JOINT AND CONDITIONAL R-NORM INFORMATION MEASURE

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The present paper depicts the joint and conditional probability distribution of two random variables ξ and η having probability distributors P and Q over the Sets $X = \{x_1, x_2, ..., x_n\}$ and $Y = \{y_1, y_2, ..., y_m\}$ respectively. Then the R-norm information of the random variables is denoted by $H_R(\xi) = H_R(P)$ and $H_R(\eta) = H_R(Q)$, where

$$p_i = P(\xi = x_i), i = 1, 2, ..., n, p_i = P(\eta = y_i), j = 1, 2, ..., m$$

are the probabilities of the possible values of the random variables. Similarly, we consider a two-dimensional discrete random variable (ξ,η) with joint probability distribution $\pi = (\pi_{11}, \pi_{12}, ..., \pi_{1n})$,

where $\pi_{ij} = P(\xi = x_{i}, \eta = y_{j})$, i = 1,2....,n, j = 1, 2...,m is the joint probability for the values (x_{i}, y_{j}) of (ξ, η) . We shall denote conditional probabilities by p_{ij} and q_{ij} such

that
$$\pi_{ij} = p_{ij} q_j = q_{ji} p_i$$
 And $p_i = \sum_{j=1}^m \pi_{ij} and q_i = \sum_{j=1}^n \pi_{ij}$.

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DEFINITION: The joint R-norm information measure for $R \in R^+$ and is given by

$$H_{R}(\xi,\eta) = \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} \pi_{ij}^{R} \right\}^{\frac{1}{R}} \right]$$
(1.1)

Proposition 1: $H_{R}(\xi,\eta)$ is symmetric in ξ and η .

Proof: The joint R-norm information measure is defined by

$$H_{R}(\xi,\eta) = \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} \pi_{ij}^{R} \right\}^{\frac{1}{R}} \right]$$
$$= \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} P^{R}(\xi = x_{i}, \eta = y_{j}) \right\}^{\frac{1}{R}} \right]$$
$$= \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} P^{R}(\xi = x_{i}) P^{R}(\eta = y_{i}) \right\}^{\frac{1}{R}} \right]$$
$$= \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} P^{R}(\eta = y_{i}) P^{R}(\xi = x_{i}) \right\}^{\frac{1}{R}} \right]$$
$$= \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} P^{R}(\eta = y_{i}, \xi = x_{j}) \right\}^{\frac{1}{R}} \right]$$
$$= \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} \pi_{ji}^{R} \right\}^{\frac{1}{R}} \right] = H_{R}(\eta, \xi)$$

This implies that $H_{R}(\xi,\eta)$ is symmetric in ξ,η .

Proposition 2: If ξ and η are stochastically independent. Then the following holds

$$H_{R}(\xi,\eta) = H_{R}(\xi) + H_{R}(\eta) - \frac{R-1}{R}H_{R}(\xi)H_{R}(\eta)$$
(1.2)

Proof: Since the joint R-norm information measure for $R \in R^+$ and is given by

$$H_{R}(\xi,\eta) = \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} \pi_{ij}^{R} \right\}^{\frac{1}{R}} \right]$$
$$= \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} P^{R}(\xi = x_{i}, \eta = y_{j}) \right\}^{\frac{1}{R}} \right]$$
$$= \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} P^{R}(\xi = x_{i}) P^{R}(\eta = y_{i}) \right\}^{\frac{1}{R}} \right]$$
$$= \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} P^{R}(\xi = x_{i}) P^{R}(\eta = y_{i}) \right\}^{\frac{1}{R}} \right]$$
(1.3)

Since ξ and η are stochastically independent, thus (1.3) becomes

$$H_{R}(\xi,\eta) = \frac{R}{R-1} \left[1 - \left[\sum_{i=1}^{n} P^{R}(\xi = x_{i}) \right]^{\frac{1}{R}} \left[\sum_{j=1}^{m} P^{R}(\eta = y_{j}) \right]^{\frac{1}{R}} \right]$$
$$= \frac{R}{R-1} - \frac{R}{R-1} \left[\left(1 - \frac{R-1}{R} H_{R}(\xi) \right) \left(1 - \frac{R-1}{R} H_{R}(\eta) \right) \right]$$
$$= H_{R}(\xi) + H_{R}(\eta) - \frac{R-1}{R} H_{R}(\xi) H_{R}(\eta) \quad \text{Thus finally}$$
$$H_{R}(\xi,\eta) = H_{R}(\xi) + H_{R}(\eta) - \frac{R-1}{R} H_{R}(\xi) H_{R}(\eta) \quad (1.4)$$

In the limiting case $R \rightarrow 1$ we find the additive form of Shannon's information measure for independent random variables.i.e. when $R \rightarrow 1$ in (1.4), then we get

$$H_{R}(\xi,\eta) = H_{R}(\xi) + H_{R}(\eta) - \frac{1-1}{1}H_{R}(\xi)H_{R}(\eta), \quad \Rightarrow H_{R}(\xi,\eta) = H_{R}(\xi) + H_{R}(\eta)$$

To construct a conditional R-norm information measure we can use a direct and an indirect method. The indirect method leads to next definition

DEFINITION: The average subtractive conditional R-norm information of η given ξ for $R \in R^+$ and is defined as

$${}^{\delta}H_{R}(\eta/\xi) = H_{R}(\xi,\eta) - H_{R}(\xi)$$

$$= \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} \pi_{ij}^{R} \right\}^{\frac{1}{R}} \right] - \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} p_{i}^{R} \right\}^{\frac{1}{R}} \right] \quad (1.4)$$
$$= \frac{R}{R-1} \left[\left\{ \sum_{i=1}^{n} p_{i}^{R} \right\}^{\frac{1}{R}} - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} \pi_{ij}^{R} \right\}^{\frac{1}{R}} \right] \quad (1.5)$$
$$= \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} \pi_{ij}^{R} \right\}^{\frac{1}{R}} \right] - \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} p_{i}^{R} \right\}^{\frac{1}{R}} \right] \quad (1.6)$$

$$=H_{R}(\eta/\xi)+H_{R}(\xi)$$

Thus $H_R(\xi,\eta) = H_R(\eta/\xi) + H_R(\xi)$

A direct way to construct a conditional R-norm information is the following.

DEFINITION: The average conditional R-norm information of η given

 ξ is for $R \in R^+$ defined as

$${}^{*}H_{R}(\eta/\xi) = \frac{R}{R-1} \left[1 - \sum_{i=1}^{n} p_{i} \left\{ \sum_{j=1}^{m} q_{ji} \right\}^{\frac{1}{R}} \right]$$
(1.7)

Or alternatively

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$${}^{**}H_{R}(\eta/\xi) = \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} p_{i} \sum_{j=1}^{m} q_{ji} \right\}^{\frac{1}{R}} \right]$$
(1.8)

The two conditional measure given in (1.7) and (1.8) differ by the way the probabilities p_i are incorporated. The expression (1.7) is a true mathematical expression over ξ , whereas the expression (1.8) is not.

Theorem: If ξ and η are statistically independent random variables then for $R \in \mathbb{R}^+$

(1)
$$^{\delta}H_{R}(\eta/\xi) = \frac{R}{R-1} \left[\left\{ \sum_{i=1}^{n} p_{i}^{R} \right\}^{\frac{1}{R}} - \left\{ \sum_{i=1}^{n} p_{i}^{R} \right\}^{\frac{1}{R}} \cdot \left\{ \sum_{j=1}^{m} q_{j}^{R} \right\}^{\frac{1}{R}} \right]$$

(2)
$${}^{\delta}H_{R}(\eta/\xi) = H_{R}(\xi,\eta) - H_{R}(\xi) = H_{R}(\eta) - \frac{R-1}{R}H_{R}(\xi)H_{R}(\eta)$$

(3)
$$^*H_R(\eta/\xi) = H_R(\eta)$$

(4) $^{**}H_R(\eta/\xi) = H_R(\eta)$

Proof: (I) Since the average subtractive conditional R-norm information of η given ξ is for $R \in R^+$ defined as

$${}^{\delta}H_{R}(\eta/\xi) = \frac{R}{R-1} \left[\left\{ \sum_{i=1}^{n} p_{i}^{R} \right\}^{\frac{1}{R}} - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} \pi_{ij}^{R} \right\}^{\frac{1}{R}} \right]$$
(1.9)

Substitute $\pi_{ij} = p_{ij}q_j$ in (1.9), we get

$${}^{\delta}H_{R}(\eta/\xi) = \frac{R}{R-1} \left[\left\{ \sum_{i=1}^{n} p_{i}^{R} \right\}^{\frac{1}{R}} - \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} (p_{ij}q_{j})^{R} \right\}^{\frac{1}{R}} \right]$$
(1.10)

Since $\,\xi\,$ and $\,\eta\,$ are stochastically independent. Thus (1.10) becomes

$${}^{\delta}H_{R}(\eta/\xi) = \frac{R}{R-1} \left[\left\{ \sum_{i=1}^{n} p_{i}^{R} \right\}^{\frac{1}{R}} - \left\{ \sum_{i=1}^{n} p_{i}^{R} \right\}^{\frac{1}{R}} \cdot \left\{ \sum_{j=1}^{m} q_{j}^{R} \right\}^{\frac{1}{R}} \right]^{\frac{1}{R}}$$

(II) Since we know that if ξ and η are stochastically independent. Then the following holds

$$H_{R}(\xi,\eta) = H_{R}(\xi) + H_{R}(\eta) - \frac{R-1}{R}H_{R}(\xi)H_{R}(\eta)$$
$$\Rightarrow H_{R}(\xi,\eta) - H_{R}(\xi) = H_{R}(\eta) - \frac{R-1}{R}H_{R}(\xi)H_{R}(\eta)$$
(1.11)

And we know

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$${}^{\delta}H_{R}(\eta/\xi) = H_{R}(\xi,\eta) - H_{R}(\xi)$$
(1.12)

Using (1.12) in (1.11), we get

$${}^{\delta}H_{R}(\eta/\xi) = H_{R}(\xi,\eta) - H_{R}(\xi) = H_{R}(\eta) - \frac{R-1}{R}H_{R}(\xi)H_{R}(\eta)$$

(III) Since the average conditional R-norm information of η given ξ for $R \in R^+$ and is defined as

$${}^{*}H_{R}(\eta/\xi) = \frac{R}{R-1} \left[1 - \sum_{i=1}^{n} p_{i} \left\{ \sum_{j=1}^{m} q_{ji} \right\}^{\frac{1}{R}} \right]$$
(1.13)

Substitute $q_{ji} = q_j$ in (1.13), we get

$${}^{*}H_{R}(\eta/\xi) = \frac{R}{R-1} \left[1 - \sum_{i=1}^{n} p_{i} \left\{ \sum_{j=1}^{m} q_{j}^{R} \right\}^{\frac{1}{R}} \right]$$
$$= \frac{R}{R-1} \left[1 - \left\{ \sum_{j=1}^{m} q_{j}^{R} \right\}^{\frac{1}{R}} \right] = H_{R}(\eta) \qquad \left[\Theta\left[\sum_{i=1}^{n} p_{i}^{R} \right] = 1 \right]$$

Hence ${}^{*}H_{R}(\eta/\xi) = H_{R}(\eta)$ (1.14)

(IV) Since the average conditional R-norm information of η given ξ for $R \in R^+$

and is defined as

**
$$H_R(\eta / \xi) = \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^n p_i \sum_{j=1}^m q_{ji}^R \right\}^{\frac{1}{R}} \right]^{\frac{1}{R}} \right]$$
 (1.15)

Substitute $q_{ji} = q_j$ in (1.15), we get

$${}^{**}H_{R}(\eta/\xi) = \frac{R}{R-1} \left[1 - \left\{ \sum_{i=1}^{n} p_{i} \sum_{j=1}^{m} q_{j}^{R} \right\}^{\frac{1}{R}} \right]$$
$$= \frac{R}{R-1} \left[1 - \left\{ \sum_{j=1}^{m} q_{j}^{R} \right\}^{\frac{1}{R}} \right] = H_{R}(\eta) \qquad \left[\Theta\left[\sum_{i=1}^{n} p_{i}^{R} \right] = 1 \right]$$

Hence ${}^{**}H_R(\eta/\xi) = H_R(\eta)$

From this theorem we may conclude that the measure ${}^{\delta}H_{R}(\eta/\xi)$, which is obtained by the formal difference between the joint and the marginal information measure, does not satisfy requirement (I). Therefore it is less attractive than the two other measure. In the next theorem we consider requirement (II), for the conditional information measures ${}^{*}H_{R}(\eta/\xi)$ and ${}^{**}H_{R}(\eta/\xi)$.

Theorem: If ξ and η are discrete random variables then for $R \in R^+$ then the following results hold.

(I) ${}^{*}H_{R}(\eta/\xi) \leq H_{R}(\eta)$ (II) ${}^{**}H_{R}(\eta/\xi) \leq H_{R}(\eta)$

(III)
$${}^{**}H_R(\eta/\xi) \leq {}^{*}H_R(\eta/\xi)$$
 (IV) ${}^{**}H_R(\eta/\xi) \leq {}^{*}H_R(\eta/\xi) \leq H_R(\eta)$

The equality signs holds if ξ and η are independent. **Proof:**

(I) Here we consider two cases: Cases I: when R < 1

We know by [4] that for R > 1.

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$$\left[\sum_{j=1}^{m} \left\{\sum_{i=1}^{n} x_{ij}\right\}^{R}\right]^{\frac{1}{R}} \leq \left[\sum_{i=1}^{n} \left\{\sum_{j=1}^{m} x_{ij}^{R}\right\}^{\frac{1}{R}}\right]$$
(1.16)

Setting $x_{ij} = \pi_{ij} \ge 0$ in (1.16), we have

$$\left[\sum_{j=1}^{m} \left\{\sum_{i=1}^{n} \pi_{ij}\right\}^{R}\right]^{\frac{1}{R}} \leq \left[\sum_{i=1}^{n} \left\{\sum_{j=1}^{m} \pi_{ij}^{R}\right\}^{\frac{1}{R}}\right]$$
(1.17)

Since
$$q_i = \sum_{j=1}^{m} \pi_{ij}$$
 and $\pi_{ij} = p_i q_{ji}$ (1.18)

Using (1.18) in (1.17), we get

$$\left[\sum_{j=1}^{m} q_{j}^{R}\right]^{\frac{1}{R}} \leq \left[\left\{\sum_{i=1}^{n} \sum_{j=1}^{m} (q_{ji} p_{i})^{R}\right\}^{\frac{1}{R}}\right]$$
(1.19)

It can be written as

$$\begin{bmatrix} \sum_{j=1}^{m} q_{j}^{R} \end{bmatrix}^{\frac{1}{R}} \leq \begin{bmatrix} \sum_{i=1}^{n} p_{i} \left\{ \sum_{j=1}^{m} q_{ji}^{R} \right\}^{\frac{1}{R}} \end{bmatrix}$$
$$-\begin{bmatrix} \sum_{j=1}^{m} q_{j}^{R} \end{bmatrix}^{\frac{1}{R}} \geq -\begin{bmatrix} \sum_{i=1}^{n} p_{i} \left\{ \sum_{j=1}^{m} q_{ji}^{R} \right\}^{\frac{1}{R}} \end{bmatrix}$$
$$1-\begin{bmatrix} \sum_{j=1}^{m} q_{j}^{R} \end{bmatrix}^{\frac{1}{R}} \geq 1-\begin{bmatrix} \sum_{i=1}^{n} p_{i} \left\{ \sum_{j=1}^{m} q_{ji}^{R} \right\}^{\frac{1}{R}} \end{bmatrix}$$
(1.20)

We know $\frac{R}{R-1} > 0$ if R > 1

Multiplying both sides of (1.20) by $\frac{R}{R-1}$, we get

$$\frac{R}{R-1} \left[1 - \left[\sum_{i=1}^{n} q_{j}^{R} \right]^{\frac{1}{R}} \right] \ge \frac{R}{R-1} \left[1 - \left[\sum_{i=1}^{n} p_{i} \left\{ \sum_{j=1}^{m} q_{ji}^{R} \right\}^{\frac{1}{R}} \right] \right]$$
(1.21)

But

t
$$\frac{R}{R-1} \left[1 - \left[\sum_{i=1}^{n} p_i \left\{ \sum_{j=1}^{m} q_{ji}^{R} \right\}^{\frac{1}{R}} \right] \right] = H_R(\eta / \xi) \text{ and}$$

$$\frac{R}{R-1} \left[1 - \left[\sum_{j=1}^{m} q_j^R \right]^{\frac{1}{R}} \right] = H_R(\eta) \text{ Thus (1.21) becomes}$$

 ${}^{*}H_{R}(\eta/\xi) \le H_{R}(\eta) \quad \text{for } \mathbb{R} > 1$ (1.22)

Cases II: when 0 < R < 1

We know by [4] that for 0 < R < 1

$$\left[\sum_{j=1}^{m} \left\{\sum_{i=1}^{n} x_{ij}\right\}^{R}\right]^{\overline{R}} \ge \left[\sum_{i=1}^{n} \left\{\sum_{j=1}^{m} x_{ij}^{R}\right\}^{\overline{R}}\right]$$
(1.23)

Setting $x_{ij} = \pi_{ij} \ge 0$ in (1.23), we have

$$\left[\sum_{j=1}^{m} \left\{\sum_{i=1}^{n} \pi_{ij}\right\}^{R}\right]^{\frac{1}{R}} \ge \left[\sum_{i=1}^{n} \left\{\sum_{j=1}^{m} \pi_{ij}^{R}\right\}^{\frac{1}{R}}\right]$$
(1.24)

Since

 $q_i = \sum_{j=1}^m \pi_{ij}$

Thus (1.24) becomes

$$\begin{bmatrix} \sum_{j=1}^{m} q_{j}^{R} \end{bmatrix}^{\frac{1}{R}} \ge \begin{bmatrix} \sum_{i=1}^{n} \left\{ \sum_{j=1}^{m} (q_{ji} p_{i})^{R} \right\}^{\frac{1}{R}} \end{bmatrix}$$
$$-\begin{bmatrix} \sum_{j=1}^{m} q_{j}^{R} \end{bmatrix}^{\frac{1}{R}} \le -\begin{bmatrix} \sum_{i=1}^{n} \left\{ \sum_{j=1}^{m} (q_{ji} p_{i})^{R} \right\}^{\frac{1}{R}} \end{bmatrix}$$

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$$\Rightarrow 1 - \left[\sum_{j=1}^{m} q_{j}^{R}\right]^{\frac{1}{R}} \le 1 - \left[\sum_{i=1}^{n} \left\{\sum_{j=1}^{m} (q_{ji} p_{i})^{R}\right\}^{\frac{1}{R}}\right]$$
(1.25)

We know $\frac{R}{R-1} < 0$ if 0 < R < 1

Multiplying both sides of (1.25) by $\frac{R}{R-1}$, we get

$$\frac{R}{R-1}\left[1-\left[\sum_{i=1}^{n}q_{j}^{R}\right]^{\frac{1}{R}}\right] \geq \frac{R}{R-1}\left[1-\left[\sum_{i=1}^{n}p_{i}\left\{\sum_{j=1}^{m}q_{ji}^{R}\right\}^{\frac{1}{R}}\right]\right]$$
(1.26)

$$\frac{R}{R-1}\left[1-\left[\sum_{i=1}^{n}p_{i}\left\{\sum_{j=1}^{m}q_{ji}^{R}\right\}^{\frac{1}{R}}\right]\right]=H_{R}(\eta/\xi) \quad \text{and}$$

$$\frac{R}{R-1}\left[1-\left[\sum_{j=1}^{m}q_{j}^{R}\right]^{\frac{1}{R}}\right]=H_{R}(\eta)$$

Thus (1.26) becomes

$$\Rightarrow^* H_R(\eta/\xi) \le H_R(\eta) \quad \text{for } 0 < R < 1.$$
(1.27)

Thus from (1.22) and (1.27), we get

$${}^{*}H_{R}(\eta/\xi) \leq H_{R}(\eta) \text{ for } \mathbf{R} \in \mathbf{R}^{+}$$

(II) H ere we consider two cases

Cases I: when R >1

From Jensen's inequality for R > 1, we find

$$\sum_{i=1}^{n} p_{i} q_{ji}^{R} \ge \left[\sum_{i=1}^{n} p_{i} q_{ji}\right]^{R} = q_{j}^{R}$$
(1.28)

After summation over j and raising both sides of (1.28) by power $\frac{1}{R}$, we have

$$\begin{bmatrix} \sum_{i=1}^{n} p_{i} \sum_{j=1}^{m} q_{ji}^{R} \end{bmatrix}^{\frac{1}{R}} \ge \begin{bmatrix} \sum_{j=1}^{m} q_{j}^{R} \end{bmatrix}^{\frac{1}{R}}$$
$$-\begin{bmatrix} \sum_{i=1}^{n} p_{i} \sum_{j=1}^{m} q_{ji}^{R} \end{bmatrix}^{\frac{1}{R}} \le -\begin{bmatrix} \sum_{j=1}^{m} q_{j}^{R} \end{bmatrix}^{\frac{1}{R}}$$
$$1-\begin{bmatrix} \sum_{i=1}^{n} p_{i} \sum_{j=1}^{m} q_{ji}^{R} \end{bmatrix}^{\frac{1}{R}} \le 1-\begin{bmatrix} \sum_{j=1}^{m} q_{j}^{R} \end{bmatrix}^{\frac{1}{R}}$$
(1.29)

Using
$$\frac{R}{R-1} > 0$$
 as R > 1, Thus (1.29) becomes

$$\frac{R}{R-1} \left[1 - \left[\sum_{i=1}^{n} p_i \sum_{j=1}^{m} q_{ji} \right]^{\frac{1}{R}} \right] \le \frac{R}{R-1} \left[1 - \left[\sum_{j=1}^{m} q_j \right]^{\frac{1}{R}} \right]^{\frac{1}{R}} \right]$$
(1.30)

But
$$\frac{R}{R-1} \left[1 - \left[\sum_{i=1}^{n} p_i \sum_{j=1}^{m} q_{ji}^{R} \right]^{\frac{1}{R}} \right]^{\frac{1}{R}} = {}^{++} H_R(\eta / \xi)$$

And
$$\frac{R}{R-1}\left[1-\left[\sum_{j=1}^{m}q_{j}^{R}\right]^{\frac{1}{R}}\right] = H_{R}(\eta)$$

Thus (1.30) becomes

$${}^{**}H_{R}(\eta/\xi) \le H_{R}(\eta) \quad \text{for } \mathbf{R} > 1 \tag{1.31}$$

Case II: when 0 < R < 1

From Jensen's inequality for 0 < R < 1 we find

$$\sum_{i=1}^{n} p_{i} q_{ji}^{R} \leq \left[\sum_{i=1}^{n} p_{i} q_{ji}\right]^{R} = q_{j}^{R}$$
(1.32)

After summation over *j* and raising both sides of (1.32) by power $\frac{1}{R}$, we have

$$\begin{bmatrix} \sum_{i=1}^{n} p_{i} \sum_{j=1}^{m} q_{ji}^{R} \end{bmatrix}^{\frac{1}{R}} \leq \begin{bmatrix} \sum_{j=1}^{m} q_{j}^{R} \end{bmatrix}^{\frac{1}{R}}$$
$$-\begin{bmatrix} \sum_{i=1}^{n} p_{i} \sum_{j=1}^{m} q_{ji}^{R} \end{bmatrix}^{\frac{1}{R}} \geq -\begin{bmatrix} \sum_{j=1}^{m} q_{j}^{R} \end{bmatrix}^{\frac{1}{R}}$$
$$1-\begin{bmatrix} \sum_{i=1}^{n} p_{i} \sum_{j=1}^{m} q_{ji}^{R} \end{bmatrix}^{\frac{1}{R}} \geq 1-\begin{bmatrix} \sum_{j=1}^{m} q_{j}^{R} \end{bmatrix}^{\frac{1}{R}}$$
(1.33)

Using
$$\frac{R}{R-1} < 0$$
 as $0 < R < 1$, Thus (1.33) becomes

$$\frac{R}{R-1} \left[1 - \left[\sum_{i=1}^{n} p_i \sum_{j=1}^{m} q_{ji}^{R} \right]^{\frac{1}{R}} \right] \le \frac{R}{R-1} \left[1 - \left[\sum_{jj=1}^{m} q_j^{R} \right]^{\frac{1}{R}} \right]$$
(1.34)

But
$$\frac{R}{R-1} \left[1 - \left[\sum_{i=1}^{n} p_i \sum_{j=1}^{m} q_{ji}^{R} \right]^{\frac{1}{R}} \right]^{\frac{1}{R}} = {}^{++} H_R(\eta / \xi)$$

And
$$\frac{R}{R-1}\left[1-\left[\sum_{jj=1}^{m}q_{j}^{R}\right]^{\frac{1}{R}}\right] = H_{R}(\eta)$$

Thus (1.34) becomes

$$^{**}H_{R}(\eta/\xi) \le H_{R}(\eta)$$
 for $0 < \mathbf{R} < 1$ (1.35)

Thus from (1.31) and (1.35), we get

$$^{**}H_{R}(\eta/\xi) \leq H_{R}(\eta)$$
 for $R \in \mathbb{R}^{+}$

(III) Here we consider two cases:

Cases I: when R >1

We know from Jensen's inequality

$$\left[\sum_{i=1}^{n} p_{i} \left\{\sum_{j=1}^{m} q_{ji}^{R}\right\}^{\frac{1}{R}}\right] \leq \left[\sum_{i=1}^{n} p_{i} \sum_{j=1}^{m} q_{ji}^{R}\right]^{\frac{1}{R}} \quad \text{for } R > 1 \quad (1.36)$$

$$-\left[\sum_{i=1}^{n} p_{i}\left\{\sum_{j=1}^{m} q_{ji}^{R}\right\}^{\frac{1}{R}}\right] \ge -\left[\sum_{i=1}^{n} p_{i}\sum_{j=1}^{m} q_{ji}^{R}\right]^{\frac{1}{R}}$$
$$1-\left[\sum_{i=1}^{n} p_{i}\left\{\sum_{j=1}^{m} q_{ji}^{R}\right\}^{\frac{1}{R}}\right] \ge 1-\left[\sum_{i=1}^{n} p_{i}\sum_{j=1}^{m} q_{ji}^{R}\right]^{\frac{1}{R}}$$
(1.37)

Using $\frac{R}{R-1} > 0$ if R >1, then (1.37) becomes

$$\frac{R}{R-1} \left[1 - \left[\sum_{i=1}^{n} p_i \left\{ \sum_{j=1}^{m} q_{ji}^{R} \right\}^{\frac{1}{R}} \right] \right] \ge \frac{R}{R-1} \left[1 - \left[\sum_{i=1}^{n} p_i \sum_{j=1}^{m} q_{ji}^{R} \right]^{\frac{1}{R}} \right]$$
(1.38)

But
$$\frac{R}{R-1}\left[1-\left[\sum_{i=1}^{n}p_{i}\left\{\sum_{j=1}^{m}q_{ji}^{R}\right\}^{\frac{1}{R}}\right]\right]=^{+}H_{R}(\eta/\xi)$$

And
$$\frac{R}{R-1} \left[1 - \left[\sum_{i=1}^{n} p_i \sum_{j=1}^{m} q_{ji}^{R} \right]^{\frac{1}{R}} \right]^{\frac{1}{R}} = {}^{++} H_R(\eta / \xi)$$

becomes ${}^{**}H_R(\eta/\xi) \leq {}^*H_R(\eta/\xi)$ for Thus (1.38)R 1 >

(1.39) Case II: when 0 < R < 1 We know from Jensen's inequality

$$\left[\sum_{i=1}^{n} p_{i} \left\{\sum_{j=1}^{m} q_{ji}^{R}\right\}^{\frac{1}{R}}\right] \ge \left[\sum_{i=1}^{n} p_{i} \sum_{j=1}^{m} q_{ji}^{R}\right]^{\frac{1}{R}} \quad \text{for } 0 < \mathbf{R} < 1 \quad (1.40)$$

$$-\left[\sum_{i=1}^{n} p_{i}\left\{\sum_{j=1}^{m} q_{ji}^{R}\right\}^{\frac{1}{R}}\right] \leq -\left[\sum_{i=1}^{n} p_{i}\sum_{j=1}^{m} q_{ji}^{R}\right]^{\frac{1}{R}}$$

$$1-\left[\sum_{i=1}^{n} p_{i}\left\{\sum_{j=1}^{m} q_{ji}^{R}\right\}^{\frac{1}{R}}\right] \leq 1-\left[\sum_{i=1}^{n} p_{i}\sum_{j=1}^{m} q_{ji}^{R}\right]^{\frac{1}{R}}$$
(1.41)

Using $\frac{R}{R-1} < 0$ if 0 < R < 1, then (3.41) becomes

$$\frac{R}{R-1} \left[1 - \left[\sum_{i=1}^{n} p_i \left\{ \sum_{j=1}^{m} q_{ji}^{R} \right\}^{\frac{1}{R}} \right] \right] \ge \frac{R}{R-1} \left[1 - \left[\sum_{i=1}^{n} p_i \sum_{j=1}^{m} q_{ji}^{R} \right]^{\frac{1}{R}} \right]$$
(1.42)

But
$$\frac{R}{R-1} \left[1 - \left[\sum_{i=1}^{n} p_i \left\{ \sum_{j=1}^{m} q_{ji} \right\}^{\frac{1}{R}} \right] \right] = H_R(\eta/\xi)$$

And
$$\frac{R}{R-1}\left[1-\left[\sum_{i=1}^{n} p_{i} \sum_{j=1}^{m} q_{ji}^{R}\right]^{\frac{1}{R}}\right]^{\frac{1}{R}}\right]^{\frac{1}{R}} = {}^{++} H_{R}(\eta/\xi) \text{ Thus (1.42) becomes}$$

$${}^{**}H_{R}(\eta/\xi) \le {}^{*}H_{R}(\eta/\xi) \quad \text{for } 0 < \mathbb{R} < 1 \tag{1.43}$$

Thus from (1.39) and (1.43), we get ${}^{**}H_R(\eta/\xi) \leq {}^*H_R(\eta/\xi)$ for $R \in \mathbb{R}^+$

(IV) From (I) and (III), we have ${}^{*}H_{R}(\eta/\xi) \le H_{R}(\eta)$ And

^{**} $H_R(\eta/\xi) \leq {}^*H_R(\eta/\xi)$ Thus finally we find

$${}^{**}H_{R}(\eta/\xi) \leq {}^{*}H_{R}(\eta/\xi) \leq H_{R}(\eta)$$

$$(1.44)$$

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