

# ASYMPTOTIC BEHAVIOR OF SEQUENTIAL DESIGN WITH COSTS OF EXPERIMENTS

(THE CASE OF NORMAL DISTRIBUTION)

BY KAZUTOMO KAWAMURA

## 1. Introduction.

Recently we showed the following fact in [2]. For two binomial trials  $E_i$  ( $i=1, 2$ ) with parameter  $p_i$  and cost  $c_i$  a procedure  $\mathfrak{G}$  is given such that, using the procedure, the sum of information discriminating two hypotheses  $p_1 > p_2$  and  $p_1 < p_2$  per unit cost is asymptotically maximized.

In this paper we shall consider two kinds of normal trials  $E_i$  ( $i=1, 2$ ) which have mean  $m_i$ , same variance  $\sigma^2$  and cost  $c_i$  where we assume  $m_1 \neq m_2$ . The object of this paper is also to discriminate the hypotheses  $m_1 > m_2$  or  $m_1 < m_2$ . Then the same procedure as in [2] is optimal and we shall show analogously the asymptotic behavior of the procedure.

## 2. Notations and definitions.

We shall denote by  $\Theta$  2-dimensional euclidean parameter space. An element of the space  $\Theta$  is expressed by  $\theta=(m_1, m_2)$  and we put

$$H_1 = \{(m_1, m_2): m_1 > m_2, (m_1, m_2) \in \Theta\},$$

$$H_2 = \{(m_1, m_2): m_1 < m_2, (m_1, m_2) \in \Theta\}$$

and

$$B = \{(m_1, m_2): m_1 = m_2, (m_1, m_2) \in \Theta\}.$$

Then  $\Theta = H_1 + H_2 + B$  is satisfied. Next let  $E^{(i)}$  be  $i$ -th experiment, and define  $X_i$  to be  $i$ -th random variable given by  $E^{(i)}$ . We assume that  $X_{i+1}$  occurs in  $E^{(i+1)}$  independently of the selection of  $E^{(1)}, E^{(2)}, \dots, E^{(i)}$  ( $i=1, 2, \dots$ ). Then we see that  $X_1, X_2, \dots, X_n, \dots$  are independent random variables. And let  $n_1$  be the number of selections of experiment  $E_1$  in the partial  $n$  experiments  $E^{(1)}, E^{(2)}, \dots, E^{(n)}$  and similarly  $n_2$  the number of selections of  $E_2$  in the partial  $n$  experiments. If  $\theta=(m_1, m_2)$  is an element of  $\Theta$ , the probability density function of  $X_i$  at  $E^{(i)}, f(x_i, \theta, E^{(i)})$  is known to be following form:

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$$\begin{aligned}
 f(x_i, \theta, E^{(i)}) &= \frac{1}{\sqrt{2\pi\sigma}} \exp\left\{-\frac{(x_i - m_1)^2}{2\sigma^2}\right\} & \text{if } E^{(i)} = E_1, \\
 &= \frac{1}{\sqrt{2\pi\sigma}} \exp\left\{-\frac{(x_i - m_2)^2}{2\sigma^2}\right\} & \text{if } E^{(i)} = E_2.
 \end{aligned}$$

Then the likelihood function of  $\theta$  over the partial  $n$  experiments is given by  $\prod_{i=1}^n f(x_i, \theta, E^{(i)})$ . This is a function of  $n$  observations  $x_1, x_2, \dots, x_n$ ,  $n$  experiments  $E^{(1)}, E^{(2)}, \dots, E^{(n)}$  and  $\theta$ . The maximum likelihood estimate  $\hat{\theta}_n$  of  $\theta$  over the partial  $n$  experiments is not only a function of  $n$  observations  $x_1, x_2, \dots, x_n$ , but also a function of  $n$  experiments  $E^{(1)}, E^{(2)}, \dots, E^{(n)}$ . Next we shall denote by  $\check{\theta}_n$  the maximum likelihood estimate of  $\theta$  on the subspace  $a(\hat{\theta}_n)$  over  $n$  experiments  $E^{(1)}, E^{(2)}, \dots, E^{(n)}$  where  $a(\hat{\theta}_n)$  is defined as follows:

$$\begin{aligned}
 a(\hat{\theta}_n) &= \Theta - H_i & \text{if } \hat{\theta}_n \in H_i & \quad (i=1, 2), \\
 &= \Theta & \text{if } \hat{\theta}_n \in B.
 \end{aligned}$$

Definition of discrimination. As a measure of discrimination between two probability density functions  $f_1, f_2$  Kullback [4] introduced

$$I(f_1, f_2) = \int \left[ \log \frac{f_1}{f_2} \right] f_1 d\mu.$$

In our case we can use this measure to express the discrimination between  $f(x, \theta, E)$  and  $f(x, \varphi, E)$ , i.e.,

$$(2.1) \quad I(\theta, \varphi, E_1) = \int_R \left[ \log \frac{f(x, \theta, E_1)}{f(x, \varphi, E_1)} \right] f(x, \theta, E_1) dx = \frac{(m_1 - m_1^*)^2}{2\sigma^2}.$$

Similarly we can verify

$$(2.2) \quad I(\theta, \varphi, E_2) = \frac{(m_2 - m_2^*)^2}{2\sigma^2}$$

where  $\theta = (m_1, m_2)$  and  $\varphi = (m_1^*, m_2^*)$ .

Definition of procedure  $\mathfrak{G}$ . We shall call next policy procedure  $\mathfrak{G}$ :  $E^{(1)} = E_1$ ,  $E^{(2)} = E_2$  and for  $n \geq 2$  successively

$$(2.3) \quad E^{(n+1)} = \begin{Bmatrix} E_1 \\ E_2 \\ E^{(n)} \end{Bmatrix} \quad \text{if} \quad \frac{I(\hat{\theta}_n, \check{\theta}_n, E_1)}{c_1} \begin{cases} > \\ < \\ = \end{cases} \frac{I(\hat{\theta}_n, \check{\theta}_n, E_2)}{c_2}.$$

### 3. Theorems.

First we put

$$D(\theta) = \{(m_1^*, m_2^*): (m_1^* \geq m_1, m_2^* \leq m_2) \text{ or } (m_1^* \leq m_1, m_2^* \geq m_2)\},$$

where  $\theta = (m_1, m_2)$ , and

$$(3.1) \quad \theta^* = \left\{ \varphi: \frac{I(\theta, \varphi, E_1)}{c_1} = \frac{I(\theta, \varphi, E_2)}{c_2}, \varphi \in D(\theta) \right\} \cap B = (m^*, m^*).$$

Using this  $m^*$ , we define

$$(3.2) \quad \lambda^* = \frac{m^* - m_2}{m_1 - m_2}.$$

Moreover, let  $\check{\theta}$  be  $\check{\theta} = (m, m)$  for fixed  $\lambda \in [0, 1]$ , where

$$(3.3) \quad m = \lambda m_1 + (1 - \lambda)m_2.$$

Then we can list the following Theorems.

**THEOREM 1.** *Our procedure  $\mathfrak{Q}$  satisfies the next relation*

$$(3.4) \quad \lim_{n \rightarrow \infty} \frac{S_n(\hat{\theta}_n, \check{\theta}_n)}{\sum_{i=1}^n C^{(i)}} = I^*(\theta)$$

with probability 1, where

$$(3.5) \quad I^*(\theta) = \frac{I(\theta, \theta^*, E_1)}{c_1} = \frac{I(\theta, \theta^*, E_2)}{c_2} \quad (\theta = (m_1, m_2)),$$

$$(3.6) \quad S_n(\hat{\theta}_n, \check{\theta}_n) = \log \frac{\prod_{i=1}^n f(x_i, \hat{\theta}_n, E^{(i)})}{\prod_{i=1}^n f(x_i, \check{\theta}_n, E^{(i)})}$$

and  $C^{(i)}$  is the cost of  $E^{(i)}$ .

**THEOREM 2.** *Any sequence of experiments  $E^{(n)}$  ( $n=1, 2, \dots$ ) such that  $\lim_{n \rightarrow \infty} (n_1/n) = \lambda^*$  satisfies also the same result as in Theorem 1, that is,*

$$\lim_{n \rightarrow \infty} \frac{S_n(\hat{\theta}_n, \check{\theta}_n)}{\sum_{i=1}^n C^{(i)}} = I^*(\theta)$$

with probability 1.

**THEOREM 3.** *Given any sequence of experiments  $E^{(n)}$  ( $n=1, 2, \dots$ ) such that  $\lim_{n \rightarrow \infty} (n_1/n) = \lambda$  ( $\lambda \in [0, 1]$ ) and  $\lim_{n \rightarrow \infty} \min(n_1, n_2) = +\infty$ , the limit*

$$(3.7) \quad \lim_{n \rightarrow \infty} \frac{S_n(\hat{\theta}_n, \check{\theta}_n)}{\sum_{i=1}^n C^{(i)}} = \frac{\lambda I(\theta, \check{\theta}, E_1) + (1-\lambda)I(\theta, \check{\theta}, E_2)}{\lambda c_1 + (1-\lambda)c_2}$$

exists with probability 1.

THEOREM 4. *The limit function (3.7) of  $\lambda \in [0, 1]$  has only one maximum value if and only if  $\lambda = \lambda^*$ .*

Theorems 1~4 explain that the procedure  $\mathfrak{P}$  has the property which is asymptotically most informative per unit cost for any other procedure.

In order to prove these Theorems 1~4 we need only the following Lemmas.

LEMMA 1. *If we execute any procedure, we have always*

$$\hat{\theta}_n = \left( \frac{1}{n_1} \sum_{E^{(i)}=E_1} x_i, \frac{1}{n_2} \sum_{E^{(i)}=E_2} x_i \right), \quad \check{\theta}_n = \left( \frac{1}{n} \sum_{i=1}^n x_i, \frac{1}{n} \sum_{i=1}^n x_i \right)$$

where  $\sum_{E^{(i)}=E_j}$  means the summation over  $i=1, 2, \dots, n$  satisfying  $E^{(i)}=E_j$  ( $j=1, 2$ ).

LEMMA 2. *Given the sequence of experiments under the procedure  $\mathfrak{P}$   $E^{(n)}$  ( $n=1, 2, \dots$ ), then the probability that  $E^{(n)}=E_1$  for all  $n \geq k$  or  $E^{(n)}=E_2$  for all  $n \geq k$  is zero where  $k$  is any fixed positive integer.*

LEMMA 3. *Under the procedure  $\mathfrak{P}$  we have*

$$\lim_{n \rightarrow \infty} \min(n_1, n_2) = +\infty$$

with probability 1.

LEMMA 4. *Under the procedure  $\mathfrak{P}$  we have*

$$\lim_{n \rightarrow \infty} \hat{\theta}_n = (m_1, m_2)$$

with probability 1.

LEMMA 5. *Under the procedure  $\mathfrak{P}$  we have*

$$\lim_{n \rightarrow \infty} \frac{n_1}{n} = \lambda^*$$

with probability 1.

LEMMA 6. *Under the procedure  $\mathfrak{P}$  we have*

$$\lim_{n \rightarrow \infty} \check{\theta}_n = \theta^*$$

with probability 1.

These proofs of Lemma 1~6 can be lead analogously as given in [2]. But proof of Lemma 5 can be given directly from equivalent condition (3. 8) of procedure  $\mathfrak{G}$  as follows.

$$(3. 8) \quad \frac{n_2}{n_1} \left\{ \begin{array}{l} > \\ < \\ = \end{array} \right\} \sqrt{\frac{c_1}{c_2}}.$$

Then under procedure  $\mathfrak{G}$  we can verify that  $n_1/n$  approaches to  $\sqrt{c_2}/(\sqrt{c_1}+\sqrt{c_2})$  as  $n \rightarrow \infty$  with probability 1, and from (2. 1), (2. 2), (3. 1) and (3. 2) the limit value  $\sqrt{c_2}/(\sqrt{c_1}+\sqrt{c_2})$  of  $n_1/n$  is equal to  $\lambda^*$ .

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#### REFERENCES

- [1] CHERNOFF, H., Sequential design of experiments. *Ann. Math. Stat.* **30** (1959), 755-770
- [2] KAWAMURA, K., Asymptotic behavior of sequential design with costs of experiments. *Kōdai Math. Sem. Rep.* **16** (1964), 169-182.
- [3] KAWATA, T., Probability theory and statistics. 5th Ed. (1964), Asakura Co. (In Japanese)
- [4] KULLBACK, S., Information theory and statistics. (1959), wiley.
- [5] KUNISAWA, K., Modern probability theory. 12th Ed. (1963), Iwanami Co. (In Japanese)
- [6] KUNISAWA, K., Introduction to information theory for operations research. 4th Ed. (1963), J.U.S.E. (In Japanese)

DEPARTMENT OF MATHEMATICS, TOKYO INSTITUTE OF TECHNOLOGY.