

SOME NEW MEASURES OF FUZZY DIRECTED DIVERGENCE AND THEIR GENERALIZATION

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ABSTRACT. There exist many measures of fuzzy directed divergence corresponding to the existing probabilistic measures. Some new measures of fuzzy divergence have been proposed which correspond to some well-known existing probabilistic measures. The essential properties of the proposed measures have been developed which contains many existing measures of fuzzy directed divergence.

1. INTRODUCTION

Zadeh [8, 9] introduced the concept of fuzzy sets in which imprecise knowledge can be used to define a event. Dubois & Prade [2] defined the distance between two fuzzy subsets on a fuzzy subset of \mathbb{R}^+ . Their definition does not generalize the shortest distance between two crisp sets. Rosenfeld [6] defined the shortest distance between two fuzzy sets as a density function on the non-negative reals, which generalizes the definition of shortest distance for crisp sets in a natural way. Using the concept of fuzzy message conditioning, a fuzzy information measure for discrimination between two fuzzy sets has been suggested by Bhandari & Pal [1].

Bhandari & Pal [1] introduced a measure of fuzzy divergence corresponding to the probabilistic directed divergence of Kullback & Leibler [4] which is given by

$$I(A : B) = \sum_{i=1}^n \left[\mu_A(x_i) \ln \frac{\mu_A(x_i)}{\mu_B(x_i)} + (1 - \mu_A(x_i)) \ln \frac{1 - \mu_A(x_i)}{1 - \mu_B(x_i)} \right], \quad (1.1)$$

where $\mu_A(x_i)$ gives the degree of belongingness of the element x_i to the set A .

The symmetric fuzzy divergence between two fuzzy sets A and B is given by

$$J(A : B) = I(A : B) + I(B : A). \quad (1.2)$$

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Lin [5] introduced a probabilistic measure

$$K(P : Q) = \sum_{i=1}^n p_i \ln \frac{p_i}{(p_i + q_i)/2} \quad (1.3)$$

of directed divergence of a probability distribution $P = (p_1, p_2, \dots, p_n)$ from another probability distribution $Q = (q_1, q_2, \dots, q_m)$.

We propose fuzzy directed divergence corresponding to (1.3) as

$$\begin{aligned} K(A : B) &= \sum_{i=1}^n \left[\mu_A(x_i) \ln \frac{\mu_A(x_i)}{(\mu_A(x_i) + \mu_B(x_i))/2} \right. \\ &\quad \left. + (1 - \mu_A(x_i)) \ln \frac{1 - \mu_A(x_i)}{(1 - \mu_A(x_i) + 1 - \mu_B(x_i))/2} \right] \end{aligned} \quad (1.4)$$

The probabilistic measure of directed divergence of Sharma & Taneja [7] is given by

$$S(P : Q) = \frac{1}{\alpha - \beta} \sum_{i=1}^n [p_i^\alpha q_i^{1-\alpha} - p_i^\beta q_i^{1-\beta}] \quad (1.5)$$

where $\alpha < 1, \beta > 1$ or $\alpha > 1, \beta < 1$.

We propose the measure of fuzzy directed divergence corresponding to (1.5) as

$$\begin{aligned} S(A : B) &= \frac{1}{\alpha - \beta} \sum_{i=1}^n \left[\mu_A^\alpha(x_i) \mu_B^{1-\alpha}(x_i) + (1 - \mu_A(x_i))^\alpha (1 - \mu_B(x_i))^{1-\alpha} \right. \\ &\quad \left. - \mu_A^\beta(x_i) \mu_B^{1-\beta}(x_i) - (1 - \mu_A(x_i))^\beta (1 - \mu_B(x_i))^{1-\beta} \right] \end{aligned} \quad (1.6)$$

where $\alpha < 1, \beta > 1$ or $\alpha > 1, \beta < 1$.

In Section 2, we prove that (1.4) and (1.6) are valid measures of fuzzy directed divergence. In Section 3, a new generalized measure of fuzzy directed divergence has been developed and many more well-known measures have been derived from it.

2. NEW MEASURES OF FUZZY DIVERGENCE

Taking

$$\sum_{i=1}^n \mu_A(x_i) = s \quad \text{and} \quad \sum_{i=1}^n \mu_B(x_i) = t,$$

where s and t may be different from unity.

We know that

$$\sum_{i=1}^n \frac{\mu_A(x_i)}{s} \ln \frac{\frac{\mu_A(x_i)}{s}}{\frac{\mu_A(x_i) + \mu_B(x_i)}{2} / \frac{s+t}{2}} \geq 0$$

that is,

$$\sum_{i=1}^n \mu_A(x_i) \ln \frac{\mu_A(x_i)}{(\mu_A(x_i) + \mu_B(x_i))/2} \geq s \ln \frac{s}{(s+t)/2}. \tag{2.1}$$

Similarly,

$$\sum_{i=1}^n (1 - \mu_A(x_i)) \ln \frac{1 - \mu_A(x_i)}{(1 - \mu_A(x_i) + 1 - \mu_B(x_i))/2} \geq (n - s) \ln \frac{n - s}{(2n - s + t)/2}. \tag{2.2}$$

Adding (2.1) and (2.2), we get

$$K(A : B) \geq f(s),$$

where

$$f(s) = s \ln \frac{s}{(s+t)/2} + (n - s) \ln \frac{n - s}{(2n - s - t)/2}.$$

Now

$$f'(s) = \ln s - \frac{s}{s+t} - \ln(s+t) - \ln(n - s) + \frac{n - s}{2n - s - t} + \ln(2n - s - t)$$

and

$$\begin{aligned} f''(s) &= \left(\frac{1}{s} - \frac{1}{s+t}\right) - \frac{t}{(s+t)^2} + \left(\frac{1}{n-s} - \frac{1}{2n-s-t}\right) - \frac{n-t}{(2n-s-t)^2} \\ &= \frac{t^2}{s(s+t)^2} + \frac{(n-t)^2}{(n-s)(2n-s-t)^2} \\ &> 0, \end{aligned}$$

so that $f(s)$ is a convex function of s which has its minimum value when $s = t$, and the minimum value is 0 so that $f(s) > 0$ and vanishes when $s = t$. Consequently, $K(A : B)$ is a convex function of $\mu_A(x_i)$.

Similarly, we can show that $K(A : B)$ is a convex function of $\mu_B(x_i)$. Thus for all values of s and t , we have

- (i) $K(A : B) \geq 0$,
- (ii) $K(A : B) = 0$ if and only if $A = B$,
- (iii) $K(A : B)$ is a convex function, and
- (iv) $K(A : B)$ does not change when $\mu_A(x_i)$ is changed to $1 - \mu_A(x_i)$ and $\mu_B(x_i)$ is changed to $1 - \mu_B(x_i)$.

Hence $K(A : B)$ is a valid measure of fuzzy directed divergence and

$$J'(A : B) = K(A : B) + K(B : A)$$

is a valid measure of fuzzy symmetric divergence.

Again, we know that

$$\sum_{i=1}^n \left[\left(\frac{\mu_A(x_i)}{s} \right)^\alpha \left(\frac{\mu_B(x_i)}{t} \right)^{1-\alpha} - 1 \right] \geq 0,$$

that is,

$$\sum_{i=1}^n \mu_A^\alpha(x_i) \mu_B^{1-\alpha}(x_i) \geq s^\alpha t^{1-\alpha}. \quad (2.3)$$

Similarly,

$$\sum_{i=1}^n (1 - \mu_A(x_i))^\alpha (1 - \mu_B(x_i))^{1-\alpha} \geq (n-s)^\alpha (n-t)^{1-\alpha}. \quad (2.4)$$

Adding (2.3) and (2.4), we get

$$\begin{aligned} \sum_{i=1}^n [\mu_A^\alpha(x_i) \mu_B^{1-\alpha}(x_i) + (1 - \mu_A(x_i))^\alpha (1 - \mu_B(x_i))^{1-\alpha}] \\ \geq s^\alpha t^{1-\alpha} + (n-s)^\alpha (n-t)^{1-\alpha}. \end{aligned} \quad (2.5)$$

Similarly,

$$\begin{aligned} \sum_{i=1}^n [\mu_A^\beta(x_i) \mu_B^{1-\beta}(x_i) + (1 - \mu_A(x_i))^\beta (1 - \mu_B(x_i))^{1-\beta}] \\ \geq s^\beta t^{1-\beta} + (n-s)^\beta (n-t)^{1-\beta}. \end{aligned} \quad (2.6)$$

Subtracting (2.6) from (2.5) and dividing by $(\alpha - \beta)$, we get

$$S(A : B) \geq F(s)$$

where

$$F(s) = \frac{1}{\alpha - \beta} [s^\alpha t^{1-\alpha} + (n-s)^\alpha (n-t)^{1-\alpha} - s^\beta t^{1-\beta} - (n-s)^\beta (n-t)^{1-\beta}].$$

Now we have

$$F'(s) = \frac{1}{\alpha - \beta} \left[\alpha \left(\frac{s}{t} \right)^{\alpha-1} - \alpha \left(\frac{n-s}{n-t} \right)^{\alpha-1} \right]$$

and

$$F''(s) = \frac{1}{\alpha - \beta} \left[\frac{\alpha(\alpha-1)}{t} \left(\frac{s}{t} \right)^{\alpha-2} + \frac{\alpha(\alpha-1)}{n-t} \left(\frac{n-s}{n-t} \right)^{\alpha-2} \right]$$

$$= \frac{\alpha(\alpha - 1)}{\alpha - \beta} \left[\frac{1}{t} \left(\frac{s}{t}\right)^{\alpha-2} + \frac{1}{n-t} \left(\frac{n-s}{n-t}\right)^{\alpha-2} \right] > 0,$$

for $\alpha > 1, \beta < 1$ or $\alpha < 1, \beta > 1$. Hence $F(s)$ is a convex function of s whose minimum value arises when

$$\frac{s}{t} = \frac{n-s}{n-t} = 1, \text{ i. e., } s = t$$

and the minimum value is 0, so that $F(s) > 0$ and vanishes only when $s = t$, i. e., when $A = B$. Consequently, $S(A : B)$ is a convex function of $\mu_A(x_i)$.

Similarly, $S(A : B)$ is a convex function of $\mu_B(x_i)$. Thus, for all values of s and t , we have

- (i) $S(A : B) \geq 0$,
- (ii) $S(A : B) = 0$ if and only if $A = B$,
- (iii) $S(A : B)$ is convex function, and
- (iv) $S(A : B)$ does not change when $\mu_A(x_i)$ is replaced by $1 - \mu_A(x_i)$ and $\mu_B(x_i)$ by $1 - \mu_B(x_i)$.

Hence $S(A : B)$ is a valid of measure of fuzzy directed divergence and $S'(A : B) = S(A : B) + S(B : A)$ is a valid measure of fuzzy symmetric divergence corresponding to the measure defined by Havrda & Charvát [3].

If we take $\beta = 1$ and $\alpha \rightarrow 1$, $S(A : B)$ becomes the measure of fuzzy directed divergence defined by Bhandari & Pal [1].

3. GENERALIZED FUZZY DIRECTED DIVERGENCE

We consider

$$I_\lambda(A : B) = \sum_{i=1}^n \left[(\lambda\mu_A(x_i) + (1 - \lambda)\mu_B(x_i))\phi\left(\frac{\mu_A(x_i)}{\lambda\mu_A(x_i) + (1 - \lambda)\mu_B(x_i)}\right) + \{\lambda(1 - \mu_A(x_i)) + (1 - \lambda)(1 - \mu_B(x_i))\} \times \phi\left(\frac{1 - \mu_A(x_i)}{\lambda(1 - \mu_A(x_i)) + (1 - \lambda)(1 - \mu_B(x_i))}\right) \right], \tag{3.1}$$

where $\phi(\cdot)$ is twice differentiable convex function for which $\phi(1) = 0$. Now

$$\frac{\partial I_\lambda(A : B)}{\partial \mu_A(x_i)}$$

$$\begin{aligned}
&= \lambda \phi \left(\frac{\mu_A(x_i)}{\lambda \mu_A(x_i) + (1-\lambda) \mu_B(x_i)} \right) \\
&+ \frac{(1-\lambda) \mu_B(x_i)}{\lambda \mu_A(x_i) + (1-\lambda) \mu_B(x_i)} \phi' \left(\frac{\mu_A(x_i)}{\lambda \mu_A(x_i) + (1-\lambda) \mu_B(x_i)} \right) \\
&- \lambda \phi \left(\frac{1 - \mu_A(x_i)}{\lambda(1 - \mu_A(x_i)) + (1-\lambda)(1 - \mu_B(x_i))} \right) \\
&- \frac{(1-\lambda)(1 - \mu_B(x_i))}{\lambda(1 - \mu_A(x_i)) + (1-\lambda)(1 - \mu_B(x_i))} \phi \left(\frac{1 - \mu_A(x_i)}{\lambda(1 - \mu_A(x_i)) + (1-\lambda)(1 - \mu_B(x_i))} \right)
\end{aligned}$$

and

$$\begin{aligned}
&\frac{\partial^2 I_\lambda(A : B)}{\partial \mu_A^2(x_i)} \\
&= \frac{\lambda^2(1-\lambda)^2(1 - \mu_B(x_i))^2}{[\lambda(1 - \mu_A(x_i)) + (1-\lambda)(1 - \mu_B(x_i))]^3} + \frac{(1-\lambda)^2 \mu_B^2(x_i)}{[\lambda \mu_A(x_i) + (1-\lambda) \mu_B(x_i)]^3} \\
&> 0,
\end{aligned}$$

so that $I_\lambda(A : B)$ is a convex function of $\mu_A(x_i)$ which has its minimum value when $\mu_A(x_i) = \mu_B(x_i)$. And the minimum value is 0 so that $I_\lambda(A : B) > 0$ and vanishes when $\mu_A(x_i) = \mu_B(x_i)$. Similarly, $I_\lambda(A : B)$ is a convex function of $\mu_B(x_i)$.

Thus for all values of $\mu_A(x_i)$ and $\mu_B(x_i)$, we have

- (i) $I_\lambda(A : B) \geq 0$,
- (ii) $I_\lambda(A : B) = 0$ if and only if $A = B$,
- (iii) $I_\lambda(A : B)$ is a convex function, and
- (iv) $I_\lambda(A : B)$ does not change when $\mu_A(x_i)$ is replaced by $1 - \mu_A(x_i)$ and $\mu_B(x_i)$ by $1 - \mu_B(x_i)$.

Hence $I_\lambda(A : B)$ is a valid generalized measure of fuzzy directed divergence.

3.1. Special Case I: Taking $\phi(x) = x \ln x$ and denoting $I_\lambda(A : B)$ in (3.1) by $I_{1,\lambda}(A : B)$, we get

$$\begin{aligned}
&I_{1,\lambda}(A : B) \\
&= \sum_{i=1}^n \left[\mu_A(x_i) \ln \frac{\mu_A(x_i)}{\lambda \mu_A(x_i) + (1-\lambda) \mu_B(x_i)} \right. \\
&\quad \left. + (1 - \mu_A(x_i)) \ln \frac{1 - \mu_A(x_i)}{\lambda(1 - \mu_A(x_i)) + (1-\lambda)(1 - \mu_B(x_i))} \right]
\end{aligned} \tag{3.2}$$

The expression (3.2) is a generalization of (1.4).

(a) If we take $\lambda = 0$ in (3.2), we get

$$I_{1,0}(A : B) = \sum_{i=1}^n \left[\mu_A(x_i) \ln \frac{\mu_A(x_i)}{\mu_B(x_i)} + (1 - \mu_A(x_i)) \ln \frac{1 - \mu_A(x_i)}{1 - \mu_B(x_i)} \right] \quad (3.3)$$

which is a measure of fuzzy directed divergence corresponding to the probabilistic measure of divergence introduced by Kullback & Leibler [4].

(b) If we take $\lambda = \frac{1}{2}$ in (3.2), we get

$$\begin{aligned} I_{1,\frac{1}{2}}(A : B) &= \sum_{i=1}^n \left[\mu_A(x_i) \ln \frac{\mu_A(x_i)}{(\lambda\mu_A(x_i) + \mu_B(x_i))/2} \right. \\ &\quad \left. + (1 - \mu_A(x_i)) \ln \frac{1 - \mu_A(x_i)}{(1 - \mu_A(x_i) + 1 - \mu_B(x_i))/2} \right] \end{aligned}$$

which is (1.4).

3.2. Special Case II: Let $\phi(x) = \frac{x^\alpha - x}{\alpha(\alpha-1)}$, $\alpha \neq 0$, $\alpha \neq 1$, and denote $I_\lambda(A : B)$ in (3.1) by $I_{2,\lambda}(A : B)$, then (3.1) gives

$$\begin{aligned} I_{2,\lambda}(A : B) &= \frac{1}{\alpha(\alpha-1)} \sum_{i=1}^n \left[\mu_A^\alpha(x_i) \{ \lambda\mu_A(x_i) + (1-\lambda)\mu_B(x_i) \}^{1-\alpha} \right. \\ &\quad \left. + (1 - \mu_A(x_i))^\alpha \{ \lambda(1 - \mu_A(x_i)) + (1-\lambda)(1 - \mu_B(x_i)) \}^{1-\alpha} - 1 \right]. \end{aligned} \quad (3.4)$$

(a) If we take $\lambda = 0$ in (3.4), we get

$$\begin{aligned} I_{2,0}(A : B) &= \frac{1}{\alpha(\alpha-1)} \sum_{i=1}^n \left[\mu_A^\alpha(x_i) \mu_B(x_i)^{1-\alpha} + (1 - \mu_A(x_i))^\alpha (1 - \mu_B(x_i))^{1-\alpha} - 1 \right] \end{aligned}$$

which is a measure of fuzzy directed divergence corresponding to the probabilistic divergence defined by Havrda & Charvát [3].

(b) From (3.4), we have

$$\lim_{\alpha \rightarrow 1} I_{2,\lambda}(A : B) = I_{1,\lambda}(A : B).$$

(c) When $\lambda = \frac{1}{2}$ and $\alpha \rightarrow 1$, (3.4) becomes $K(A : B)$.

(d) If we take $\lambda = 0$, $\alpha \rightarrow 1$ in (3.4), we get the measure of fuzzy directed divergence defined by Bhandari & Pal [1].

3.3. Special Case III: If we take $\phi(x) = \frac{x^\alpha - x^\beta}{\alpha - \beta}$ and denote $I_\lambda(A : B)$ in (3.1) by $I_{3,\lambda}(A : B)$, we get

$$\begin{aligned} & I_{3,\lambda}(A : B) \\ &= \frac{1}{\alpha - \beta} \sum_{i=1}^n \left[\mu_A^\alpha(x_i) \{ \lambda \mu_A(x_i) + (1 - \lambda) \mu_B(x_i) \}^{1-\alpha} \right. \\ &\quad + (1 - \mu_A(x_i))^\alpha \{ \lambda (1 - \mu_A(x_i)) + (1 - \lambda) (1 - \mu_B(x_i)) \}^{1-\alpha} \quad (3.5) \\ &\quad - \mu_A^\beta(x_i) \{ \lambda \mu_A(x_i) + (1 - \lambda) \mu_B(x_i) \}^{1-\beta} \\ &\quad \left. - (1 - \mu_A(x_i))^\beta \{ \lambda (1 - \mu_A(x_i)) + (1 - \lambda) (1 - \mu_B(x_i)) \}^{1-\beta} \right] \end{aligned}$$

which is a generalization of (1.6).

(a) If we take $\lambda = 0$ in (3.5), we get

$$\begin{aligned} & I_{3,0}(A : B) \\ &= \frac{1}{\alpha - \beta} \sum_{i=1}^n \left[\mu_A^\alpha(x_i) \mu_B^{1-\alpha}(x_i) + (1 - \mu_A(x_i))^\alpha (1 - \mu_B(x_i))^{1-\alpha} \mu_A^\beta(x_i) \mu_B^{1-\beta}(x_i) \right. \\ &\quad \left. - (1 - \mu_A(x_i))^\beta (1 - \mu_B(x_i))^{1-\beta} \right] \end{aligned}$$

which of (1.6).

(b) If we take $\lambda = 0$ and $\beta = 1$ in (3.5), we get

$$I'_{3,0}(A : B) = \frac{1}{\alpha - 1} \sum_{i=1}^n \left[\mu_A^\alpha(x_i) \mu_B^{1-\alpha}(x_i) + (1 - \mu_A(x_i))^\alpha (1 - \mu_B(x_i))^{1-\alpha} - 1 \right]$$

which is measure of fuzzy directed divergence corresponding to the probabilistic directed divergence defined by Havrda & Charvát [3].

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