

# ON SEQUENTIAL DISTINGUISHABILITY FOR THE EXPONENTIAL FAMILY\*

RASUL A. KHAN

(Received Feb. 15, 1972)

## 1. Introduction

Let  $\{X_n, n \geq 1\}$  be an iid (independent and identically distributed) stochastic sequence assumed to be governed by a member of a countable family of probability measures  $\mathcal{P} = \{P_\theta: \theta \in \Omega\}$  where  $P_\theta$  are defined on an appropriate probability space and  $\Omega$  is countable. Observing sequentially the stochastic sequence  $\{X_n, n \geq 1\}$  we want to stop at some finite stage and decide in favour of a member of the family  $\mathcal{P}$  with a uniformly small probability of error. The family  $\mathcal{P}$  is said to be "Sequentially Distinguishable" if for any given  $\varepsilon$  ( $0 < \varepsilon < 1$ ) there exists a stopping time  $t$  and a terminal decision function  $\delta(X_1, \dots, X_t)$  such that  $P_\theta(t < \infty) = 1 \forall \theta \in \Omega$  and  $\sup_{\theta \in \Omega} P_\theta(\delta(X_1, \dots, X_t) \neq \theta) \leq \varepsilon$ .

The family  $\mathcal{P}$  being countable, there is no loss of generality in assuming the existence of probability densities  $\{f_\theta: \theta \in \Omega\}$  with respect to some  $\sigma$ -finite measure  $\mu$ . To simplify notations we write  $f_i = f_{\theta_i}$ , and  $P_i = P_{\theta_i}$ , etc. Further, let  $f_{i,n}$  be the joint probability density function of  $(X_1, X_2, \dots, X_n)$  with respect to  $\mu_n$  (the  $\mu$ -measure in  $n$ -dimensions). In what follows we shall take a doubly indexed sequence of constants  $\{a_{ij}\}$  such that  $a_{ij} > 1$  and  $\sum_{i \neq j} a_{ij}^{-1} \leq \varepsilon$  for a given  $\varepsilon$  ( $0 < \varepsilon < 1$ ) and  $\forall j$ . Motivated by Wald's sequential probability ratio test (SPRT) Robbins [7] defined a general stopping time for the sequential distinguishability problem as follows:

$$(1.1) \quad N = \inf \{n \geq 1: f_{i,n} \geq \sup_{j \neq i} a_{ij} f_{j,n} \text{ for some } i\} \\ = \infty \quad \text{if no such } n,$$

and assert  $P_i (\iff \theta_i)$  if  $N$  stops with  $i$ . Let  $a_i = \{\text{accept } \theta_i\}$ . By assuming  $N$  terminates, it follows that

$$P_j(\delta(X_1, \dots, X_N) \neq \theta_j) \\ = \sum_{i \neq j} P_j(a_i) = \sum_{i \neq j} \sum_{n=1}^{\infty} \int_{\{N=n, a_i\}} f_{j,n} d\mu_n \leq \sum_{i \neq j} a_{ij}^{-1} P_i(a_i) \leq \varepsilon \quad \forall j.$$

---

\* Part of this paper was written while the author was at Columbia University.

This stopping time has been studied by the author ([5], [6]) and a number of results have been obtained. The object of this paper is to generalize some of the specific examples of [6] to the case where  $f_\theta$  is the one parameter exponential probability density function. In Section 2 we give some definitions and results from [6] which are essential for the succeeding main sections.

## 2. Preliminaries

Let  $I(f_i : f_j)$  denote the Kullback-Leibler information measure between  $P_i$  and  $P_j$ , and is defined as

$$I(f_i : f_j) = E_i \log (f_i / f_j) = \int f_i \log (f_i / f_j) d\mu.$$

We assume that  $0 < \inf_{j \neq i} I(f_i : f_j) \leq \infty \forall i$ . It has been shown in [6] that

$$(2.1) \quad E_i N \geq \sup_{j \neq i} \{(\log a_{ij}) / I(f_i : f_j)\}.$$

This inequality is universal for the stopping time (1.1).

We note that the problem of sequential distinguishability can be done (at least in principle) by a sequence of SPRT's. Consequently, let  $t_{ij}$  denote the stopping time of an SPRT for testing  $H_i: f = f_i$  against  $H_j: f = f_j$ , when the error probabilities are  $\alpha = \beta = \varepsilon$ . The following definition is due to Robbins [7].

**DEFINITION.** The stopping rule  $N$  is said to be asymptotically optimal if

$$\lim_{\varepsilon \rightarrow 0} \frac{E_i N}{\sup_{j \neq i} E_i t_{ij}} = 1.$$

The definition is interesting because of the known optimality of SPRT. In [6] we proved the following elementary lemma.

**LEMMA 2.1.** *The stopping rule  $N$  is asymptotically optimal if*

$$E_i N \sim (-\log \varepsilon) / \inf_{j \neq i} I(f_i : f_j) \quad \text{as } \varepsilon \rightarrow 0.$$

We now proceed with the main problem of this paper.

## 3. The problem and the stopping rule

Let  $f(x, \theta) = \exp(\theta x - b(\theta))$  be the p.d.f. of a random variable  $X$  with respect to some  $\sigma$ -finite measure  $\mu$ . It is known that the natural pa-

parameter set  $\Theta = \left\{ \theta : \int \exp(\theta x - b(\theta)) d\mu(x) < \infty \right\}$  is a convex set. Further, it is well known that  $b(\theta)$  is differentiable on the interior of  $\Theta$ , and  $E_\theta X = b'(\theta)$ ,  $\sigma_x^2(\theta) = b''(\theta) > 0$ , so that  $b'(\theta)$  is strictly increasing and  $b(\theta)$  is a strict convex function. Let  $\Omega = \{\theta_i : i \in Z\}$ , where  $\theta_i$ 's are the interior points of  $\Theta$ , and  $Z$  is the set of integers. With no loss of generality we can assume that  $\Omega$  is an ordered set in the usual direction, i.e.  $\dots < \theta_{i-1} < \theta_i < \theta_{i+1} < \dots$ . Let  $P_\theta$  denote the probability measure pertaining to  $f(x, \theta)$ , and set  $\Phi = \{P_\theta : \theta \in \Omega\}$ . Let  $X_1, X_2, \dots$  be an iid sequence assumed to be governed by a member of  $\Phi$ . We want to find a sequential procedure  $(N, \delta)$  where  $N$  is a stopping rule and  $\delta$  a terminal decision function which accepts a member  $\theta_i \in \Omega$  such that (i)  $P_{\theta_i}(N < \infty) = 1 \forall \theta_i \in \Omega$ , and (ii)  $\sup_{\theta_i \in \Omega} P_{\theta_i}(\text{error}) \leq \varepsilon$  for a given  $\varepsilon$  ( $0 < \varepsilon < 1$ ).

First we make some useful observations. We write  $P_i = P_{\theta_i}$ ,  $E_i = E_{\theta_i}$ ,  $f_i = f(X, \theta_i)$ , and  $I(\theta_i : \theta_j) = I(f_i : f_j)$ , etc. without any further comment. The Kullback-Leibler information measure is

$$(3.1) \quad \begin{aligned} I(\theta_i : \theta_j) &= E_i \log(f_i/f_j) \\ &= \{(\theta_i - \theta_j)b'(\theta_i) - (b(\theta_i) - b(\theta_j))\} > 0. \end{aligned}$$

If we set  $F(\theta_j) = (b(\theta_j) - b(\theta_i))/(\theta_j - \theta_i)$ ,  $j \neq i$ , ( $\theta_i$  fixed), then  $\partial F/\partial \theta_j = (I(\theta_i : \theta_j))/(\theta_i - \theta_j)^2 > 0$ . Hence  $F(\theta_j)$  is increasing in  $\theta_j$  for each fixed  $\theta_i$ . It follows from (3.1) that  $\partial I/\partial \theta_j \geq 0$  according as  $\theta_j > \theta_i$  or  $\theta_j < \theta_i$  (since  $b'(\cdot)$  is increasing). Thus  $I(\theta_i : \theta_j)$  is increasing (decreasing) in  $\theta_j$  according as  $\theta_j > \theta_i$  or  $\theta_j < \theta_i$ . Before choosing  $a_{ij}$  for the proposed stopping time (1.1) we make the following assumptions.

Let  $g(x)$  be a real function such that

- (i)  $g'(x) > 0$ ,  $g''(x) \geq 0$ , so that  $g(\cdot)$  is a strictly increasing convex function and  $g'(\cdot)$  is non-decreasing.
- (ii)  $g(\theta_{i+1}) - g(\theta_i) \geq 1 \forall i \in Z$ .
- (iii)  $\phi(\theta_j) = \{(b(\theta_j) - b(\theta_i))/(\theta_j - \theta_i) - (g(\theta_j) - g(\theta_i))/(\log \alpha)/n(\theta_j - \theta_i)\}$  ( $\alpha > 1$ ), is increasing in  $\theta_j > \theta_i$  for some  $n \geq m < \infty$ .
- (iv)  $d(\theta_i, \theta_j) = (I(\theta_i : \theta_j))/(g(\theta_j) - g(\theta_i))$  is increasing in  $\theta_j > \theta_i$ .

We now choose  $a_{ij} = \alpha^{|g(\theta_i) - g(\theta_j)|}$ ,  $\alpha > 1$ . Assumption (ii)  $\Rightarrow |g(\theta_i) - g(\theta_j)| \geq |j - i|$ , and hence

$$(3.2) \quad \sum_{i \neq j} a_{ij}^{-1} \leq \sum_{i \neq j} \alpha^{-|i-j|} \leq 2/(\alpha - 1).$$

Recalling the stopping time (1.1) we have

$$(3.3) \quad \begin{aligned} N &= \inf \{n > 1 : f_{i,n} \geq \sup_{j \neq i} a_{ij} f_{j,n} \text{ for some } i\} \\ &= \inf \{n > 1 : 0 \geq \max_{j > i} [\sup R_n(i, j), \sup_{j < i} R_n(i, j)] \text{ for some } i\}, \end{aligned}$$

where  $R_n(i, j) = |g(\theta_i) - g(\theta_j)|(\log \alpha)/n + (\theta_j - \theta_i)S_n/n - (b(\theta_j) - b(\theta_i))$ , and

where  $S_n = X_1 + X_2 + \dots + X_n$ . Using assumptions (i) and (iii), simple computations simplify (3.3) to as follows:

$$(3.4) \quad N = \inf \left\{ n \geq m : \frac{b(\theta_i) - b(\theta_{i-1})}{\theta_i - \theta_{i-1}} + \frac{g(\theta_i) - g(\theta_{i-1})}{\theta_i - \theta_{i-1}} \frac{\log \alpha}{n} \leq \frac{S_n}{n} \right. \\ \left. \leq \frac{b(\theta_{i+1}) - b(\theta_i)}{\theta_{i+1} - \theta_i} - \frac{g(\theta_{i+1}) - g(\theta_i)}{\theta_{i+1} - \theta_i} \frac{\log \alpha}{n} \text{ for some } i \right\},$$

and accept  $\theta_i$  ( $a_i$ ) if  $N$  stops with  $i$ . First we have the following.

LEMMA 3.1. (i)  $P_i(N < \infty) = 1 \forall i \in Z$ , and (ii)  $P_i(\text{error}) \leq 2/(\alpha - 1) \forall i \in Z$ .

PROOF. Since by the strong law of large numbers  $S_n/n \rightarrow b'(\theta_i)$  a.s.  $P_i$  (as  $n \rightarrow \infty$ ), (i) follows from the fact that  $b'(\cdot)$  is increasing. To prove the second part, we have

$$P_j(\text{error}) = \sum_{i \neq j} P_j(a_i) \\ = \sum_{i \neq j} \sum_{n=1}^{\infty} \int_{\{N=n, a_i\}} f_{j,n} d\mu_n \\ = \sum_{i < j} \sum_{n=1}^{\infty} \int_{\{N=n, a_i\}} f_{j,n} d\mu_n + \sum_{i > j} \sum_{n=1}^{\infty} \int_{\{N=n, a_i\}} f_{j,n} d\mu_n.$$

Note that  $f_{j,n}/f_{i,n} = \exp((\theta_j - \theta_i)S_n - n(b(\theta_j) - b(\theta_i)))$ . Consider  $i < j \Leftrightarrow \theta_i < \theta_j$ . On  $\{N=n, a_i\}$ ,  $S_n/n \leq (b(\theta_{i+1}) - b(\theta_i))/(\theta_{i+1} - \theta_i) - (g(\theta_{i+1}) - g(\theta_i))(\log \alpha)/n(\theta_{i+1} - \theta_i)$ , and note that the right-hand side of this inequality is the infimum (assumption (iii)) of  $\psi(\theta_j) = (b(\theta_j) - b(\theta_i))/(\theta_j - \theta_i) - (g(\theta_j) - g(\theta_i))/(\log \alpha)/n(\theta_j - \theta_i)$  over  $\theta_j > \theta_i$ . Hence on the set  $\{N=n, a_i\}$  we have

$$f_{j,n}/f_{i,n} \leq \exp(-(g(\theta_j) - g(\theta_i)) \log \alpha) \leq \alpha^{-(g(\theta_j) - g(\theta_i))}.$$

The case  $i > j$  can be considered in a similar fashion. At any rate

$$P_j(\text{error}) \leq \sum_{i \neq j} \alpha^{-|g(\theta_i) - g(\theta_j)|} \leq \sum_{i \neq j} \alpha^{-|i-j|} \leq 2/(\alpha - 1).$$

#### 4. Bounds for $E_i N$ and an asymptotic expression

From (2.1) we have

$$E_i N \geq \sup_{j \neq i} [(\log a_{ij})/I(\theta_i : \theta_j)]$$

where  $I(\theta_i : \theta_j)$  is the Kullback-Leibler information measure. It follows from the choice of  $a_{ij}$  that

$$(4.1) \quad E_i N \geq (\log \alpha) / \min_{j > i} [d(\theta_i, \theta_j)], \min_{j < i} [d(\theta_i, \theta_j)]$$

where  $d(\theta_i, \theta_j) = (I(\theta_i : \theta_j))/|g(\theta_i) - g(\theta_j)|$ ,  $i \neq j$ . It follows from assumption (iv) that

$$\inf_{j>i} d(\theta_i, \theta_j) = d(\theta_i, \theta_{i+1}) = I(\theta_i : \theta_{i+1})(g(\theta_{i+1}) - g(\theta_i))^{-1}.$$

For  $j < i$ ,  $\partial d / \partial \theta_j = -[(b(\theta_i) - b(\theta_j))(g(\theta_i) - g(\theta_j)) - Ig(\theta_j)](g(\theta_i) - g(\theta_j))^{-2}$ . Since  $g'(\cdot)$  is increasing, hence

$$\partial d / \partial \theta_j \leq -[(b(\theta_i) - b(\theta_j))(g(\theta_i) - g(\theta_j)) - Ig(\theta_i)](g(\theta_i) - g(\theta_j))^{-2}.$$

By assumption (iv) it follows that  $\partial d / \partial \theta_j \leq 0$  for  $j < i$ , so that  $\inf_{j<i} d(\theta_i, \theta_j) = d(\theta_i, \theta_{i-1})$ . Thus from (4.1) we have

$$E_i N \geq (\log \alpha) / \min \{d(\theta_i, \theta_{i+1}), d(\theta_i, \theta_{i-1})\},$$

i.e.

$$(4.2) \quad E_i N \geq K_i^{-1} \log \alpha$$

where

$$(4.3) \quad K_i = \min [I(\theta_i : \theta_{i+1}) / (g(\theta_{i+1}) - g(\theta_i)), I(\theta_i : \theta_{i-1}) / (g(\theta_i) - g(\theta_{i-1}))].$$

Hence

$$(4.4) \quad \liminf_{\alpha \rightarrow \infty} (K_i E_i N) / (\log \alpha) \geq 1.$$

Now we want to find an upper bound and an asymptotic expression for  $E_i N$ . To this end, we set  $r = m \log \alpha$ , where  $m > K_i^{-1}$  and assume for simplicity that  $r$  is an integer. From the stopping rule (3.4) we have

$$(4.5) \quad P_i(N > r) \leq P_i(S_r / r > a) + P_i(S_r / r < c)$$

where  $a = (b(\theta_{i+1}) - b(\theta_i)) / (\theta_{i+1} - \theta_i) - (g(\theta_{i+1}) - g(\theta_i))m^{-1} / (\theta_{i+1} - \theta_i)$ , and  $c = (b(\theta_i) - b(\theta_{i-1})) / (\theta_i - \theta_{i-1}) + (g(\theta_i) - g(\theta_{i-1}))m^{-1} / (\theta_i - \theta_{i-1})$ . It follows from the Definition (4.3) that  $m > K_i^{-1} > (g(\theta_{i+1}) - g(\theta_i)) / I(\theta_i : \theta_{i+1}) \Rightarrow a > (b(\theta_{i+1}) - b(\theta_i)) / (\theta_{i+1} - \theta_i) - I(\theta_i : \theta_{i+1}) / (\theta_{i+1} - \theta_i)$ . On substituting the value of  $I$  we see that  $a > b'(\theta_i) = E_i X$ , and hence a theorem of Chernoff [1] implies

$$P_i(S_r / r > a) \leq \rho_1^r$$

where  $\rho_1 = \rho_1(a) = \inf_t e^{-at} M(t)$ ,  $M(t) = E_i e^{tX} = e^{b(\theta_i+t) - b(\theta_i)}$ . One can show that  $0 < \rho_1 < 1$ . A similar argument shows that

$$P_i(S_r / r < c) \leq \rho_2^r, \quad 0 < \rho_2 < 1$$

where  $\rho_2 = \rho_2(c) = \inf_t e^{-ct} M(t)$ . It follows from (4.5) that

$$(4.6) \quad P_i(N > r) \leq \begin{cases} \rho_1^r + \rho_2^r, & 0 < \rho_1, \rho_2 < 1 \\ 2\rho^r, & \rho = \max(\rho_1, \rho_2). \end{cases}$$

Note that (4.6) is sufficient to imply: (i)  $E_i N < \infty \forall i$ , and (ii)  $E_i e^{tN} < \infty$  for some  $t > 0$  ( $\forall i$ ). Moreover,  $N \sim K_i^{-1} \log \alpha$  in probability  $P_i$  (as  $\alpha \rightarrow \infty$ ). To get the bound for  $E_i N$  we have

$$\begin{aligned} E_i N &= \sum_{n=1}^{\infty} n P_i(N=n) = \sum_{n \leq r} n P_i(N=n) + \sum_{n > r} n P_i(N=n) \\ &\leq r + (r+1) P_i(N > r) + \sum_{n > r} P_i(N > n) \\ &\leq r + (r+1) \{\rho_1^r + \rho_2^r\} + \sum_{n > r} \{\rho_1^n + \rho_2^n\}. \end{aligned}$$

Since  $r = m \log \alpha$ , the last series  $\rightarrow 0$  as  $\alpha \rightarrow \infty$ . Thus we have

$$(4.7) \quad E_i N \leq m \log \alpha + (m \log \alpha + 1) \{\rho_1^{m \log \alpha} + \rho_2^{m \log \alpha}\} + o(1),$$

so that

$$(4.8) \quad \limsup_{\alpha \rightarrow \infty} (K_i E_i N) / (\log \alpha) \leq 1.$$

From (4.4) and (4.8) we have

$$(4.9) \quad E_i N \sim K_i \log \alpha \quad \text{as } \alpha \rightarrow \infty.$$

## 5. Asymptotic optimality and special cases

Regarding the asymptotic optimality we have the following theorem.

**THEOREM 5.1.** *If  $g(\theta_{k+1}) - g(\theta_k) = 1 \forall k \in Z$ , then the stopping rule defined by (3.4) is asymptotically optimal.*

**PROOF.** Recall that the uniform bound on the error probability is  $\varepsilon = 2/(\alpha - 1)$ . By using the condition  $g(\theta_{k+1}) - g(\theta_k) = 1 \forall k \in Z$ , it follows from (4.3) and (4.9) that

$$(5.1) \quad E_i N \sim (-\log \alpha) / \min [I(\theta_i : \theta_{i+1}), I(\theta_i : \theta_{i-1})] \quad \text{as } \alpha \rightarrow \infty.$$

But since  $I(\theta_i : \theta_j)$  is increasing in  $\theta_j > \theta_i$  and decreasing in  $\theta_j < \theta_i$ , hence we have

$$(5.2) \quad E_i N \sim (-\log \varepsilon) / \inf_{j \neq i} I(\theta_i : \theta_j) \quad \text{as } \alpha \rightarrow \infty.$$

Hence the conclusion follows from Lemma 2.1.

**COROLLARY 1.** *Let  $\Omega = \{\theta_i : i \in Z\}$  be an ordered set in the usual direction with positive minimum spacing  $\delta$  ( $\delta > 0$ ). Then a possible choice of  $g(x)$  is  $g(x) = x/\delta$ . Moreover, if there is uniform spacing, then the corresponding rule  $N$  is asymptotically optimal.*

**COROLLARY 2.** *If  $\theta_k = ak + c$ ,  $a > 0$ , then we can take  $g(x) = (x - c)/a$ , and the rule would be asymptotically optimal.*

*Remark.* Theorem 5.1 gives asymptotically optimal rules for the sequences which are uniformly spaced relative to  $g(\cdot)$ . However, we can always modify our choice of  $a_{ij}$  to overcome this restriction. Assume for simplicity that  $\Omega = (\theta_1 < \theta_2 < \dots)$ , and modify  $a_{ij}$  as follows:

$$a_{ij} = \begin{cases} \alpha^{(g(\theta_j) - g(\theta_i)) / (g(\theta_{i+1}) - g(\theta_i))}, & j > i \\ \alpha^{(g(\theta_i) - g(\theta_j)) / (g(\theta_i) - g(\theta_{i-1}))}, & j < i. \end{cases}$$

Then it is easy to show that the modified rule (3.4) is asymptotically optimal under mild conditions ensuring  $\sum_{i \neq j} a_{ij}^{-1} \leq 2/\alpha + o(\alpha^{-1})$ . For example, let  $g(\cdot)$  satisfy the previous conditions and the following:

$$(1) \inf_i \inf_{j \neq i} |g(\theta_i) - g(\theta_j)| = \delta > 0$$

$$(2) g(\theta_{i+1}) - g(\theta_i) < \Delta, \Delta > 0, i > 1.$$

Then,  $\sum_{i \neq j} a_{ij}^{-1} \leq 2/\alpha + 2/\alpha(\alpha^{\delta/\Delta} - 1) = 2/\alpha + o(\alpha^{-1})$ . That the associated stopping rule for the modified choice of  $a_{ij}$  is asymptotically optimal follows from the fact that  $E_i N \sim (-\log \epsilon) / \inf_{j \neq i} I(\theta_i : \theta_j)$ , as  $\alpha \rightarrow \infty$ , where  $\epsilon = 2\alpha^{-1}$ .

### Acknowledgement

The author wishes to thank Professor Herbert Robbins for his help during this work. The author also wishes to thank Professor Robert Berk for several helpful suggestions.

KENT STATE UNIVERSITY AND MATHEMATICS RESEARCH CENTER, UNIVERSITY OF WISCONSIN

### REFERENCES

- [1] Chernoff, H. (1952). A measure of asymptotic efficiency for tests of a hypothesis based on the sum of observations, *Ann. Math. Statist.*, **23**, 493-507.
- [2] Freedman, David A. (1967). A remark on sequential discrimination, *Ann. Math. Statist.*, **38**, 1666-1670.
- [3] Hammersley, J. M. (1950). On estimating restricted parameters, *J. Roy. Statist. Soc.*, Ser. B, **XII**, 192-240.
- [4] Hoeffding, W. and Wolfowitz, J. (1958). Distinguishability of sets of distributions, *Ann. Math. Statist.*, **29**, 700-718.
- [5] Khan, Rasul A. (1971). On sequential distinguishability, *MRC Tech. Report*, No. 1133, Madison, Wisconsin.
- [6] Khan, Rasul A. (1973). On sequential distinguishability, *Ann. Statist.*, **1**, 838-850.
- [7] Robbins, Herbert E. (1969). *Sequential Estimation of an Integer Mean*, Herman Wold Festschrift.
- [8] Wald, A. (1947). *Sequential Analysis*, John Wiley, New York.