

MAX-MIN AND MIN-MAX VALUES OF VARIOUS MEASURES OF FUZZY DIVERGENCE

R.K.Tuli
 Department of Mathematics
 S.S.M. College
 Dinanagar (India)

Amarjit Singh
 Department of Mathematics
 Adesh Institute of Engg. & Tech.
 Faridkot (India)

ABSTRACT

In the present manuscript, we have considered some new non-probabilistic (fuzzy) measures of directed divergence, and keeping in view the importance and areas of applications of these measures, we have investigated their optimum values.

Keywords: Distance measure, Fuzzy entropy, Fuzzy directed divergence, Convexity.

INTRODUCTION

The measure of distance is an important term that describes the difference between fuzzy sets and can be considered as a dual concept of similarity measure. Many researchers have used distance measure to define fuzzy entropy. Using the axiom definition of distance measure, Fan, Ma and Xie [2] developed some new formulas of fuzzy entropy induced by distance measure and studied some new properties of distance measure. Rosenfeld [10] defined the shortest distance between two fuzzy sets as a density function on the non - negative reals. Corresponding to the probabilistic measure of divergence due to Kullback and Leibler [5], Bhandari and Pal [1] introduced the following measure of fuzzy directed divergence:

$$I(A: B) = \sum_{i=1}^n \left[\mu_A(x_i) \log \frac{\mu_A(x_i)}{\mu_B(x_i)} + (1 - \mu_A(x_i)) \log \frac{1 - \mu_A(x_i)}{1 - \mu_B(x_i)} \right]$$

(1.1)

Corresponding to Renyi's [9] and Havrada and Charvat's [3] divergence measures, Kapur [4] took the following expressions of measures of fuzzy directed divergence:

$$D^\alpha(A: B) = \frac{1}{\alpha - 1} \sum_{i=1}^n \log \left[\mu_A^\alpha(x_i) \mu_B^{1-\alpha}(x_i) + (1 - \mu_A(x_i))^\alpha (1 - \mu_B(x_i))^{1-\alpha} \right] \quad (1.2)$$

$$D_\alpha(A: B) = \frac{1}{\alpha - 1} \sum_{i=1}^n \left[\mu_A^\alpha(x_i) \mu_B^{1-\alpha}(x_i) + (1 - \mu_A(x_i))^\alpha (1 - \mu_B(x_i))^{1-\alpha} - 1 \right]$$

(1.3)

Tran and Duckstein [11] developed a new approach for ranking fuzzy numbers based on a distance measure. Parkash [6] introduced a generalized fuzzy divergence, given by

$$D_\alpha^\beta(A, B) = [(\alpha - 1) \beta]^{-1} \sum_{i=1}^n \left[\left\{ \mu_A^\alpha(x_i) \mu_B^{1-\alpha}(x_i) + (1 - \mu_A(x_i))^\alpha (1 - \mu_B(x_i))^{1-\alpha} \right\}^\beta - 1 \right]$$

(1.4)

Many measures of fuzzy divergence along with their detailed properties and important applications have been discussed by various authors including those of Kapur [4], Parkash [6], Parkash and Sharma [7], Parkash and Tuli [8] etc. In fact, Kapur [4] has developed many expressions for the measures of fuzzy directed divergence corresponding to probabilistic measures of divergence due to Harvada and Charvat [3], Renyi [9] etc.

2. OPTIMIZATION OF VARIOUS MEASURES OF DIVERGENCE

In this section, we consider Renyi's [9] measure of fuzzy directed divergence given in (1.2) and examine it for its maximum and minimum values.

I. Minimum values of Renyi's [9] measure of fuzzy directed divergence

We now find the minimum value of $D^\alpha(A: B)$. Since $D^\alpha(A: B)$ is a convex function, its minimum value exists. For minimum value, we put

$$\frac{\partial D^\alpha(A: B)}{\partial \mu_A(x_i)} = 0 \text{ which gives } \mu_A(x_i) = 1 - \mu_B(x_i) \Rightarrow \mu_A(x_i) = \frac{1}{2}$$

Now $\sum_{i=1}^n \mu_A(x_i) = k$ gives $\frac{n}{2} = k \Rightarrow \frac{k}{n} = \frac{1}{2} = \mu_A(x_i) \forall i$

$$\therefore \text{Min.} D^\alpha(A: B) = \frac{1}{\alpha - 1} \sum_{i=1}^n \log \left[\left(\frac{k}{n} \right)^\alpha \mu_B^{1-\alpha}(x_i) + \left(1 - \frac{k}{n} \right)^\alpha (1 - \mu_B(x_i))^{1-\alpha} \right]$$

Case-I. When $k = 0$, then

$$\text{Min.} D^\alpha(A: B) = \frac{1}{\alpha - 1} \sum_{i=1}^n \log (1 - \mu_B(x_i))^{1-\alpha} = - \sum_{i=1}^n \log (1 - \mu_B(x_i))$$

Case-II. When $k = \frac{n}{2}$, then

$$\text{Min.} D^\alpha(A: B) = \frac{1}{\alpha - 1} \sum_{i=1}^n \log \left[\frac{(\mu_B(x_i))^{1-\alpha} + (1 - \mu_B(x_i))^{1-\alpha}}{2^\alpha} \right]$$

Case-III. When $k = n$, then

$$\text{Min.} D^\alpha(A: B) = \frac{1}{\alpha - 1} \sum_{i=1}^n \log (\mu_B(x_i))^{1-\alpha} = - \sum_{i=1}^n \log (\mu_B(x_i))$$

Illustration. To illustrate the above process, we consider $\mu_B(x_i) = \left(\frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \dots, \frac{1}{n+1} \right)$

For $k = 0$,

$$\begin{aligned} \text{Min.} D^\alpha(A: B) &= - \sum_{i=1}^n \log (1 - \mu_B(x_i)) = - \left(\log \frac{1}{2} + \log \frac{2}{3} + \log \frac{3}{4} + \dots + \log \frac{n}{n+1} \right) \\ &= \left(\log 2 + \log \frac{3}{2} + \log \frac{4}{3} + \dots + \log \frac{n+1}{n} \right) \\ &= \left(\log 2 \cdot \frac{3}{2} \cdot \frac{4}{3} \dots \frac{n+1}{n} \right) = \log(n+1) \end{aligned}$$

For $k = \frac{n}{2}$,

$$\begin{aligned} \text{Min.} D^\alpha(A: B) &= \frac{1}{\alpha - 1} \left[\log \frac{2^{\alpha-1} + 2^{\alpha-1}}{2^\alpha} + \log \frac{3^{\alpha-1} + \left(\frac{3}{2} \right)^{\alpha-1}}{2^\alpha} + \log \frac{4^{\alpha-1} + \left(\frac{4}{3} \right)^{\alpha-1}}{2^\alpha} + \log \frac{(n+1)^{\alpha-1} + \left(\frac{n+1}{n} \right)^{\alpha-1}}{2^\alpha} \right] \\ &= \log \frac{(n+1)!}{2^{n\alpha}} + \frac{1}{\alpha - 1} \left[\log \left(1 + \frac{1}{1^{\alpha-1}} \right) \cdot \left(1 + \frac{1}{2^{\alpha-1}} \right) \cdot \left(1 + \frac{1}{3^{\alpha-1}} \right) \dots \left(1 + \frac{1}{n^{\alpha-1}} \right) \right] \end{aligned}$$

For $k = n$,

$$\begin{aligned} \text{Min.}D^\alpha(A: B) &= \frac{1}{\alpha-1} \sum_{i=1}^n \log(\mu_B(x_i))^{1-\alpha} = -\sum_{i=1}^n \log(\mu_B(x_i)) \\ &= \log 2.3.4.....(n+1) = \log(n+1)! \end{aligned}$$

II. Maximum values of Renyi's [9] measure of fuzzy directed divergence

We now find maximum value of $D^\alpha(A: B)$.

Case-I: When k is any +ve integer, then we can choose k values of $\mu_A(x_i)$ as unity and others $(n-k)$ as 0, that is, $\mu_A(x_i) = \{1, 1, 1, \dots, 1, 0, 0, \dots, 0\}$. Now, we can write

$$D^\alpha(A: B) = \frac{1}{\alpha-1} \left[\sum_{i=1}^m \log \left[\mu_A^\alpha(x_i) \mu_B^{1-\alpha}(x_i) + (1-\mu_A(x_i))^\alpha (1-\mu_B(x_i))^{1-\alpha} \right] + \sum_{i=m+1}^n \log \left[\mu_A^\alpha(x_i) \mu_B^{1-\alpha}(x_i) + (1-\mu_A(x_i))^\alpha (1-\mu_B(x_i))^{1-\alpha} \right] \right]$$

Thus, the maximum value of $D^\alpha(A: B)$ is given as

$$\text{Max.}D^\alpha(A: B) = \frac{1}{\alpha-1} \left[\sum_{i=1}^m \log \mu_B^{1-\alpha}(x_i) + \sum_{i=m+1}^n \log (1-\mu_B(x_i))^{1-\alpha} \right]$$

Illustration. To illustrate the above process, we consider $\mu_B(x_i) = \left(\frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \dots, \frac{1}{n+1}\right)$

$$\begin{aligned} \text{For } m=0, \text{Min.}D^\alpha(A: B) &= \frac{1}{\alpha-1} \sum_{i=1}^n \log (1-\mu_B(x_i))^{1-\alpha} = -\sum_{i=1}^n \log (1-\mu_B(x_i)) \\ &= \left(\log 2. \frac{3}{2}. \frac{4}{3} \dots \frac{n+1}{n} \right) = \log(n+1) \end{aligned}$$

For $m=1$,

$$\begin{aligned} \text{Min.}D^\alpha(A: B) &= \frac{1}{\alpha-1} \left[\log(\mu_B^{1-\alpha}(x_1)) + \sum_{i=2}^n \log (1-\mu_B(x_i))^{1-\alpha} \right] \\ &= \left(\log 2 + \log \frac{3}{2} + \log \frac{4}{3} + \dots \log \frac{n+1}{n} \right) \\ &= \left(\log 2. \frac{3}{2}. \frac{4}{3} \dots \frac{n+1}{n} \right) = \log(n+1) \end{aligned}$$

For $m=2$,

$$\text{Max.}D^\alpha(A: B) = \log 2 + \log 3 + \log \frac{4}{3} + \log \frac{5}{4} + \dots \log \left(\frac{n+1}{n} \right) = \log 2! + \log(n+1)$$

For $m=3$,

$$\begin{aligned} \text{Max.}D^\alpha(A: B) &= \frac{1}{\alpha-1} \left(\log 2^{\alpha-1} + \log 3^{\alpha-1} + \log 4^{\alpha-1} + \log \left(\frac{5}{4} \right)^{\alpha-1} + \log \left(\frac{6}{5} \right)^{\alpha-1} + \dots \log \left(\frac{n+1}{n} \right)^{\alpha-1} \right) \\ &= \log 2 + \log 3 + \log 4 + \log \frac{5}{4} + \log \frac{6}{5} \dots \log \left(\frac{n+1}{n} \right) = \log 3! + \log(n+1) \end{aligned}$$

For $m=n$,

$$\begin{aligned} \text{Max.D}^\alpha(A: B) &= \frac{1}{\alpha-1} \sum_{i=1}^n \log(\mu_B(x_i))^{1-\alpha} = -\sum_{i=1}^n \log(\mu_B(x_i)) \\ &= -\left(\log \frac{1}{2} + \log \frac{1}{3} + \log \frac{1}{4} + \dots + \log \frac{1}{n+1}\right) = (\log 2.3.4\dots(n+1)) \\ &= \log(n+1)! \end{aligned}$$

The above values show that $\text{Max.D}^\alpha(A: B)$ is piecewise convex function.

Case-II: If k is any fraction, then, we can write $k = m + \xi$, where m is a +ve integer and ξ is a positive fraction. We can choose m fuzzy values of $\mu_A(x_i)$ as unity, $(m+1)^{\text{th}}$ value of $\mu_A(x_i)$ as ξ and remaining $(n-m-1)$ values of $\mu_A(x_i)$ as 0, that is, $\mu_A(x_i) = \{1, 1, \dots, 1, \xi, 0, 0, \dots, 0\}$. Thus,

$$\begin{aligned} D^\alpha(A: B) &= \frac{1}{\alpha-1} \left[\sum_{i=1}^m \log \mu_B^{1-\alpha}(x_i) + \log \xi^\alpha \mu_B^{1-\alpha}(x_{m+1}) + (1-\xi)^\alpha (1-\mu_B(x_{m+1}))^{1-\alpha} + \sum_{i=m+2}^n \log (1-\mu_B(x_i))^{1-\alpha} \right] \\ &= -\sum_{i=1}^m \log \mu_B(x_i) - \sum_{i=m+2}^n \log (1-\mu_B(x_i)) + \frac{1}{\alpha-1} \log \left[\xi^\alpha \mu_B^{1-\alpha}(x_{m+1}) + (1-\xi)^\alpha (1-\mu_B(x_{m+1}))^{1-\alpha} \right] \end{aligned}$$

To illustrate the above process, we consider $\mu_B(x_i) = \left(\frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \dots, \frac{1}{n+1}\right)$

$$\begin{aligned} \therefore \text{Max.D}^\alpha(A: B) &= \log 2 + \log 3 + \dots + \log(m+1) + \log \frac{m+3}{m+2} + \log \frac{m+4}{m+3} + \dots + \log \frac{n+1}{n} \\ &\quad + \frac{1}{\alpha-1} \log \left[\xi^\alpha (m+2)^{\alpha-1} + (1-\xi)^\alpha \left(\frac{m+2}{m+1}\right)^{\alpha-1} \right] \\ &= \log(m+1)! + \log \frac{n+1}{m+1} + \frac{1}{\alpha-1} \log \left[\xi^\alpha (m+1)^{\alpha-1} + (1-\xi)^\alpha \right] \\ &= \log(n+1)m! + \phi(\xi) \end{aligned}$$

where $\phi(\xi) = \frac{1}{\alpha-1} \log \left[\xi^\alpha (m+1)^{\alpha-1} + (1-\xi)^\alpha \right]$

We, now check the convexity of $\phi(\xi)$.

Take $h(\xi) = \xi^\alpha (m+1)^{\alpha-1} + (1-\xi)^\alpha$,

$$\text{Thus } \frac{d}{d\xi} h(\xi) = \alpha \left[\xi^{\alpha-1} (m+1)^{\alpha-1} - (1-\xi)^{\alpha-1} \right]$$

$$\begin{aligned} \text{Also } \frac{d^2}{d\xi^2} h(\xi) &= \alpha(\alpha-1) \left[\xi^{\alpha-2} (m+1)^{\alpha-1} + (1-\xi)^{\alpha-2} \right] \\ &= (\alpha^2 - \alpha) \left[\xi^{\alpha-2} (m+1)^{\alpha-1} + (1-\xi)^{\alpha-2} \right] \end{aligned}$$

If $\alpha > 1$, then $\frac{d^2}{d\xi^2} h(\xi) > 0 \Rightarrow h(\xi)$ is a convex function of ξ

$\Rightarrow \log h(\xi)$ is a convex function of ξ

$\Rightarrow \frac{1}{\alpha-1} \log h(\xi)$ is a convex function of ξ for $\alpha > 1$,

If $\alpha < 1$, then $\frac{d^2}{d\xi^2} h(\xi) < 0 \Rightarrow h(\xi)$ is a concave function of ξ

$\Rightarrow \log h(\xi)$ is a concave function of ξ

$\Rightarrow \frac{1}{\alpha-1} \log h(\xi)$ is a convex function of ξ for $0 < \alpha < 1$,

Hence, $\phi(\xi)$ is a convex function of ξ for each α . Its minimum value exists at

$$\xi = \frac{1}{m+2}$$

Also, the minimum value of $\text{Max.D}^\alpha(A: B)$ is given as

$$\begin{aligned} \text{Min.Max.D}^\alpha(A: B) &= \log(n+1)m! + \phi\left(\frac{1}{m+2}\right) \\ &= \log(n+1)m! + \frac{1}{\alpha-1} \log\left(\frac{(m+1)^{\alpha-1}}{(m+2)^\alpha} + \frac{(m+1)^\alpha}{(m+2)^\alpha}\right) \\ &= \log(n+1)m! + \log\frac{(m+1)}{(m+2)} \\ &= \log(n+1) + \log\frac{(m+1)m!}{(m+2)} = \log(n+1) + \log\frac{(m+1)!}{(m+2)} \end{aligned}$$

For $m=0$, $\text{Min.Max.D}^\alpha(A: B) = \log(n+1) + \log\frac{1!}{2}$

For $m=1$, $\text{Min.Max.D}^\alpha(A: B) = \log(n+1) + \log\frac{2!}{3}$

For $m=2$, $\text{Min.Max.D}^\alpha(A: B) = \log(n+1) + \log\frac{3!}{4}$

For $m=3$, $\text{Min.Max.D}^\alpha(A: B) = \log(n+1) + \log\frac{4!}{5}$

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For $m=n$, For $m=2$, $\text{Min.Max.D}^\alpha(A: B) = \log(n+1) + \log\frac{(n+1)!}{n+2}$

Conclusions: When $\mu_B(x_i)$ is a monotonically decreasing, the **Max.** cross entropy is an increasing function. It can also be proved that if $\mu_B(x_i)$ is a monotonically increasing, the **Max.** cross entropy is a decreasing function. Also in both cases, $\text{Max.D}^\alpha(A: B)$ is a piecewise convex function of k . In the literature of distance measures, there exist many parametric and non-parametric measures of fuzzy divergence introduced by various researchers. Proceeding on similar way as done in section 2, the optimum values of other divergence measures can be studied.

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