=1}^n \left(\frac{p_i - q_i}{2}\right) \log\left(\frac{p_i + q_i}{2q_i}\right) = \frac{1}{2} J_R(P, Q) \quad (2.12)$$

- If $f(t) = (1 - \sqrt{t})$ then Hellinger discrimination is given by

$$S_f(P, Q) = \left[1 - B\left(\frac{P+Q}{2}, Q\right) \right] = h\left(\frac{P+Q}{2}, Q\right) \quad (2.13)$$

- If $f(t) = \begin{cases} [\alpha(\alpha-1)]^{-1} [t^\alpha - 1], & \alpha \neq 0, 1 \\ -\log t & \text{if } \alpha = 0 \\ t \log t & \text{if } \alpha = 1 \end{cases}$ (2.14)

Then Unified relative Jensen-Shannon and Arithmetic-Geometric divergence measure of type α is given by

$$S_f(P, Q) = \Omega_\alpha(Q, P) = \begin{cases} FG_\alpha(Q, P) = [\alpha(\alpha-1)]^{-1} \left[\sum_{i=1}^n q_i \left(\frac{p_i + q_i}{2q_i}\right)^\alpha - 1 \right], & \alpha \neq 0, 1 \\ F(Q, P) = \sum_{i=1}^n q_i \log\left(\frac{2q_i}{p_i + q_i}\right), & \alpha = 0 \\ G(Q, P) = \sum_{i=1}^n \left(\frac{p_i + q_i}{2}\right) \log\left(\frac{p_i + q_i}{2q_i}\right), & \alpha = 1 \end{cases} \quad (2.15)$$

3. SOME INEQUALITIES BETWEEN NEW F-DIVERGENCE AND THE CHI-SQUARE DIVERGENCE MEASURE

The following theorem concerning inequalities among new f-divergence measure and Chi-square divergence measure holds. Its particular cases are given in Section 4.

The results are on similar lines to the result presented by Dragomir [6] and Jain & Saraswat [9].

3.1 THEOREM

Let $f : (0, \infty) \rightarrow \mathbf{R}$ is normalized mapping i.e. $f(1) = 0$ and satisfy the assumptions.

- (i) f is twice differentiable on (r, R) , where $0 \leq r \leq 1 \leq R \leq \infty$
(ii) There exist constants m, M such that

$$2m \leq f''(t) \leq 2M \quad (3.1)$$

If P, Q are discrete probability distributions satisfying the assumptions

$$r < \frac{1}{2} \leq r_i = \frac{p_i + q_i}{2q_i} \leq R, \forall i \in \{1, 2, \dots, n\} \quad (3.2)$$

Then we have the following inequality

$$\frac{m}{4} \chi^2(P, Q) \leq S_f(P, Q) \leq \frac{M}{4} \chi^2(P, Q) \quad (3.3)$$

Proof: - Define a mapping $F_m : (0, \infty) \rightarrow \mathbf{R}, F_m(t) = f(t) - m(t-1)^2$. Then $F_m(\cdot)$ is normalized, twice differentiable and since

$$F_m''(t) = f''(t) - 2m = [f''(t) - 2m] \geq 0 \quad (3.4)$$

For all $t \in (r, R)$, it follows that $F_m(\cdot)$ is convex on (r, R) . Applying non-negativity property of new f -divergence measure for $F_m(\cdot)$ and by proposition 2.2, we may state that

$$\begin{aligned} 0 \leq S_{F_m}(P, Q) &= S_f(P, Q) - m S_{(t-1)^2}(P, Q) = S_f(P, Q) - \frac{m}{4} \chi^2(P, Q) \\ \Rightarrow 0 &\leq S_f(P, Q) - \frac{m}{4} \chi^2(P, Q) \end{aligned} \quad (3.5)$$

from where the first inequality in (3.3).

Now we again Define a mapping $F_M : (0, \infty) \rightarrow \mathbf{R}, F_M(t) = M(t-1)^2 - f(t)$, which is obviously normalized, twice differentiable and by (3.1), convex on (r, R) . Applying non-negativity property of new f -divergence measure for $F_M(\cdot)$ and the linearity property, we obtain the second part of (3.3) i.e.

$$0 \leq \frac{M}{4} \chi^2(P, Q) - S_f(P, Q) \quad (3.6)$$

from results (3.5) and (3.6) give result (3.3).

REMARK.1 If we have strict inequality " $>$ " in (3.3) for any $t \in (r, R)$ then the mapping $F_m(\cdot)$ and $F_M(\cdot)$ are strictly convex and equality holds in (3.3) iff $P = Q$

REMARK.2 It is important note that f is twice differentiable on $(0, \infty)$ and $m \leq f''(t) \leq M < \infty, \forall t \in (0, \infty)$, then inequality (3.1) holds for any probability distributions P, Q .

4. SOME PARTICULAR CASES

Using equation (3.3) of Theorem 3.1 we able to point out the following particular cases which may be interested in Information Theory and Statistics.

The results are on similar lines to the result presented by Dragomir [6] and Jain & Saraswat [9].

4.1 PROPOSITION

Let $P, Q \in \Gamma_n$ be two probability distributions with the property that

$$r < \frac{1}{2} \leq r_i = \frac{p_i + q_i}{2q_i} \leq R, \forall i \in \{1, 2, \dots, n\}$$

Then we have the following inequality

$$\frac{1}{4R^2} \chi^2(P, Q) \leq F(Q, P) \leq \frac{1}{4r^2} \chi^2(P, Q) \quad (4.1)$$

Proof:-Consider the mapping $f : (r, R) \rightarrow \mathbf{R}$.

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$$f(t) = -\log t, f'(t) = -\frac{1}{t}, f''(t) = \frac{1}{t^2} > 0, \forall t > 0$$

$f''(t) \geq 0$ and $f(1) = 0$, So function f is convex and normalized.

$$\text{Define } g(t) = f''(t) = \frac{1}{t^2}$$

Then obviously

$$M = \inf_{t \in [r, R]} g(t) = \frac{1}{R^2}, m = \sup_{t \in [r, R]} g(t) = \frac{1}{r^2} \quad (4.2)$$

Also $S_f(P, Q) = F(Q, P)$ from equation (2.9)

From equation (2.9), (3.3) & (4.2) give the result (4.1).

4.2 PROPOSITION

Let $P, Q \in \Gamma_n$ be two probability distributions satisfying (3.2) then we have the following inequality

$$\frac{1}{4R} \chi^2(P, Q) \leq G(Q, P) \leq \frac{1}{4r} \chi^2(P, Q) \quad (4.3)$$

Proof:- Consider the mapping $f : (r, R) \rightarrow \mathbf{R}$.

$$f(t) = t \log t, f'(t) = 1 + \log t, f''(t) = \frac{1}{t} > 0, \forall t > 0$$

$f''(t) \geq 0$ and $f(1) = 0$, So function f is convex and normalized.

$$\text{Define } g(t) = f''(t) = \frac{1}{t}$$

Then obviously

$$M = \inf_{t \in [r, R]} g(t) = \frac{1}{R}, m = \sup_{t \in [r, R]} g(t) = \frac{1}{r} \quad (4.4)$$

Since $S_f(P, Q) = G(Q, P)$ from equation (2.10)

From equation (2.10), (3.3), & (4.4) give the result (4.3).

4.3 PROPOSITION

Let $P, Q \in \Gamma_n$ be two probability distributions satisfying (3.2) then we have the following inequality

$$\frac{1}{R^3} \chi^2(P, Q) \leq \Delta(P, Q) \leq \frac{1}{r^3} \chi^2(P, Q) \quad (4.5)$$

Proof:- Consider the mapping $f : (r, R) \rightarrow \mathbf{R}$.

$$f(t) = \frac{(t-1)^2}{t} = \left(t + \frac{1}{t} - 2 \right), f'(t) = \left(1 - \frac{1}{t^2} \right), f''(t) = \frac{2}{t^3}$$

$f''(t) \geq 0$ and $f(1) = 0$, So function f is convex and normalized.

$$\text{Define } g(t) = f''(t) = \frac{2}{t^3}$$

Then obviously

$$M = \sup_{t \in [r, R]} g(t) = \frac{2}{r^3}, m = \inf_{t \in [r, R]} g(t) = \frac{2}{R^3} \quad (4.6)$$

Since $S_f(P, Q) = \frac{1}{2} \Delta(P, Q)$ from equation (2.11)

From equation (2.11), (3.3) & (4.6) give the result (4.5).

4.4 PROPOSITION

Let $P, Q \in \Gamma_n$ be two probability distributions satisfying (3.2) then we have the following inequality

$$\frac{1+R}{2R^2} \chi^2(P, Q) \leq J_R(P, Q) \leq \frac{1+r}{2r^2} \chi^2(P, Q) \quad (4.7)$$

Proof:-Consider the mapping $f : (r, R) \rightarrow \mathbf{R}$.

$$f(t) = (t-1) \log t, f'(t) = \left(1 - \frac{1}{t}\right) + \log t, f''(t) = \frac{(1+t)}{t^2} > 0, \forall t > 0$$

$f''(t) \geq 0$ and $f(1) = 0$, So function f is convex and normalized.

$$\text{Define } g(t) = f''(t) = \frac{(1+t)}{t^2}$$

$g(t)$ is monotonic decreasing $\forall t \geq 0$

Then obviously

$$M = \sup_{t \in [r, R]} g(t) = \frac{(1+r)}{r^2}, m = \inf_{t \in [r, R]} g(t) = \frac{(1+R)}{R^2} \quad (4.8)$$

Since $S_f(P, Q) = \frac{1}{2} J_R(P, Q)$ from equation (2.12)

From equation (2.12), (3.3) & (4.8) give the result (4.7).

4.5 PROPOSITION

Let $P, Q \in \Gamma_n$ be two probability distributions satisfying (3.2) then we have the following inequality

$$\frac{r^{\alpha-2}}{4} \chi^2(P, Q) \leq \Omega_\alpha(Q, P) \leq \frac{R^{\alpha-2}}{4} \chi^2(P, Q), \quad \alpha \geq 2 \quad (4.9)$$

$$\frac{R^{\alpha-2}}{4} \chi^2(P, Q) \leq \Omega_\alpha(Q, P) \leq \frac{r^{\alpha-2}}{4} \chi^2(P, Q), \quad \alpha < 2 \quad (4.10)$$

Proof:-Consider the mapping $f : (r, R) \rightarrow \mathbf{R}$.

$$f(t) = [\alpha(\alpha-1)]^{-1} [t^\alpha - 1], \quad \alpha \neq 0, 1$$

$$f(t) = [\alpha(\alpha-1)]^{-1} [t^\alpha - 1], f'(t) = [\alpha-1]^{-1} t^{\alpha-1}, f''(t) = t^{\alpha-2} > 0, \forall t > 0$$

$f''(t) \geq 0$ and $f(1) = 0$. So function f is convex and normalized.

Define $g(t) = f''(t) = t^{\alpha-2}$

Then obviously

$$M = \sup_{t \in [r, R]} g(t) = R^{\alpha-2}, m = \inf_{t \in [r, R]} g(t) = r^{\alpha-2} \quad (4.11)$$

Since $S_f(P, Q) = \Omega_\alpha(Q, P)$ from equation (2.14)

From equation (2.14), (3.3) & (4.11) give the result (4.9) & (4.10)

4.5.1 COROLLARY

$\alpha = \frac{1}{2}$ for result (4.10) of proposition 4.5 and Let $P, Q \in \Gamma_n$ be two probability distributions satisfying (3.2) then we have the following inequality

$$\frac{1}{16R^{3/2}} \chi^2(P, Q) \leq \left[1 - B\left(\frac{P+Q}{2}, Q\right)\right] \leq \frac{1}{16r^{3/2}} \chi^2(P, Q) \quad (4.12)$$

and

$$\frac{1}{16R^{3/2}} \chi^2(P, Q) \leq h\left(\frac{P+Q}{2}, Q\right) \leq \frac{1}{16r^{3/2}} \chi^2(P, Q) \quad (4.13)$$

Proof: - Consider the mapping $f : (r, R) \rightarrow \mathbf{R}$. If $\alpha = \frac{1}{2}$ then function

$$f(t) = 4(1-t^{\frac{1}{2}}), f'(t) = -2t^{-\frac{1}{2}}, f''(t) = t^{-\frac{3}{2}} > 0, \forall t > 0$$

$f''(t) \geq 0$ and $f(1) = 0$, So function f is convex and normalized.

$$g(t) = f''(t) = t^{-\frac{3}{2}}$$

$$M = \sup_{t \in [r, R]} g(t) = r^{-\frac{3}{2}}, m = \inf_{t \in [r, R]} g(t) = R^{-\frac{3}{2}} \quad (4.14)$$

$$\text{Since } S_f(P, Q) = 4 \left[1 - B\left(\frac{P+Q}{2}, Q\right) \right] = 4h\left(\frac{P+Q}{2}, Q\right) \text{ from (2.13)} \quad (4.15)$$

From equation (2.13), (3.3), (4.14) & (4.15) give the result (4.12) & (4.13)

4.5.2 Corollary

For $\alpha = 0$ & 1 of result (4.9) are already proved in propositions (4.1) and (4.2).

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