

Generalized Useful Information Generating Function and Applications

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Abstract

In this paper, new generalized 'useful' information generating function have been defined with their particular and limiting cases. On the differentiation of this generating function, it gives some well known results available in the literature of information theory. Some examples are worked out for discrete and continuous distributions like Uniform, Geometric, Normal, Exponential and Pareto distribution.

Keywords: Information generating functions; Entropy; Useful information measure; Holders inequality; Probability density function; Derivative.

2020 Mathematics Subject Classification: 94A17, 94A24, 94A15, 26D15.

1. Introduction

The moment generating functions and characteristics functions in probability theory are conveniently used for calculating the moments of a probability distribution and investigating various properties of the probability distribution for analytical purposes. Much work have been done in this connection by Hooda and Sharma [11], Srivastava and Shikha [12], Kharami and Balakrishanan [13], Shital and Suchandan [14] etc. and found very interesting results. Golomb [2] defined an information generating function of a probability distribution and discussed some of its properties. He established that the first moment of the self information is Shannon entropy [10]. We defined a generalized useful information generating function as follows.

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2. Main Results

Suppose $P = \{p_i\}$, $p_i \geq 0$, $\sum_{i=1}^n p_i = 1$, $i = 1, 2, \dots, n$ is a discrete probability distribution. Golomb [2] defined information generating function of a probability distribution P as

$$T(t) = \sum_{i=1}^n p_i^t, \quad (1)$$

where t is a real (or complex) variable. It may be noted that

$$\left[-\frac{\delta T(t)}{\delta t} \right]_{t=1} = -\sum_{i=1}^n p_i \log_D p_i = H(P) \quad (2)$$

Which is Shannon's entropy [10] of the given probability distribution P .

Consider a model A for a finite scheme random experiment having $A_1, A_2, \dots, A_n$ as the complete system of events happening with probabilities $p_1, p_2, \dots, p_n$ and credited with utilities $u_1, u_2, \dots, u_n$ respectively, $u_i > 0$, $i = 1, 2, \dots, n$. We write

$$A = \begin{bmatrix} A_1, A_2, \dots, A_n \\ p_1, p_2, \dots, p_n \\ u_1, u_2, \dots, u_n \end{bmatrix} \quad (3)$$

we call the scheme A as utility information scheme. Belis and Guiasu [1] proposed a measure of information (called useful information) for the utility information scheme in scheme in (3) as follows

$$H(U; P) = -\sum_{i=1}^n u_i p_i \log_D p_i \quad (4)$$

where $u_i > 0$ and $\sum_{i=1}^n p_i = 1$. It reduces to Shannon entropy when utility aspect of the scheme is ignored by taking $u_i = 1$ for every i . Gurdial and Pessoa [4] considered the generalized additive useful information of order α given by

$$H_\alpha(U; P) = \frac{1}{1-\alpha} \log_D \left[\frac{\sum_{i=1}^n u_i p_i}{\sum_{j=1}^n u_j p_j} \right] \quad (5)$$

The measure (5) resembles Renyi's entropy of order α given in [9]. Khan [6] defined a generalized additive useful information of order α and type β as

$$H_\alpha^\beta(U; P) = \frac{1}{1-\alpha} \log_D \left[\frac{\sum_{i=1}^n u_i p_i^{\alpha+\beta-1}}{\sum_{i=1}^n u_i p_i^\beta} \right] \quad (6)$$

where, $\alpha > 0$, $\alpha \neq 1$, $\beta > 0$, $\alpha + \beta > 1$ and $\sum_{i=1}^n p_i \leq 1$. Consider the weighted mean of order $\alpha - 1$ of p_i with weights $u_i p_i^{\beta_i}$ and utilities u_i of the events A_i as

$$M_{\alpha, \beta_i}(P; U) = \left[\frac{\sum_{i=1}^n u_i p_i^{\alpha+\beta-1}}{\sum_{i=1}^n u_i p_i^{\beta_i}} \right], \alpha > 0, \alpha \neq 1, \beta_i \geq 1 \quad (7)$$

The generalized additive useful information generating function is now defined as

$$M_{\alpha, \beta_i}(P, U; t) = [M_{\alpha, \beta_i}(P; U)]^{-t} \quad (8)$$

where t is a real (or complex) variable. Since $0 \leq p_i^{\alpha+\beta-1} \leq 1$ for each i and $t \geq 0$ and $\{u_i\}$ is bounded for any experiment under consideration, therefore, the expression (8) for $M_{\alpha, \beta_i}(P, U; t)$ is convergent for all $t \geq 0$.

Particular cases:

(i) Taking $\beta_i = \beta$ for every i , $M_{\alpha, \beta_i}(P, U; t)$ reduces to

$$M_{\alpha, \beta}(P, U; t) = \left[\frac{\sum_{i=1}^n u_i p_i^{\alpha+\beta-1}}{\sum_{i=1}^n u_i p_i^{\beta}} \right]^{\frac{t}{1-\alpha}} \quad (9)$$

which may be treated as generating function of useful information measure proposed by Khan [6].

(ii) If the utility of the scheme is ignored i.e, if $u_i = 1$ for every i then $M_{\alpha, \beta_i}(P; U; t)$ reduces to

$$M_{\alpha, \beta_i}(P; t) = \left[\frac{\sum_{i=1}^n p_i^{\alpha+\beta-1}}{\sum_{i=1}^n p_i^{\beta_i}} \right]^{\frac{t}{1-\alpha}} \quad (10)$$

which may be consider as generating function of entropy of order α and type $\{\beta_i\}$ proposed by Rathie [8]. Further if $\beta_i = \beta$ for every i then it will give the following generating function

$$M_{\alpha, \beta}(P, t) = \left[\frac{\sum_{i=1}^n p_i^{\alpha+\beta-1}}{\sum_{i=1}^n p_i^{\beta}} \right]^{\frac{t}{1-\alpha}} \quad (11)$$

which may be treated as generating function of Kapur's entropy [5] of order α and type β .

(iii) If $\beta_i = 1$ for every i then $M_{\alpha, \beta_i}(P, U; t)$ reduces to the generating function

$$M_{\alpha}(P, U; t) = \left[\frac{\sum_{i=1}^n u_i p_i^{\alpha}}{\sum_{i=1}^n u_i p_i} \right]^{\frac{t}{1-\alpha}} \quad (12)$$

which may be generating function of a measure of useful information of order α proposed by Gurdial and Pessoa [4].

(iv) If $\beta_i = 1$ for every i , then

$$\lim_{\alpha \rightarrow 1} M_{\alpha, \beta_i}(P, U; t) = M(P, U; t) = 2^{-t} \frac{\left(\sum_{i=1}^n u_i p_i \log_D p_i \right)}{\sum_{i=1}^n u_i p_i} \quad (13)$$

(13) reduces to the generating function of Belis and Guiasu [1] useful information for incomplete discrete distribution.

3. Derivatives

The value of the first derivative of $M_{\alpha, \beta_i}(P, U; t)$ with respect to t at $t = 0$ is

$$\left[\frac{\delta M_{\alpha, \beta_i}(P, U; t)}{\delta t} \right]_{t=0} = \frac{1}{1-\alpha} \log_D \frac{\sum_{i=1}^n u_i p_i^{\alpha+\beta_i-1}}{\sum_{i=1}^n u_i p_i^{\beta_i}} = H_{\alpha}^{\beta_i}(P; U) \quad (14)$$

which is generalization to Khan's [6] additive useful information of order α and type β . If $\beta_i = \beta$ for every i , then we see that the value of first order derivative of $M_{\alpha, \beta_i}(P, U; t)$ at $t = 0$ is exactly Khan's [6] generalized additive useful information of order α and type β . The other information measures, such as Kapur [5], Rathie [8], Gurdial and Pessoa [4] may be obtained as its particular cases. The r -th derivative of $M_{\alpha, \beta_i}(P, U; t)$ at $t = 0$ is as below.

$$\left[\frac{\delta^r M_{\alpha, \beta_i}(P, U; t)}{\delta t^r} \right]_{t=0} = \left[\frac{1}{1-\alpha} \log_D \frac{\sum_{i=1}^n u_i p_i^{\alpha+\beta_i-1}}{\sum_{i=1}^n u_i p_i^{\beta_i}} \right]^r$$

Applications

(i) **Uniform Distribution:** For a uniform distribution $\left\{ \frac{1}{N}, \frac{1}{N}, \dots, \frac{1}{N} \right\}$ and utility distribution $\{u, u, \dots, u\}$ of the discrete sample space, we get

$$M_{\alpha, \beta}(P, U; t) = u N^t \quad (15)$$

and

$$\left[\frac{\delta M_{\alpha,\beta}(P, U; t)}{\delta t} \right]_{t=0} = u \log N \quad (16)$$

which is entropy of order α and type β and is independent of α and β . Gurdial and Pessoa [4] entropy of any order and Belis and Guiasu [1] entropy will also have the same value. In case when utilities are ignored (16) reduces to $\log N$, a result due to Golomb [2] and Mathur and Kashyap [7].

- (ii) **Geometric distribution:** For the geometric distribution $\{q, qp, qp^2, \dots\}$, $p + q = 1$, and geometric utility distribution $\{v, vu, vu^2, \dots\}$, the proposed information generating function for this distribution is obtained as

$$M_{\alpha,\beta}(P, U; t) = \left[\frac{q^{\alpha-1} (1 - up^\beta)}{1 - up^{\alpha+\beta-1}} \right]^{\frac{t}{1-\alpha}} \quad (17)$$

The value of the first derivative at $t = 0$ is

$$\left[\frac{\delta M_{\alpha,\beta}(P, U; t)}{\delta t} \right]_{t=0} = \frac{1}{1-\alpha} \log \left[\frac{q^{\alpha-1} (1 - up^\beta)}{1 - up^{\alpha+\beta-1}} \right] \quad (18)$$

If utilities are ignored then (18) reduces to $\frac{1}{1-\alpha} \log \left[\frac{q^{\alpha-1} (1 - p^\beta)}{1 - p^{\alpha+\beta-1}} \right]$, a quantity obtained by Mathur and Kashyap [7].

- (iii) **Normal distribution:** For the normal distribution with mean zero and variance σ^2 and normal utility distribution with mean zero and variance θ^2 on $(-\infty, \infty)$ i.e.,

$$p(x) = \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{x^2}{2\sigma^2}}, \sigma > 0, \quad -\infty < x < \infty$$

$$u(x) = \frac{1}{\sqrt{2\pi}\theta^2} e^{-\frac{u^2}{2\theta^2}}, \theta > 0, \quad -\infty < x < \infty$$

Then we have

$$M_{\alpha,\beta}(P, U; t) = \left[\frac{\sqrt{\sigma^2 + \beta\theta^2}}{\sqrt{\sigma^2 + (\alpha + \beta - 1)\theta^2} (2\pi\sigma^2)^{\frac{\alpha-1}{2}}} \right] \quad (19)$$

and

$$\left[\frac{\delta M_{\alpha,\beta}(P, U; t)}{\delta t} \right]_{t=0} = \frac{1}{1-\alpha} \log \left[\frac{\sqrt{\sigma^2 + \beta\theta^2}}{\sqrt{\sigma^2 + (\alpha + \beta - 1)\theta^2} (2\pi\sigma^2)^{\frac{\alpha-1}{2}}} \right] \quad (20)$$

Assuming $\beta = 1$ in (19) and (20) we get result for Renyi's entropy and taking limit as $\alpha \rightarrow 1$ it reduces for Shannon's entropy.

- (iv) **Exponential distribution:** For the exponential probability distribution with mean $\frac{1}{\lambda}$ and assuming the corresponding exponentail distribution with mean $\frac{1}{\mu}$. Then

$$p(x) = \lambda e^{-\lambda x}, \lambda > 0, \quad x \in [0, \infty)$$

$$u(x) = \mu e^{-\mu x}, \mu > 0$$

Then we have

$$M_{\alpha,\beta}(P, U; t) = \left[\frac{\lambda^{\alpha-1}(\lambda\beta + \mu)}{\lambda(\alpha + \beta - 1) + \mu} \right]^{\frac{t}{1-\alpha}} \quad (21)$$

and

$$\left[\frac{\delta M_{\alpha,\beta}(P, U; t)}{\delta t} \right]_{t=0} = \frac{1}{1-\alpha} \log \left[\frac{\lambda^{\alpha-1}(\lambda\beta + \mu)}{\lambda(\alpha + \beta - 1) + \mu} \right] \quad (22)$$

If utilities are ignored then (22) reduces to a result due to Mathur and Kashyap [7]. Further if $\beta = 1$ in (21) and (22) we get result for Renyi's entropy and taking limit as $\alpha \rightarrow 1$ it reduces to result for Shannon entropy.

- (v) **Pareto Distribution:** For the Pareto probability distribution with exponent λ on $[1, \infty)$ and assuming the corresponding Pareto utility distribution with exponent μ on $(-\infty, 1]$

$$p(x) = (\lambda - 1)x^{-\lambda}, x > 0$$

$$u(x) = (1 - \mu)x^{-\mu}, \mu < 1 \text{ and } x \in [1, \infty)$$

Then we have

$$M_{\alpha,\beta}(P, U; t) = \left[\frac{(\lambda - 1)^{\alpha-1}(\lambda\beta + \mu - 1)}{\lambda(\alpha + \beta - 1) + \mu - 1} \right]^{\frac{t}{1-\alpha}} \quad (23)$$

and

$$\left[\frac{\delta M_{\alpha,\beta}(P, U; t)}{\delta t} \right]_{t=0} = \frac{1}{1-\alpha} \log \left[\frac{(\lambda - 1)^{\alpha-1}(\lambda\beta + \mu - 1)}{\lambda(\alpha + \beta - 1) + \mu - 1} \right] \quad (24)$$

If the utilities are ignored and $\beta = 1$ then (24) have a result for Renyi's entropy. Further taking limit as $\alpha \rightarrow 1$ it reduces to a result for Shannon's entropy.

4. Inversion

Given the generalized additive useful information generating function $M_{\alpha,\beta}(P, U; t)$, we can easily determine the probability and utility distribution corresponding to it. In the discrete case the generalized additive useful information $M_{\alpha,\beta}(P, U; t)$ is evidently a symmetric function of $u_1 p_1, u_2 p_2, \dots, u_n p_n$. Therefore without loss of generality we can assume that $p_1 \geq p_2 \geq \dots \geq p_n$ and $u_1 \geq u_2 \geq \dots \geq u_n$. So that $u_1 p_1 \geq u_2 p_2 \geq \dots \geq u_n p_n$. Let us consider a function

$$M_{\alpha,\beta}^0(P, U; t) = [M_{\alpha,\beta}(P, U; t)]^{\frac{1-\alpha}{t}} \quad (25)$$

Then

$$\begin{aligned} \lim_{\alpha \rightarrow \infty} \left[M_{\alpha, \beta}^0(P, U; t) \right]^{\frac{1}{\alpha}} &= \lim_{\alpha \rightarrow \infty} \left[\frac{\sum_{i=1}^n u_i p_i^{\alpha+\beta-1}}{\sum_{i=1}^n u_i p_i^{\beta}} \right]^{\frac{1}{\alpha}} \\ &= \max_i (u_i p_i) = u_1 p_1 \end{aligned} \quad (26)$$

Now taking $u_i = 1$ for each i in (26), we get

$$\lim_{\alpha \rightarrow \infty} \left[\frac{\sum_{i=1}^n p_i^{\alpha+\beta-1}}{\sum_{i=1}^n p_i^{\beta}} \right]^{\frac{1}{\alpha}} = \max_i (p_i) = p_1 \quad (27)$$

Next, on dividing (26) by (27) we get u_1 . Thus the largest probability and utility is obtained from the generalized additive useful information generating function using (25), (26) and (27). Suppose

$$\begin{aligned} M_{\alpha, \beta}^1(P, U; t) &= M_{\alpha, \beta}^0(P, U; t) - \frac{u_1 p_1^{\alpha+\beta-1}}{\sum_{i=1}^n u_i p_i^{\beta}} \\ &= \frac{\sum_{i=2}^n u_i p_i^{\alpha+\beta-1}}{\sum_{i=1}^n u_i p_i^{\beta}} \end{aligned}$$

Thus

$$\lim_{\alpha \rightarrow \infty} \left[M_{\alpha, \beta}^1(P, U; t) \right]^{\frac{1}{\alpha}} = u_2 p_2 \quad (28)$$

Again, if we put $u_i = 1$ for each i , we get

$$\lim_{\alpha \rightarrow \infty} \left[M_{\alpha, \beta}^1(P, U; t) \right]^{\frac{1}{\alpha}} = p_2 \quad (29)$$

(29) and (28) gives u_2 . Continuing in this way we can uniquely determine $p_1, p_2, \dots, p_n$ and $u_1, u_2, \dots, u_n$ in the decreasing (or non-decreasing) order. In general we can write

$$\begin{aligned} \lim_{\alpha \rightarrow \infty} \left[M_{\alpha, \beta}^r(P, U; t) \right]^{\frac{1}{\alpha}} &= \lim_{\alpha \rightarrow \infty} \left[M_{\alpha, \beta}^{r-1} - \frac{u_r p_r^{\alpha+\beta-1}}{\sum_{i=1}^n u_i p_i^{\beta}} \right]^{\frac{1}{\alpha}} \\ &= (u_{r+1} p_{r+1}) \end{aligned}$$

Again if we put $u_i = 1$ for each i , we have

$$\lim_{\alpha \rightarrow \infty} \left[M_{\alpha, \beta}^r(P, t) \right]^{\frac{1}{\alpha}} = p_{r+1}$$

5. Joint Distribution

Let X and Y be two independent random variables having probability distribution $P = \{p_1, p_2, \dots, p_n\}$ and $Q = \{q_1, q_2, \dots, q_m\}$ respectively with utility distribution $U = \{u_1, u_2, \dots, u_n\}$ and $V = \{v_1, v_2, \dots, v_m\}$. Suppose the variable $Z = X \times Y$ is the cartesian product of X & Y , whose probability distribution is given by $R = \{p_i q_j\}$ and utility distribution is given by $W = \{u_i v_j\}$, $i = 1, 2, \dots, n$; $j = 1, 2, \dots, m$. If $M_{\alpha, \beta}(P, U; t)$ and $M_{\alpha, \beta}(Q, V; t)$ are the generalized generating functions of random variables X and Y respectively, then the generalized additive useful information generating function of Z is given by

$$M_{\alpha, \beta}(R, W; t) = M_{\alpha, \beta}(P, U; t) \cdot M_{\alpha, \beta}(Q, V; t) \quad (30)$$

$$\left[\frac{\delta M_{\alpha, \beta}(R, W; t)}{\delta t} \right]_{t=0} = H_{\alpha}^{\beta}(P; V) + H_{\alpha}^{\beta}(Q; U) \quad (31)$$

6. Conjugate relation

Two real number α_1 and α_2 are said to be conjugate if

$$\frac{1}{\alpha_1} + \frac{1}{\alpha_2} = 1 \quad (32)$$

since we restrict (32) to be useful information of positive orders only, therefore it is obvious that $\alpha_1 > 1$ and $\alpha_2 > 1$. Now we show that

$$M_{1, \beta}(P, U; t) > M_{\alpha_1, \beta}(P, U; \alpha_1^* t) \cdot M_{\alpha_2, \beta}(P, U; \alpha_2^* t) \quad (33)$$

where $\alpha_1^* = \frac{\alpha_1 - 1}{\alpha_1}$ and $\alpha_2^* = \frac{\alpha_2 - 1}{\alpha_2}$ and $M_{1, \beta}(P, U; t)$ is the limiting case of $M_{\alpha, \beta}(P, U; t)$ as $\alpha \rightarrow 1$. Using Jensen's inequality [4], we have

$$\frac{\sum_{i=1}^n u_i p_i^{\beta} \log u_i p_i}{\sum_{i=1}^n u_i p_i^{\beta}} < \log \left[\frac{\sum_{i=1}^n u_i p_i^{\beta+1}}{\sum_{i=1}^n u_i p_i^{\beta}} \right] \quad (34)$$

Further, Using Holder's inequality [4], we have

$$\log \left[\frac{\sum_{i=1}^n u_i p_i^{\beta+1}}{\sum_{i=1}^n u_i p_i^{\beta}} \right] \leq \log \left\{ \left[\frac{\sum_{i=1}^n u_i p_i^{\alpha_1 + \beta - 1}}{\sum_{i=1}^n u_i p_i^{\beta}} \right]^{\frac{1}{\alpha_1}} \left[\frac{\sum_{i=1}^n u_i p_i^{\alpha_2 + \beta - 1}}{\sum_{i=1}^n u_i p_i^{\beta}} \right]^{\frac{1}{\alpha_2}} \right\} \quad (35)$$

or

$$-t \log \left[\frac{\sum_{i=1}^n u_i p_i^{\beta+1}}{\sum_{i=1}^n u_i p_i^{\beta}} \right] \geq \log \left\{ \left[\frac{\sum_{i=1}^n u_i p_i^{\alpha_1+\beta-1}}{\sum_{i=1}^n u_i p_i^{\beta}} \right]^{\frac{\alpha_1^* t}{1-\alpha_1}} \left[\frac{\sum_{i=1}^n u_i p_i^{\alpha_2+\beta-1}}{\sum_{i=1}^n u_i p_i^{\beta}} \right]^{\frac{\alpha_2^* t}{1-\alpha_2}} \right\} \quad (36)$$

using (36) and (34) and simplifying, we get the required result (33). If the utilities are ignored i.e, $u_i = 1$ for each i , (33) reduces to

$$M_{1,\beta}(P, t) > M_{\alpha_1,\beta}(P, \alpha_1^* t) \cdot M_{\alpha_2,\beta}(P, \alpha_2^* t). \quad (37)$$

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