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RATE OF CONVERGENCE OF THE INFORMATION  
IN A SAMPLE CONCERNING A PARAMETER

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Let us consider, for  $n = 1, 2, \dots, \infty$ , the classical statistical decision problem with a finite parameter probability space  $(X, \mathcal{X}, \mu)$ , an abstract sample space

$$(Y^n, \mathcal{Y}^n) = \bigotimes_{i=1}^n (Y_i, \mathcal{Y}_i),$$

a set of probability measures

$$v^n(\cdot | x) = \bigotimes_{i=1}^n v_i(\cdot | x), \quad x \in X,$$

on  $\mathcal{Y}^n$ , a decision space  $(X, \mathcal{X})$ , and a weight function  $w$ . We shall assume without loss of generality that  $\mathcal{X}$  contains all subsets of  $X$  and that  $\mu(x) > 0$  for every  $x \in X$ . If we define a probability measure  $\omega^n$  on  $\mathcal{X} \otimes \mathcal{Y}^n$  by

$$\omega^n(E) = \sum_{x \in X} \mu(x) v^n(\{y^n : (x, y^n) \in E\}), \quad E \in \mathcal{X} \otimes \mathcal{Y}^n$$

and if we denote by  $\tilde{\omega}^n$  the marginal measure induced by  $\omega^n$  on  $\mathcal{Y}^n$ , then the average information  $I_n$  in a sample  $y^n \in Y^n$  concerning the parameter  $x$  can be defined as follows (cf. [2], [3], [4]):

$$(1) \quad I_n = \int \log f \, d\omega^n \geq 0,$$

where  $f$  is the Radon-Nikodym density of the joint probability measure  $\omega^n$  with respect to the product measure  $\mu \otimes \tilde{\omega}^n$  (note that  $\omega^n \ll \mu \otimes \tilde{\omega}^n$  holds). According to Theorem 11 in [2],  $I_n, n = 1, 2, \dots$ , is a non-decreasing sequence and  $\lim I_n = I_\infty$ .

It has recently become clear that there is a relation between the Bayes risk  $r_n$  of the problem we have considered and  $I_n$ . For example the results of the data reduction theory, developed by Perez [3], yield in our case

$$(2) \quad 0 \leq r_n - r_\infty < \sqrt{(2w_0 r_n (I_\infty - I_n))}$$

where  $w_0$  is a constant defined by  $w \leq w_0$ . That is why the evaluation of  $I_n$  plays an important role in the statistical decision theory.

This paper deals with the rate of convergence of  $I_n$  to  $I_\infty$  and with the value of  $I_\infty$ .

In the sequel we shall use a distance measure  $\Delta$  of two probability measures, say  $\eta_1, \eta_2$ , defined on a measurable space  $(Y, \mathcal{Y})$ :

$$\Delta(\eta_1, \eta_2) = \frac{1}{2} |\eta_1 - \eta_2| (Y)$$

where  $|\eta_1 - \eta_2|$  denotes the total variation of the signed measure  $\eta_1 - \eta_2$ . It is clear that  $\Delta$  is a metric taking values between 0 and 1, and, in view of the Jordan decomposition theorem, there is  $F_0 \in \mathcal{Y}$  such that

$$(3) \quad \Delta(\eta_1, \eta_2) = \eta_1(F_0) - \eta_2(F_0) = \sup_{F \in \mathcal{Y}} \{\eta_1(F) - \eta_2(F)\}.$$

Let us point out that  $\Delta(\eta_1, \eta_2)$  is a measure of divergence of  $\eta_1$  and  $\eta_2$ ,  $\Delta(\eta_1, \eta_2) = 0$  if and only if  $\eta_1 = \eta_2$ ,  $\Delta(\eta_1, \eta_2) = 1$  if and only if  $\eta_1 \perp \eta_2$ .

If we denote by  $H(\mu)$  the entropy of  $(X, \mathcal{X}, \mu)$  i.e.

$$H(\mu) = - \sum_{x \in X} \mu(x) \log \mu(x)$$

then the results of the paper may be summarized as follows.

**Theorem.** *If*

$$(4) \quad \inf_{n=1,2,\dots} \frac{1}{n} \sum_{i=1}^n \Delta(v_i(\cdot | x'), v_i(\cdot | x'')) > 0$$

for every  $x', x'' \in X$ ,  $x' \neq x''$ , then there exist numbers  $A > 0$  and  $0 < \lambda < 1$  such that

$$(5) \quad 0 \leq I_\infty - I_n < A\lambda^n,$$

where

$$(6) \quad I_\infty = H(\mu).$$

The inequality

$$(7) \quad 0 \leq I_\infty \leq H(\mu)$$

always holds.

**Remark.** If  $v_i(\cdot | x)$ ,  $x \in X$ , are mutually different for every  $i = 1, 2, \dots$  and if there is a disjoint decomposition  $\{1, 2, \dots\} = N_1 \cup N_2 \cup \dots \cup N_k$  such that

$$(Y_i, \mathcal{Y}_i, v_i(\cdot | x)) = (Y_j, \mathcal{Y}_j, v_j(\cdot | x))$$

for every  $i, j \in N_m, m = 1, 2, \dots, k$  and  $x \in X$ , then condition (4) is satisfied. Therefore the Theorem contains as a special case the results of RÉNYI [4] assuming that the sequence of samples is a stationary finite-state process.

Assertions (5) and (6) are based on the following property of independent processes:

**Lemma 1.** *If*

$$(8) \quad \inf_{n=1,2,\dots} \frac{1}{n} \sum_{i=1}^n \Delta(v_i(\cdot | x'), v_i(\cdot | x'')) = \alpha > 0 \quad \text{for some } x', x'',$$

then there is a number  $0 < \beta \leq \exp(-\alpha/4)$  such that  $\Delta(v^n(\cdot | x'), v^n(\cdot | x'')) > 1 - 4\beta^n$ .

*Proof.* If  $\alpha = 1$ , then  $v^n(\cdot | x') \perp v^n(\cdot | x'')$  for every  $n$  and Lemma 1 holds for every  $\beta > 0$ . In the case  $\alpha < 1$  we proceed in the following manner. In view of (3), there is  $F_i \in \mathscr{A}_i$  such that

$$v_i(F_i | x') - v_i(F_i | x'') = \Delta(v_i(\cdot | x'), v_i(\cdot | x'')) \quad \text{for every } i = 1, 2, \dots$$

so that, in view of (8),

$$(9) \quad \frac{1}{n} \sum_{i=1}^n v_i(F_i | x') \geq \frac{1}{n} \sum_{i=1}^n v_i(F_i | x'') + \alpha, \quad n = 1, 2, \dots$$

Define on  $(Y^n, \mathscr{A}^n)$  a sequence of measurable functions  $f_1, f_2, \dots, f_n$  by

$$f_i(y^n) = \chi_{F_i}((y^n)_i), \quad i = 1, 2, \dots, n,$$

where  $(y^n)_i$  denotes the  $i$ -th coordinate of the  $n$ -vector  $y^n$  and  $\chi$  is the characteristic function. It can be seen that, for every measure  $v^n(\cdot | x)$  on  $\mathscr{A}^n$ ,  $f_i$  are independent random variables,  $0 \leq f_i \leq 1$ , with expectations  $v_i(F_i | x)$  and with variances bounded from above by  $\frac{1}{4}$ . Therefore, using the inequality § 18.1. A in [1], Chapter V, we obtain for every  $0 < \tau < \frac{1}{4}$  and  $n = 1, 2, \dots$

$$(10) \quad v^n(Y^n - E_n(x, \tau) | x) < 2 \exp(-n\tau),$$

where

$$E_n(x, \tau) = \left\{ y^n : \frac{1}{n} \left| \sum_{i=1}^n (f_i(y^n) - v_i(F_i | x)) \right| \leq \tau \right\}.$$

Let us put  $E_n(x') = E_n(x', \tau)$ ,  $E_n(x'') = E_n(x'', \tau)$  for  $\tau = \frac{1}{4}\alpha$ . As  $0 < \alpha < 1$ , the condition  $0 < \tau < \frac{1}{4}$  is satisfied and using (10), we obtain

$$v^n(E_n(x') | x') > 1 - 2\beta^n, \quad v^n(Y^n - E_n(x'') | x'') < 2\beta^n$$

for  $\beta = \exp(-\frac{1}{4}\alpha)$ . Since in view of (9),  $E_n(x')$  and  $E_n(x'')$  are disjoint, we have

$$v^n(E_n(x') \mid x') - v^n(E_n(x') \mid x'') > 1 - 4\beta^n,$$

which, according to (3), completes the proof.

On the base of Lemma 1 we can immediately prove (6). Namely, Lemma 1 implies that the measures  $v^\infty(\cdot \mid x)$ ,  $x \in X$  are mutually singular and, consequently, there is a disjoint decomposition  $Y^\infty = \bigcup_{x \in X} G_x$  where  $G_x \in \mathcal{Y}^\infty$ ,  $v^\infty(G_x \mid x) = 1$  for every  $x \in X$ . Define  $\mathcal{X} \otimes \mathcal{Y}^\infty$ -measurable function  $f$  by

$$f(x, y^\infty) = \frac{1}{\mu(x)} \chi_{G_x}(y^\infty) \quad \text{for every } (x, y^\infty) \in X \otimes Y^\infty.$$

It is easily proved that for every  $E \in \mathcal{X} \otimes \mathcal{Y}^\infty$

$$\int_E f d(\mu \otimes \tilde{\omega}^\infty) = \sum_{x \in X} \frac{1}{\mu(x)} \int_{\{x\} \otimes (E_x \cap G_x)} d(\mu \otimes \tilde{\omega}^\infty) = \sum_{x \in X} \mu(x) v^\infty(E_x \cap G_x \mid x) = \omega^\infty(E)$$

where

$$E_x = \{y^\infty : (x, y^\infty) \in E\};$$

hence  $f$  is the Radon-Nikodym density of  $\omega^\infty$  with respect to  $\mu \otimes \tilde{\omega}^\infty$  and we can write

$$I_\infty = \sum_{x \in X} \int_{\{x\} \otimes G_x} \log f d\omega^\infty = \sum_{x \in X} \omega^\infty(\{x\} \otimes G_x) \log \frac{1}{\mu(x)}.$$

The desired result follows from the equality  $\omega^\infty(\{x\} \otimes G_x) = \mu(x)$ .

The proof of (5) is based on the following

**Lemma 2.** *If  $Y_1, Y_2, \dots$  are finite sets and if (4) holds, then there exist  $A > 0$  and  $0 < \lambda < 1$  such that (5) is valid.*

*Proof.* We may clearly suppose that  $\mathcal{Y}_i$  contains all subsets of  $Y_i$ ,  $i = 1, 2, \dots$ . In the sequel we shall use the following convention: By writing  $a_n < \Theta(n)$  for a sequence  $a_n \geq 0$ ,  $n = 1, 2, \dots$ , we shall always mean that there is  $A > 0$  and  $0 < \lambda < 1$  such that  $a_n < A\lambda^n$ , for every  $n = 1, 2, \dots$

A routine verification (using (6) and the expression

$$f(x, y^n) = \frac{v^n(y^n \mid x)}{\sum_{x' \in X} \mu(x') v^n(y^n \mid x')}$$

for the Radon-Nikodym density  $d\omega^n/d(\mu \otimes \tilde{\omega}^n)$  provided  $Y^n$  is finite) gives

$$(11) \quad I_\infty - I_n = H(\mu) - I_n = \sum_{y^n \in Y^n} \sum_{x \in X} \psi(x, y^n),$$

where

$$(12) \quad \psi(x, y^n) = \mu(x) v^n(y^n | x) \log \left( \frac{\sum_{x' \in X} \mu(x') v^n(y^n | x')}{\mu(x) v^n(y^n | x)} \right) \geq 0.$$

The left inequality in (5) follows from (11) and (12). Further, in view of Lemma 1 and (3), there exist sequences  $E_n(x) \in \mathcal{Q}^n$  such that

$$(13) \quad v^n(E_n(x) | x') < \Theta(n)$$

$$(14) \quad v^n(Y^n - E_n(x') | x') < \Theta(n) \quad \text{for every } x, x' \in X, \quad x \neq x'.$$

In view of the fact that  $a_n^{(i)} < \Theta(n)$  for  $i = 1, 2, \dots, k$  implies  $\sum_{i=1}^k a_n^{(i)} < \Theta(n)$ , it remains to prove that, for every  $x, x^* \in X$ ,

$$(15) \quad \sum_{y^n \in E_n(x^*)} \psi(x, y^n) < \Theta(n),$$

$$(16) \quad \sum_{\substack{y^n \in Y^n - \bigcup_{x^* \in X} E_n(x^*)}} \psi(x, y^n) < \Theta(n).$$

To prove (16) we use the following easily verified inequality:

$$(17) \quad \psi(x, y^n) \leq \sum_{x' \neq x} \mu(x') v^n(y^n | x').$$

In view of (14), (17), and in view of the inclusion

$$Y^n - \bigcup_{x^* \in X} E_n(x^*) \subset Y^n - E_n(x'),$$

(16) is valid.

To prove (15) under  $x = x^*$  we use (17) obtaining

$$\sum_{E_n(x)} \psi(x, y^n) \leq \sum_{x' \neq x} \mu(x) v^n(E_n(x) | x')$$

and then apply (13).

Suppose now that  $x \neq x^*$ . Since  $\log(1+z) \leq \sqrt{z}$  holds for every real  $z > 0$ , the following inequality holds

$$\psi(x, y^n) \leq \sqrt{(\mu(x) v^n(y^n | x))} \sqrt{\left[ \sum_{x' \neq x} \mu(x') v^n(y^n | x') \right]}$$

(cf. (12)) and hence, using Schwarz's inequality, we can write

$$\begin{aligned} \sum_{E_n(x^*)} \psi(x, y^n) &\leq \sqrt{\left[ \sum_{E_n(x^*)} \mu(x) v^n(y^n | x) \right]} \sqrt{\left[ \sum_{E_n(x^*)} \sum_{x' \neq x} \mu(x') v^n(y^n | x') \right]} \leq \\ &\leq \sqrt{[\mu(x) v^n(E_n(x^*) | x)]} < \Theta(n) \end{aligned}$$

(cf. (13)) and the proof of the Lemma is complete.

To prove (5) we proceed in the following manner. According to (3) and (4), there exist  $F_i(x', x'') \in \mathcal{Y}_i$ ,  $i = 1, 2, \dots$  such that

$$\inf_{n=1,2,\dots} \frac{1}{n} \sum_{i=1}^n (v_i(F_i | x') - v_i(F_i | x'')) > 0 \quad \text{for every } x' \neq x''.$$

If we denote by  $\mathcal{Y}_i^*$  the  $\sigma$ -algebra generated by the class of all  $F_i(x', x'')$ ,  $x', x'' \in X$  then  $\mathcal{Y}_1^*, \mathcal{Y}_2^*, \dots$  are finite sets and (4) holds for

$$A^*(v_i(\cdot | x'), v_i(\cdot | x'')) = \sup_{F \in \mathcal{Y}_i^*} \{v_i(F | x') - v_i(F | x'')\}.$$

If we put in Lemma 2:  $Y_i = \tilde{\mathcal{Y}}_i$ ,  $\mathcal{Y}_i = \mathcal{Y}_i^*$  where  $\tilde{\mathcal{Y}}_i \subset \mathcal{Y}_i^*$  is a disjoint decomposition of  $Y_i$  such that the  $\sigma$ -algebra generated by itself is  $\mathcal{Y}_i^*$ , then we obtain positive numbers  $A$  and  $\lambda < 1$  such that  $0 \leq I_\infty^* - I_n^* < A\lambda^n$ , where  $I_n^*$ ,  $n = 1, 2, \dots, \infty$ , is the information obtained by replacing  $\mathcal{Y}_i$  by  $\mathcal{Y}_i^*$ ,  $i = 1, 2, \dots$ . Since in view of  $\mathcal{Y}_i^* \subset \mathcal{Y}_i$  we have  $I_n^* \leq I_n$ ,  $n = 1, 2, \dots$  (cf. [2]), and since we have, according to (6),  $I_\infty^* = I_\infty$ , the right inequality in (5) holds for the given  $A$  and  $\lambda$ . To prove the left inequality we refer again to [2].

It remains to prove (7). Using the notation employed above we have, according to (11) and (12),  $H(\mu) \geq I_n^*$ ,  $n = 1, 2, \dots$ , for every sequence  $\mathcal{Y}_i^*$ ,  $i = 1, 2, \dots$  of finite sub- $\sigma$ -algebras of  $\mathcal{Y}_i$ 's. Hence, by Theorem 13 in [2], the following inequality holds  $H(\mu) \geq I_n$ ,  $n = 1, 2, \dots$ ; considering the limit for  $n \rightarrow \infty$  we obtain the desired result (7) and the proof of the Theorem is complete.

Let us end the paper by the evaluation of the Bayes risk  $r_n$  in the statistical decision problem we have considered under the assumption that (4) holds. An easy verification (using Lemma 1) gives  $r_\infty = 0$ . Using (2) we obtain  $0 \leq r_n < 2w_0(I_\infty - I_n)$  so that, in view of the Theorem, there exists  $A > 0$  and  $0 < \lambda < 1$  such that

$$(20) \quad 0 \leq r_n < A\lambda^n.$$

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## Резюме

### СКОРОСТЬ СХОДИМОСТИ ИНФОРМАЦИИ В ВЫБОРКЕ ОТНОСИТЕЛЬНО ПАРАМЕТРА

ИГОР ВАЙДА (Igor Vajda), Прага

В работе рассматривается средняя информация  $I_n$  содержащаяся в выборке  $(y_1, y_2, \dots, y_n) \in \bigotimes_{i=1}^n Y_i$ ,  $n = 1, 2, \dots, \infty$  (где  $Y_i$ ,  $i = 1, 2, \dots$  абстрактные пространства) относительно параметра  $x$  принимающего значения из конечного множества  $X$ . Показывается, что всегда имеет место неравенство (7), где  $H(\mu)$  обозначает энтропию параметрового пространства  $X$  при распределении вероятностей  $\mu$ . Если случайная последовательность  $y_1, y_2, \dots$  независима для каждого значения параметра  $x$  и если выполняется условие (4), то для некоторых  $A$  и  $\lambda$  имеет место (5), где  $A > 0$  и  $0 < \lambda < 1$ . Этот результат представляет собой обобщение ранее полученного результата Рени [4], предполагающего конечность пространств  $Y_i$ ,  $i = 1, 2, \dots$  и стационарность последовательности  $y_1, y_2, \dots$  для каждого значения параметра  $x$ .