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THE PROBLEMS OF CALCULUS AND APPROXIMATION OF THE AMOUNT OF INFORMATION

by ION MIHOC (Cluj-Napoca)

1. Let $\{\Omega, K, P\}$ be a probability space generated by a experiment A and let A_1, A_2, \ldots, A_N be the possible autcomes of random experiment A.

If the set $\{A_1, A_2, \ldots, A_N\}$ formes a partition Π for the sure event Ω , then [2], [4]

(1.1)
$$H(\Pi) = H(X) = -k \sum_{i=1}^{N} p_{i} \log_{e} p_{i}$$

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 where
$$(1.2) \quad p_i = P(A_i) \ge 0, \ i = 1, 2, \dots, N; \sum_{i=1}^{N} p_i = 1, \ k = \log_2 e,$$

represents the amount of information furnished by the experiment A. The quantity (1.1) is called the entropy of the partition Π and it measures either the uncertainty of the experiment A, if this experiment not yet performed or the amount of information of the experiment A, if this experiment has been performed. Also, we can speak as well that the quantity (1.1) represents the amount of information contained by the random variable X generated by the experiment A.

2. Application of Taylor's series to evaluation of $\mathbf{H}(X)$

THEOREM 1. If X is a discret random variable then

$$(2.1) \quad H(X) = -\frac{k}{n} \left\{ (n-N) - n \cdot \log_e n + \sum_{i=1}^N \sum_{s=2}^\infty \frac{1}{s^{(2)}} \sum_{i=0}^s C_s^i (-np_i)^i \right\},$$

where n is a natural number.

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Proof. Consider Consi

(2.2)
$$p_i = \pi_i + \frac{1}{n}, \ i = 1, 2, \ldots, N,$$

where
$$\pi_i \in \left(-\frac{1}{n}, \frac{1}{n}\right]$$
 then when $p_i \in (0, 1]$.

Because the function $\log_e p_i$ is infinite derivable in the neighbourhood of the point $\frac{1}{n}$, it follows that the function

(2.3)
$$f(n\pi_i) = \log_e \left(\pi_i + \frac{1}{n}\right) = \log_e (1 + n\pi_i) - \log_e n$$

admits the expansion in the power series AD AC ANALISMOST AFT

(2.4)
$$f(n\pi_i) = -\log_e n + (n\pi_i) - \frac{(n\pi_i)^2}{2} + \frac{(n\pi_i)^3}{3} - \dots,$$

where the power series

$$(2.5) \quad \log_e(1+n\pi_i) = (n\pi_i) - \frac{(n\pi_i)^2}{2} + \ldots + (-1)^{s-1} \frac{(n\pi_i)^s}{s} + \ldots$$

is convergent for $|n\pi_i| < 1$, respectively, for $|\pi_i| < \frac{1}{n}$.

Therefore, the function $p_i \log_e p_i$ has the following expansion

$$(2.6) p_i \log_e p_i = -\frac{1 + n\pi_i}{n} \log_e n + \frac{1}{n} \left\{ n\pi_i + \sum_{s=2}^{\infty} (-1)^s \frac{(n\pi_i)^s}{s^{(2)}} \right\},$$

where
$$x^{(v)} = x(x-1)(x-2) \dots (x-v+1)$$
.

Having in view that

(2.7)
$$\sum_{i=1}^{N} n p_i = n - N$$

$$(2.8) (-1)^s (n\pi_i)^s = (1 - np_i)^s = \sum_{t=0}^s C_s^t (-np_i)^t,$$

and the development (2.6), we obtain for H(X) the following form

$$(2.9) \ \ H(X) = -\frac{k}{n} \left\{ (n-N) - n \cdot \log_e n + \sum_{i=1}^N \sum_{s=2}^\infty \frac{1}{s^{(2)}} \sum_{t=0}^s C_s^t (-np_i)^t \right\}.$$

Remark 1.2. Because the series (2.5) is convergent both for $|n\pi_i| < 1$ and for $n\pi_i = 1$, it follows that the Taylor's series which correspond to the function $\log_e p_i$, will be convergent if $p_i \in \left(0, \frac{2}{n}\right]$. This series will be convergent for $p_i \in (0, 1]$ only if n = 2.

Corollary 2.1. If n=2, then H(X) has the form

(2.10)
$$H(X) = 1 - \frac{k}{2} \left\{ (2 - N) + \sum_{i=1}^{N} \sum_{s=2}^{\infty} \frac{1}{s^{(2)}} C_s^i (-2p_i)^i \right\}$$

where $k = \log_2 e$.

Remark 2.2. According to the Remark 2.1 it seems that the formula (2.9) is available only for n=2, then when $p_i \in (0,1]$.

If we have in view the condition (1.2) it follows that among the probabilities p_1, p_2, \ldots, p_N exist all the most a probability p_k so that $p_k \ge \frac{1}{2}$, (N > 2).

If the probability p_h is sufficient near to one, then, evident, the others probabilities p_i , $i=1, 2, \ldots, N$, $i \neq h$, will be situated sufficient near to zero. In other words, if $p_h \to 1$, then is possible to find a natural number n so that all probabilities p_i , $i=1,2,\ldots,N$; $i\neq h$, to be situate in the interval $\left(0,\frac{2}{n}\right|$.

Corollary 2.2. If X is a discret random variable which satisfies the conditions

$$p_i > 0, i = 1, 2, \ldots, N; \sum_{i=1}^{N} p_i = 1$$

and if

$$1^{0} p_{h} = \max \{p_{1}, p_{2}, \ldots, p_{N}\}, p_{h} \in [1 - \varepsilon, 1], \varepsilon > 0,$$

20 there is a natural number n so that $p_i \in \left[0, \frac{2}{x}\right], i = 1, 2, \ldots, N$; $i \neq h$, then, for the measure H(X), we have the following form

$$H(X) = -\frac{h}{n} \left\{ (1 - N) + n p_h \log_e p_h + n(1 - p_h) \left[\log_e n - 1 \right] + (2.11) \right\}$$

$$+ \sum_{i=1}^{N} \sum_{s=2}^{\infty} \frac{1}{s^{(2)}} \sum_{t=0}^{s} C_{s}^{t} (-n p_{i})^{t} \Big\}.$$

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Corollary 2.3. If n = N, N — the number of the possible values of discret random variable X, then the amount of information, H(X), has the

(2.12)
$$H(X) = \log_2 N - \frac{k}{N} \left\{ \sum_{i=1}^{N} \sum_{s=2}^{\infty} \frac{1}{s^{(2)}} \sum_{t=2}^{s} C_s^t (-N p_i)^t \right\}.$$

More, if X_1 is a random variable uniformly distributed, then $H(X_1) =$ $= \log_2 N$.

Corollary 2.4. For any random variable X, we have

$$(2.13) H(X) \le \log_2 N = H(X_1),$$

where X_1 is uniformly distributed.

Proof. This corollary is a fundamental property of the measure H(X), [1]. In ours case, the proof of the inequality (2.13) to came back to show that $D \ge 0$, where distinction is because it is the property of the property

$$(2.14) D = \sum_{i=1}^{N} \sum_{s=2}^{\infty} \frac{1}{s^{(2)}} \sum_{i=0}^{s} C_{r}^{i} (-Np_{i})^{i} = \sum_{i=1}^{N} \sum_{s=2}^{\infty} (-1)^{s} \frac{(N\pi_{i})^{s}}{s^{(2)}}.$$

Indeed, the sign of D depends by the sign of power series

Indeed, the sign of D depends by the sign of particles,
$$\sum_{s=2}^{N} (-1)^s \frac{(N\pi_i)^s}{s^{(2)}},$$

which, for $|N\pi| < 1$, is convergent and consequently, his sum, $S(N, \pi_i)$, satisfies the condition page and a very same a

$$0 < S(N\pi_i) < \frac{(N\pi_i)^2}{1\cdot 2}.$$

This last inequality proves Corallary 2.4.

3. The Aproximation of H(X)

It is know that if the function f(x) has the derivates tell the order m+1 inclusively, in the vecinity of the point x_0 , then it is expandable in Taylor series [3] and we have

(3.1)
$$f(x) = f(x_0) + \frac{x - x_0}{1 + x_0} f'(x_0) + \dots + \frac{(x - x_0)^m}{m!} f^m(x_0) + r_m(x),$$
where

where

(3.2)
$$r_m(x) = \frac{(x-x_0)^{m+1}}{(m+1)!} f^{m(+1)} [x+\theta(x-x_0)], \quad 0<\theta<1,$$

is Lagrange's form of the remainder.

THEOREM 3.1. Let X be a discret random variable. Then the measure, H(X), of the amount of information of X, has the form

$$(3.3) H(X) = H_m(X) + R_m(n\pi_i),$$

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(3.4)
$$H_m(X) = -\frac{k}{n} \left\{ (n-N) - n \log_e n + \sum_{i=1}^N \sum_{s=2}^m (-1)^s \frac{(n\pi_i)^s}{s^{(2)}} \right\},$$

(3.5)
$$R_m(n\pi_i) = (-1)^m \frac{k}{n} \sum_{i=1}^N (n\pi_i)^{m+1} \left[\frac{1}{m} - \frac{1}{m+1} \cdot \frac{1+n\pi_i}{1+\theta n\pi_i} \right],$$
$$0 < \theta < 1, \text{ and } n\pi_i = np_i - 1.$$

Proof. As an application of the formula (3.1), let us expand into the power series the function $p_i \log_e p_i$.

We have

(3.6)
$$p_{i} \log_{e} p_{i} = -\frac{1 + n\pi_{i}}{n} \log_{e} n + \frac{1}{n} \left\{ n\pi_{i} + \frac{(n\pi_{i})^{3}}{1 \cdot 2} - \frac{(n\pi_{i})^{3}}{2 \cdot 3} + \dots + (-1)^{m} \frac{(n\pi_{i})^{m}}{(m-1) \cdot m} + \bar{r}_{m}(n\pi_{i}) \right\},$$

where

(3.7)
$$\tilde{r}_m(n\pi_i) = (-1)^{m-1} (n\pi_i)^{m+1} \left[\frac{1}{m} - \frac{1}{m+1} \cdot \frac{1+n\pi_i}{1+\theta n\pi_i} \right].$$

The expansion (3.6) with the remainder (3.7), give us just the form (3.3) of the measure H(X).

Corollary 3.1. Because $n\pi_i = np_i - 1$, it follows that the measure H(X) has and the form

(3.8)
$$H(X) = -\frac{h}{n} \left\{ (n - N) - n \log_e n + \sum_{i=1}^{N} \sum_{s=2}^{m} \frac{1}{s^{(2)}} \sum_{i=0}^{N} C_s^{t} (-np_i)^{t} \right\} + R_m(np_i - 1)$$

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$$(3.9) \quad R_m(np_i - 1) = -\frac{h}{n} \sum_{i=1}^{N} \sum_{t=0}^{m+1} C_{m+1}^t (-np_i)^t \left[\frac{1}{m} - \frac{1}{m+1} \cdot \frac{np_i}{1 + \theta(np_i - 1)} \right],$$

$$0 < \theta < 1$$

Remark 3.1. If X is a random variable uniformly distributed, then H(X), given in the relation (3.8), to came return to $H(X) = \log_2 N$.

Corollary 3.2. The relation (3.3) give us the possibility to approximate the measure H(X) in the following form

(3.10)
$$H(X) \approx H_m(X) = -\frac{k}{n} \left\{ (n-k) - n \log_e n + \sum_{i=1}^N \sum_{s=2}^m (-1)^s \frac{(n\pi_i)^s}{s^{(2)}} \right\}$$

The error in this case is just the value of the remainder (3.5).

Remark 3.2. The remainder $R_m(n\pi_i)$, given in the relation (3.5), can be write in the following form

(3.11)
$$R_m(n\pi_i) = (-1)^n \frac{k}{n} \sum_{i=1}^N (n\pi_i)^{m+1} \left[\frac{1}{m} - \frac{1}{m+1} \cdot g(\theta, \pi_i) \right],$$

where the function

(3.12)
$$g(\theta, \pi_i) = \frac{1 + n\pi_i}{1 + \theta n\pi_i}, \quad (i = 1, 2, ..., N,$$

is defined for $\theta \in (0, 1)$ and $n\pi_i = np_i - 1$.

Now, insted of the function $g(\theta, \pi_i)$, we introduce a new function namely

(3.13)
$$\overline{g}(\theta, p_i) = \frac{np_i}{1 + \theta(np_i - 1)} = \begin{cases} 1, & \text{if } \theta = 1, p_i \in (0, 1] \\ np_i = \begin{cases} 0, & \text{if } \theta = 0, p_i = 0 \\ n, & \text{if } \theta = 0, p_i = 1 \end{cases} \\ g(\theta, p_i), & \text{if } \theta \in (0, 1) \end{cases}$$

where $n\pi_i = np_i - 1$, i = 1, 2, ..., N.

If 0 = 1, then for any $p_i \in (0,1]$, respectively, for any $\pi_i \in \left(-\frac{1}{n}, \frac{1}{n}\right)$, we have $\overline{g}(1, p_i) = 1$. Making this change the remainder $R_m(n\pi_i)$ can be written as

(3.3) of the measure H(N) Fill

$$\overline{R}_m(n\pi_i) = (-1)^m \frac{h}{n} \sum_{i=1}^N \frac{(n\pi_i)^{m+1}}{m(m+1)}.$$

Now, replacing in the relation (3.3), the remainder $R_m(n\pi_i)$ through the new form (3.14), we obtain the following approximation for H(X).

(3.15)
$$H(X) \approx H_{m+1}(X) = -\frac{h}{n} \left\{ (n-N) - n \log_e n + \sum_{i=1}^{N} \sum_{s=2}^{m+1} \frac{1}{s^{(2)}} \sum_{t=2}^{m} C_s^t (-np_i)^t \right\}.$$

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Universitatea Babeș — Bolyai Facultatea de științe economice Cluj-Napoca