

# NOTES

## NOTE ON A SEQUENTIAL CLASSIFICATION PROBLEM<sup>1</sup>

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**1. Summary.** This note describes explicitly a minimal complete class of decision rules for the problem of sequentially classifying the individuals of a group which is known to come from one of two completely specified populations.

**2. Theorem and discussion.** Two populations,  $\pi_0$  and  $\pi_1$  are given, and an individual is classified to belong to either  $\pi_0$  or  $\pi_1$  on the basis of an observation  $x$  on a r.v.  $X$ , where the distributions  $P_\theta$  corresponding to  $\pi_\theta$ , for  $\theta = 0, 1$  are completely specified. We may without loss of generality assume that  $P_\theta$ ,  $\theta = 0, 1$  are specified in terms of their density functions  $f(x, \theta)$ ,  $\theta = 0, 1$  with respect to a specified measure space  $(\mathcal{X}, \mathcal{G}, \mu)$ .

Consider the following classification problem: A group of  $n$  individuals is known to belong to either  $\pi_0$  or  $\pi_1$ . The individuals of the group arrive sequentially for inspection and classification, the classification of the  $i$ th individual has to be made immediately after he has been inspected,  $i = 1, \dots, n$ .

Assume the following loss structure for classifying an individual:

|     |      |          |         |
|-----|------|----------|---------|
|     |      | decision |         |
|     |      | $\pi_0$  | $\pi_1$ |
| (1) | true | $\pi_0$  | $\pi_1$ |
|     |      | 0        | $b$     |
|     |      | $\pi_1$  | $a$     |
|     |      | $a$      | 0       |

where  $a$  and  $b$  are two given positive numbers. For any classification procedure, we are interested in the average (or equivalently: total) expected loss due to misclassification.

Let the r.v.'s of the individuals be  $X_1, \dots, X_n$  with observed values  $x_1, \dots, x_n$  and let  $\mathbf{x}_i = (x_1, \dots, x_i)$ ,  $i = 1, \dots, n$ . Then any (randomized) decision rule for the above problem can be written as  $T_n = (t_1(\mathbf{x}_1), t_2(\mathbf{x}_2), \dots, t_n(\mathbf{x}_n))$  with  $0 \leq t_i(\mathbf{x}_i) \leq 1$  being measurable functions in the  $i$ th product space, where  $t_i(\mathbf{x}_i)$  and  $1 - t_i(\mathbf{x}_i)$  are the probabilities with which one classifies the  $i$ th individual to come from  $\pi_1$  and  $\pi_0$  respectively, when  $\mathbf{X}_i = \mathbf{x}_i$  is observed. Set  $f(\mathbf{x}_i, \theta) = \prod_{j=1}^i f(x_j, \theta)$ ,  $i = 1, \dots, n$ ,  $\theta = 0, 1$ . Let  $R(T_n, \theta)$  denote the risk, i.e. average expected loss, incurred by using  $T_n$  when the group actually

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Received March 12, 1962; revised March 1, 1963.

<sup>1</sup> This research was sponsored by the Office of Naval Research under Contract Number Nonr-266(33), Project Number NR 042-034. Reproduction in whole or in part is permitted for any purpose of the United States Government.

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belongs to  $\pi_\theta$ ,  $\theta = 0, 1$ . Then

$$\begin{aligned}
 R(T_n, \theta) &= \frac{1}{n} \left[ b(1 - \theta) \sum_{i=1}^n \int t_i(\mathbf{x}_i) f(\mathbf{x}_i, \theta) d\mu^i \right. \\
 (2) \qquad &\quad \left. + a\theta \sum_{i=1}^n \int (1 - t_i(\mathbf{x}_i)) f(\mathbf{x}_i, \theta) d\mu^i \right] \\
 &= \frac{a\theta}{n} + \frac{b(1 - \theta) - a\theta}{n} \sum_{i=1}^n \int t_i(\mathbf{x}_i) f(\mathbf{x}_i, \theta) d\mu^i
 \end{aligned}$$

where the integral is taken over the  $i$ th product space of  $\mathfrak{X}$ .

We can now state the following

**THEOREM.** *A complete class of decision rules  $T_n$  for the above problem is:  $\{T_n^\eta, 0 \leq \eta \leq 1\}$  where  $T_n^\eta = (t_1^\eta(\mathbf{x}_1), \dots, t_n^\eta(\mathbf{x}_n))$  with*

$$\begin{aligned}
 (3) \qquad t_i^\eta(\mathbf{x}_i) &= 1 && \text{if } a\eta f(\mathbf{x}_i, 1) > b(1 - \eta)f(\mathbf{x}_i, 0) \\
 &= 0 && \text{if } a\eta f(\mathbf{x}_i, 1) < b(1 - \eta)f(\mathbf{x}_i, 0) \\
 &= \text{arbitrary in } [0, 1] && \text{if } a\eta f(\mathbf{x}_i, 1) = b(1 - \eta)f(\mathbf{x}_i, 0).
 \end{aligned}$$

(Notice that  $T_n^\eta$ , for fixed  $\eta$ , stands for a whole class of decision rules, and thus the notation is actually incomplete.)

Moreover, if in (3) the arbitrary part is taken to be 1 for  $\eta = 0$  and  $f(\mathbf{x}_i, 0) = 0$ , and to be 0 for  $\eta = 1$  and  $f(\mathbf{x}_i, 1) = 0$  then the class obtained is minimal complete.

**PROOF.** Let  $\eta$  be the ‘‘a priori probability’’ that the group comes from  $\pi_1$ , i.e.  $P\{\pi_\theta = \pi_1\} = \eta = 1 - P\{\pi_\theta = \pi_0\}$  and let  $R(T_n, \eta) = \eta R(T_n, 1) + (1 - \eta)R(T_n, 0)$ . Then from (1) one has

$$(4) \quad R(T_n, \eta) = \frac{a\eta}{n} + \frac{1}{n} \sum_{i=1}^n \int [b(1 - \eta)f(\mathbf{x}_i, 0) - a\eta f(\mathbf{x}_i, 1)] t_i(\mathbf{x}_i) d\mu^i$$

and for fixed  $\eta$  (4) is minimized by minimizing the integrand in its right hand side, thus, is minimized by any  $T_n^\eta$  defined through (3). The theorem thus follows from the completeness of the class of Bayes rules for our problem, and from the fact that with the modifications mentioned above the rules defined through (3) are admissible. ((3) are the Bayes rules for deciding on  $\theta_i$  on the basis of  $\mathbf{x}_i$ , and by chapter 7 of [1] the class of Bayes rules is complete, and with the proper modifications the rules are admissible. Averaging over the components for  $i = 1, \dots, n$  does not change these properties.)

**REMARKS.**

(a) It should be noticed that the rules  $T_n^\eta$  are ‘‘strongly sequential’’, in the sense that if one lets  $T^\eta = (t_1^\eta(\mathbf{x}_1), t_2^\eta(\mathbf{x}_2), \dots)$  then for every  $n, n = 1, 2, \dots$   $T_n^\eta$  is the initial  $n$ -vector of the sequence  $T^\eta$ . One does therefore *not need advance knowledge of the number  $n$  of individuals* belonging to the group, in order to apply  $T_n^\eta$ .

(b) Various interpretations for the rule  $T_n^\eta$  are possible:

I. It is easy to prove that for fixed  $i$  the rules  $t_i^\eta(\mathbf{x}_i)$ , for fixed  $\eta$ , are ‘‘Bayes

with respect to a priori distribution  $\eta$ , for the following fixed-sample-size  $i$  hypothesis testing problem:  $X_1, \dots, X_i$  are independent identically distributed r. v.'s distributed according to  $P_\theta$ .

$$(5) \quad \begin{cases} H_0 : \theta = 0 \\ H_1 : \theta = 1 \end{cases}$$

with loss structure corresponding to (1) (with  $\pi_i$  there replaced by  $H_i$ ). Thus  $T_n^\eta$  can be described as a rule which at each stage uses *all previous observations* to conduct a test of (5), and the  $i$ th individual is classified to belong to  $\pi_\theta$  if and only if  $H_\theta$  is accepted  $\theta = 0, 1$ . (The "size"  $\alpha$  of the test for the various values of  $i$  is however usually not constant in  $i$ . It depends on  $\eta, b, a, f(x, 0), f(x, 1)$ , and  $i$ .)

II. Let

$$\eta_{i-1}(\mathbf{x}_{i-1}) = \eta f(\mathbf{x}_{i-1}, 1) / [\eta f(\mathbf{x}_{i-1}, 1) + (1 - \eta) f(\mathbf{x}_{i-1}, 0)].$$

$\eta_{i-1}(\mathbf{x}_{i-1})$  is the a posteriori probability of  $\pi_\theta = \pi_1$  when  $\mathbf{X}_{i-1} = \mathbf{x}_{i-1}$  has been observed. Now (3) can also be written as:

$$(6) \quad \begin{aligned} t_i(\mathbf{x}_i) &= 1 && \text{if } a\eta_{i-1}(\mathbf{x}_{i-1})f(x_i, 1) > b[1 - \eta_{i-1}(\mathbf{x}_{i-1})]f(x_i, 0) \\ &= 0 && \text{if } a\eta_{i-1}(\mathbf{x}_{i-1})f(x_i, 1) < b[1 - \eta_{i-1}(\mathbf{x}_{i-1})]f(x_i, 0) \\ &= \text{arbitrary} && \text{if } a\eta_{i-1}(\mathbf{x}_{i-1})f(x_i, 1) = b[1 - \eta_{i-1}(\mathbf{x}_{i-1})]f(x_i, 0). \\ &\text{in } [0, 1] \end{aligned}$$

Notice, however, that the Bayes rule, with respect to a priori distribution  $\eta$ , for classifying any single individual, is:

$$(7) \quad \begin{aligned} t(x) &= 1 && \text{if } a\eta f(x, 1) > b(1 - \eta) f(x, 0) \\ &= 0 && \text{if } a\eta f(x, 1) < b(1 - \eta) f(x, 0) \\ &= \text{arbitrary in } [0, 1] && \text{if } a\eta f(x, 1) = b(1 - \eta) f(x, 0). \end{aligned}$$

Comparing (6) and (7) we see that the decision on the  $i$ th individual is of structure (7), except that the "a priori distribution  $\eta$ " has in (6) been replaced by the "a posteriori distribution of  $\theta$ , given  $\mathbf{x}_{i-1}$ ". (Notice that although  $\eta_i(\mathbf{x}_i)$  is known at the  $i$ th decision, only  $\eta_{i-1}(\mathbf{x}_{i-1})$  is used in (6).)

For asymptotically "optimal" solutions of the general sequential 2-way classification problem, where the  $n$  individuals need not necessarily come from the same population, see [2].

REFERENCES

[1] BLACKWELL, DAVID and GIRSHICK, M. A. (1954). *Theory of Games and Statistical Decisions*. Wiley, New York.  
 [2] SAMUEL, ESTER (1963). Asymptotic solutions of the sequential compound decision problem. *Ann. Math. Statist.* **34** 1079-1094.