BOUNDED LENGTH CONFIDENCE INTERVALS FOR THE p-POINT OF A DISTRIBUTION FUNCTION, III $^{\scriptscriptstyle 1}$

By R. H. FARRELL

Cornell University

1. Introduction. Let $0 . A number <math>\gamma_{p,F}$ is a p-point of the distribution function F if $F(\gamma_{p,F}) \geq p$ and $F(\gamma_{p,F^-}) \leq p$. Given L > 0 and $0 < \alpha < 1$, a L- α bounded length confidence interval procedure operates successfully for F means that when sampling stops an interval of length not exceeding L is given which covers $\gamma_{p,F}$ with probability at least $1 - \alpha$. It is the purpose of this paper to give the construction of two L- α bounded length confidence interval procedures which operate successfully for all $F \in F$. F will be the set of all distribution functions F such that $\epsilon_F > 0$. ϵ_F is defined below in (1.10).

Throughout we let $\{X_n, n \geq 1\}$ be a sequence of independently and identically distributed random variables such that F is the distribution function of X_1 . As we allow different choices of F, we indicate the choice when computing expectations by use of "F" as a subscript.

The procedures constructed are measurable functions of the random variables $\{X_n, n \geq 1\}$. Two sets of functions $\{u_{i,n}, n \geq 1\}$ and $\{v_{i,n}, n \geq 1\}$, i = 1, 2, are constructed. Properties of the procedures are as follows:

- (1.1) If i = 1, 2 and if $n \ge 1$ then $u_{i,n}$ and $v_{i,n}$ are real valued Borel measurable functions defined on Euclidean n-space, and $u_{i,n}(x_1, \dots, x_n) \le v_{i,n}(x_1, \dots, x_n)$ for all (x_1, \dots, x_n) in n-space.
- (1.2) If i=1, 2 and if $n \ge 1$ let random variables be defined by $U_{i,n} = u_{i,n}(X_1, \dots, X_n)$ and $V_{i,n} = v_{i,n}(X_1, \dots, X_n)$. There exist real numbers α and β such that $0 < \alpha < 1$ and $0 < \beta < 1$ and such that if $F \in \mathbf{F}$ then

$$P_F(\text{all } n \geq 1, U_{i,n} \leq \gamma_{p,F}) \geq 1 - \beta;$$

$$P_F(\text{all } n \geq 1, V_{i,n} \geq \gamma_{p,F}) \geq 1 - \alpha.$$

(1.3) If F is a distribution function and $\gamma_{p,F}$ is the unique p-point of F then if i = 1, 2,

$$P_{F}(\lim_{n\to\infty} (V_{i,n} - U_{i,n}) = 0) = 1.$$

(1.4) If $f: (-\infty, \infty) \to (-\infty, \infty)$ is strictly increasing, then for $i = 1, 2, n \ge 1$, and all x_1, \dots, x_n ,

$$u_{i,n}(f(x_1), \cdots, f(x_n)) = f(u_{i,n}(x_1, \cdots, x_n));$$

Received 3 September 1965.

¹ Research sponsored in part by the Office of Naval Research under Contract Nonr 401(50) with Cornell University. Part of this work appears in the author's Ph.D. dissertation, University of Illinois.

$$v_{i,n}(f(x_1), \dots, f(x_n)) = f(v_{i,n}(x_1, \dots, x_n)).$$

(1.5) If
$$i = 2$$
 and $n \ge 1$ then $u_{i,n} \le u_{i,n+1} \le v_{i,n+1} \le v_{i,n}$.

In this paper we will discuss various stopping variables. An integer valued random variable N will be called a stopping variable (relative to $\{X_n, n \geq 1\}$ if $N \geq 1$ and the event $\{N \geq i\}$ is independent of $\{X_n, n \geq i\}$, $i \geq 1$. A basic theorem is as follows.

THEOREM 1.1. Let N be a stopping variable. If F is a distribution function then $P_F(U_{i,N} \leq \gamma_{p,F} \leq V_{i,N}) \geq 1 - \alpha - \beta$. If F is a continuous distribution function then the numbers $P_F(\text{all } n \geq 1, U_{i,n} \leq \gamma_{p,F})$ and $P_F(\text{all } n \geq 1, V_{i,n} \geq \gamma_{p,F})$ do not depend on F. If N is a stopping variable and if G is obtained from F by translation of the random variables then

$$P_{\sigma}(U_{i,N} \leq \gamma_{p,\sigma} \leq V_{i,N}) = P_{F}(U_{i,N} \leq \gamma_{p,F} \leq V_{i,N}).$$

Proof.

$$1 - P_{F}(U_{i,N} \leq \gamma_{p,F} \leq V_{i,N}) \leq P_{F}(\text{some } n \geq 1, U_{i,n} > \gamma_{p,F}) + P_{F}(\text{some } n \geq 1, V_{i,n} < \gamma_{p,F}) < \alpha + \beta.$$

To prove that various probabilities are independent of F, if F has a continuous distribution function then we may choose a strictly increasing function f such that if Y_1 has a uniform distribution on [0, 1] then $f(Y_1)$ has F as distribution function. Then, if $\{Y_n, n \geq 1\}$ is a sequence of independently and uniformly distributed random variables, if i = 1, 2,

$$P(\text{all } n \ge 1, u_{i,n}(Y_1, \dots, Y_n) \le p)$$

$$= P(\text{all } n \ge 1, u_{i,n}(f(Y_1), \dots, f(Y_n)) \le f(p))$$

$$= P_{\mathbb{F}}(\text{all } n \ge 1, U_{i,n} \le \gamma_{\mathbb{F},\mathbb{F}}).$$

Similarly for the proofs of the remaining parts of the theorem.

We shall usually choose N to be the least integer n such that $V_{i,n} - U_{i,n} \leq L$, i = 1, 2. By virtue of (1.3), $P_F(N < \infty) = 1$ if N is defined in this manner.

The functions $u_{i,n}$ and $v_{i,n}$, i=1, 2, and $n \ge 1$ are constructed from the order statistics. If $\{x_n, n \ge 1\}$ is a real number sequence we let $x_{n,1} \le x_{n,2} \le \cdots \le x_{n,n}$ be the rearrangement of x_1, \dots, x_n into ascending order. We will use integer sequences $\{a_n, n \ge 1\}$ and $\{b_n, n \ge 1\}$ satisfying

(1.6) if
$$n \ge 1$$
 then $a_n > b_n$; $\lim_{n\to\infty} a_n/n = \lim_{n\to\infty} b_n/n = p$.

As an indication of method, we define $u_{1,n}$ and $v_{1,n}$, $n \ge 1$, as follows:

(1.7)
$$u_{1,n}(x_1, \dots, x_n) = x_{n,b_n+1};$$
$$v_{1,n}(x_1, \dots, x_n) = x_{n,a_n}.$$

The functions so defined clearly satisfy (1.1) and (1.4). (1.3) follows from Theorem 1.2 below.

THEOREM 1.2. Let $\gamma_{p,F,+} = \inf \{ \gamma \mid F(\gamma) > p \}$ and $\gamma_{p,F,-} = \sup \{ \gamma \mid F(\gamma) . Then <math>1 = P_F(\liminf_{n \to \infty} X_{n,b_n+1} \ge \gamma_{p,F,-}) = P_F(\limsup_{n \to \infty} X_{n,a_n} \le \gamma_{p,F,+})$. Proof. The following notation will be used throughout the paper:

(1.8) If t is a real number and if $n \ge 1$, then $S_n(t)$ is the number of integers i such that $1 \le i \le n$ and $X_i \le t$.

Then $\{X_{n,b_n+1} \leq t\}$ is the same event as $\{S_n(t) > b_n\}$ and $\{X_{n,a_n} > t\}$ is the same event as $\{S_n(t) < a_n\}$. Therefore $P_F(\liminf_{n \to \infty} X_{n,b_n+1} \geq t) \geq P_F(\text{all but a finite number of } n, S_n(t) \leq b_n)$. $S_n(t)$ is a sum of n independently and identically distributed Bernoulli random variables such that $P_F(S_1(t) = 1) = F(t)$. Therefore, if $t < \gamma_{p,F,-}$, then F(t) < p, and since $\lim_{n \to \infty} b_n/n = p$, it follows from the law of large numbers that $P_F(\text{all but a finite number of } n, S_n(t) \leq b_n) = 1$. Since this holds for all $t < \gamma_{p,F,-}$, the first half of Theorem 1.2 follows. A similar argument proves the other half.

As observed earlier, if N is the least integer n such that $V_{1,n} - U_{1,n} \leq L$ then $P_F(N < \infty) = 1$ will follow if (1.6) holds and if $\gamma_{p,F,+} - \gamma_{p,F,-} < L$.

In our introduction to methods, the last item is verification of (1.2). This has to do with proper choice of the integer sequences $\{a_n, n \geq 1\}$ and $\{b_n, n \geq 1\}$. The basic discussion is contained in Farrell [2] and [3]. It has been shown there that it is possible to choose sequences satisfying (1.6) such that for all distributions F,

(1.9) if
$$F(t) \leq p$$
 then $P_F(\text{some } n \geq 1, S_n(t) \geq a_n) \leq \alpha;$
if $F(t) \geq p$ then $P_F(\text{some } n \geq 1, S_n(t) \leq b_n) \leq \beta.$

All that is needed in the sequel is (1.9). Therefore we refer the reader to Farrell [2] and [3] for method.

For method 1 we may now calculate that

$$\begin{split} P_{\mathit{F}}(\text{some } n \, \geqq \, 1, \, U_{1,n} > \gamma_{\mathit{p},\mathit{F}}) \, &= \, P_{\mathit{F}}(\text{some } n \, \geqq \, 1, \, X_{n,b_{n}+1} > \gamma_{\mathit{p},\mathit{F}}) \\ &= \, P_{\mathit{F}}(\text{some } n \, \geqq \, 1, \, S_{n}(\gamma_{\mathit{p},\mathit{F}}) \, \leqq \, b_{n}) \\ & \leq \, \beta. \end{split}$$

Similarly,

$$\begin{split} P_{\textit{\textbf{F}}}(\text{some } n \, \geq \, 1, \, V_{1,n} \, < \, \gamma_{\textit{\textbf{p}},\textit{\textbf{F}}}) \, &= \, P_{\textit{\textbf{F}}}(\text{some } n \, \geq \, 1, \, X_{n,a_n} < \, \gamma_{\textit{\textbf{p}},\textit{\textbf{F}}}) \\ &= \, P_{\textit{\textbf{F}}}(\text{some } n \, \geq \, 1, \, S_n(\gamma_{\textit{\textbf{p}},\textit{\textbf{F}}}) \, \geq \, a_n) \\ &\leq \, \alpha. \end{split}$$

Therefore (1.2) follows.

The discussion shows that the first method will always give an interval covering $\gamma_{p,F}$ with probability not less than $1 - (\alpha + \beta)$. But closure of the stopping rule and more generally the expected sample size, depends on the flatness of F about its p-points. In Farrell [3] we have defined

(1.10)
$$\epsilon_F = \sup_{0 < \rho < 1} \min \left(F(\gamma_{p,F} + \rho L) - p, p - F(\gamma_{p,F} + (\rho - 1)L) \right).$$
 The following theorem was proven there:

THEOREM 1.3. Suppose **F** contains all F having bimodal density functions which are continuous and everywhere positive. Suppose L>0 and $0<\alpha<1$, and a L- α bounded length confidence interval procedure for $\gamma_{p,F}$ is given which works successfully for all $F \in \mathbf{F}$. If N is the stopping variable for the confidence interval procedure then

$$\lim \sup_{\epsilon_{F}\to 0+, F\in F} (\epsilon_{F})^{2} (\log (\log (\epsilon_{F})^{-1}))^{-1} E_{F} N \geq 2(1-2\alpha)p(1-\rho).$$

In Section 2 we detail the construction of the second procedure. In Section 3 we examine the question of the expected sample size. In particular we prove the following result.

THEOREM 1.4. There exist choices of the sequences $\{a_n, n \ge 1\}$ and $\{b_n, n \ge 1\}$ such that if $F = \{F \mid \epsilon_F > 0 \text{ and } F \text{ is continuous}\}$, then

$$\lim \sup_{\epsilon_F \to 0+} (\epsilon_F)^2 (\log (\log (\epsilon_F)^{-1}))^{-1} E_F N \leq 4(1 - \alpha) p(1 - p).$$

It should be noted that the discrepancy between the constants in Theorems 1.3 and 1.4 is between $2(1-2\alpha)$ and $2(2-2\alpha)$. Therefore, the method of Section 2 is close to being minimax.

The author wishes to thank D. L. Burkholder for suggesting this problem and for many helpful discussions. We wish to thank J. Kiefer for helpful discussions and to acknowledge unpublished work of J. Kiefer and L. Weiss in which they construct yet another (sequential) L- α bounded length confidence interval procedure.

2. The second procedure. We begin by considering tests of $\gamma_{p,F} < t$ against the alternative $\gamma_{p,F} > t$. Let the sequences $\{a_n, n \geq 1\}$ and $\{b_n, n \geq 1\}$ satisfy (1.6). Take for a sequential procedure the following: Let N_t be the least integer n such that $S_n(t) \leq b_n$ or $S_n(t) \geq a_n$, $S_n(t)$ as in (1.8). If $S_{N_t}(t) \leq b_{N_t}$ decide $t < \gamma_{p,F}$; if $S_{N_t}(t) \geq a_{N_t}$ decide $t > \gamma_{p,F}$. By the law of large numbers,

$$\lim_{n\to\infty} S_n(t)/a_n = \lim_{n\to\infty} S_n(t)/b_n = F(t)/p.$$

Therefore, if $F(t) \neq p$, $P_F(N_t < \infty) = 1$.

We now consider performing simultaneously for all $t, -\infty < t < \infty$, the tests described above. As is easily seen, if w < t and if $S_{N_t}(t) \leq b_{N_t}$ then $S_{N_w}(w) \leq b_{N_w}$; if $S_{N_w}(w) \geq a_{N_w}$ then $S_{N_t}(t) \geq a_{N_t}$. We define random variables

(2.1)
$$U_{2,n} = \sup \{t \mid N_t \leq n, S_{N_t}(t) \leq b_{N_t}\};$$

$$V_{2,n} = \inf \{t \mid N_t \leq n, S_{N_t}(t) \geq a_{N_t}\}.$$

It is clear that the definitions (2.1) can be given in terms of a real number sequence $\{x_n, n \geq 1\}$. Consequently explicit definitions of $u_{2,n}, v_{2,n}, n \geq 1$ can be given by a parallel construction.

THEOREM 2. Let the sequences $\{a_n, n \geq 1\}$ and $\{b_n, n \geq 1\}$ satisfy (1.6).

Using the above definitions,

- (2.2) if $n \ge 1$ then $U_{2,n}$ and $V_{2,n}$ are random variables;
- $(2.3) \quad \text{if} \quad n \ge 1 \quad \text{then} \quad U_{2,n} \le U_{2,n+1} \le V_{2,n+1} \le V_{2,n} ;$
- (2.4) if $n \ge 1$ then $U_{2,n} < V_{2,n}$ if and only if $U_{2,n} = \max_{1 \le i \le n} X_{i,b_i+1} < \min_{1 \le i \le n} X_{i,a_i} = V_{2,n};$
- (2.5) if the p-point of F is unique then $P_F(\lim_{n\to\infty} (V_{2,n} U_{2,n}) = 0) = 1;$
- (2.6) given $0 < \alpha < 1$ and $0 < \beta < 1$, if in addition to (1.6) the sequences $\{a_n, n \geq 1\}$ and $\{b_n, n \geq 1\}$ satisfy (1.9), then

$$P_F(\text{all } n \ge 1, U_{2,n} \le \gamma_{p,F}) \ge 1 - \beta;$$

 $P_F(\text{all } n \ge 1, V_{2,n} \ge \gamma_{p,F}) \ge 1 - \alpha.$

(2.7) If $f: (-\infty, \infty) \to (-\infty, \infty)$ is a strictly increasing function, if for $n \geq 1$, $X_n^* = f(X_n)$, and if for $n \geq 1$, $U_{2,n}^*$ and $V_{2,n}^*$ are defined by (2.1) using $\{X_n^*, n \geq 1\}$ instead of $\{X_n, n \geq 1\}$, then if $n \geq 1$, $U_{2,n}^* = f(U_{2,n})$ and $V_{2,n}^* = f(V_{2,n})$.

PROOF OF THEOREM 2. We prove (2.3) first. By the definitions it is immediate that $V_{2,n} \geq V_{2,n+1}$ and $U_{2,n} \leq U_{2,n+1}$. Suppose that $N_t \leq n$ and that $S_{N_t}(t) \leq b_{N_t}$. Then if $i \leq N_t$ it follows that $S_i(t) < a_i$. Since $S_i(\cdot)$ is a nondecreasing function, if w < t then $S_i(w) < a_i$, $i = 1, \dots, N_t$, and $S_{N_t}(w) \leq b_{N_t}$. Therefore if w < t, $N_w \leq N_t \leq n$ and $S_{N_w}(w) \leq b_{N_w}$. Similarly if $N_t \leq n$ and w > t then $N_w \leq N_t$ and $S_{N_w}(w) \geq a_{N_w}$. Therefore $U_{2,n} \leq V_{2,n}$.

To prove (2.2), that is, the measurability of $U_{2,n}$ and $V_{2,n}$, let $A_1(t) = \{\text{sample points} \mid N_t \leq n, S_{N_t}(t) \leq b_{N_t} \}$. In the preceding paragraph we have shown that if w < t then $A_1(w) \supset A_1(t)$. Then

{sample points | $U_{2,n} > a$ }

= {sample points | some
$$t > a$$
, $N_t \le n$ and $S_{N_t}(t) \le b_{N_t}$ }
= $U_{t>a,t \text{ rational}} A_1(t)$.

Since this holds for all real numbers a, it follows $U_{2,n}$ is measurable, $n \ge 1$. By a similar argument, $V_{2,n}$ is measurable, $n \ge 1$.

To prove (2.4) it is first shown that $U_{2,n} \leq \max_{1 \leq i \leq n} X_{i,b_i+1}$ and $V_{2,n} \geq \min_{1 \leq i \leq n} X_{i,a_i}$. Suppose $t < U_{2,n}$. Then for some $i \leq n$, $S_i(t) \leq b_i$. Therefore, for some $i \leq n$, $X_{i,b_i+1} > t$, i.e., $\max_{1 \leq i \leq n} X_{i,b_i+1} > t$. Since this holds for all $t < U_{2,n}$, the first inequality follows. Suppose $t > V_{2,n}$. Then for some $i \leq n$, $S_i(t) \geq a_i$, and $X_{i,a_i} \leq t$. Therefore $\min_{1 \leq i \leq n} X_{i,a_i} \leq t$. As this holds for all $t > V_{2,n}$, the second inequality follows. Suppose $U_{2,n} < t < V_{2,n}$. Then, if $1 \leq i \leq n$ it follows that $b_i < S_i(t) < a_i$, therefore that $X_{i,b_i+1} \leq t < X_{i,a_i}$, and therefore that $\max_{1 \leq i \leq n} X_{i,b_i+1} \leq t \leq \min_{1 \leq i \leq n} X_{i,a_i}$. Since this holds

for all t satisfying $U_{2,n} < t < V_{2,n}$ it follows that $\max_{1 \le i \le n} X_{i,b_i+1} \le U_{2,n} < V_{2,n} \le \min_{1 \le i \le n} X_{i,a_i}$. That completes the proof of (2.4).

To prove (2.5) assume $\gamma_{p,F}$ is unique. If $U_{2,i} = V_{2,i}$ for some i then for all $n \geq i$, $U_{2,n} = V_{2,n}$. On the complementary event, for all $n \geq 1$, $U_{2,n} < V_{2,n}$. Conditional on $U_{2,n} < V_{2,n}$ for all $n \geq 1$ we have for $1 \leq i \leq n$ by (2.4) that $X_{i,b_i+1} \leq U_{2,n} < V_{2,n} \leq X_{i,a_i}$. By Theorem 1.2, with probability one, $\lim_{i\to\infty} X_{i,b_i+1} = \lim_{i\to\infty} X_{i,a_i} = \gamma_{p,F}$. Therefore conditional on $U_{2,n} < V_{2,n}$ for all $n \geq 1$, with probability one, $\lim_{n\to\infty} (V_{2,n} - U_{2,n}) = 0$.

for all $n \ge 1$, with probability one, $\lim_{n\to\infty} (V_{2,n} - U_{2,n}) = 0$. To prove (2.6), observe that P_F (for all $n \ge 1$, $U_{2,n} \le \gamma_{p,F}$) = $1 - P_F$ (some $n \ge 1$, $U_{2,n} > \gamma_{p,F}$). Since if $n \ge 1$, $U_{2,n+1} \ge U_{2,n}$ we find P_F (some $n \ge 1$, $U_{2,n} > \gamma_{p,F}$) = $\lim_{n\to\infty} P_F(U_{2,n} > \gamma_{p,F})$. Next,

$$\begin{split} P_{F}(U_{2,n} > \gamma_{p,F}) &= P_{F}(\text{some } t > \gamma_{p,F}, N_{t} \leq n, S_{N_{t}}(t) \leq b_{N_{t}}) \\ &\leq P_{F}(\text{some } t > \gamma_{p,F}, N_{t} < \infty, S_{N_{t}}(t) \leq b_{N_{t}}) \\ &= \lim_{t \to \gamma_{p,F}^{+}} P_{F}(N_{t} < \infty, S_{N_{t}}(t) \leq b_{N_{t}}) \\ &\leq \lim_{t \to \gamma_{p,F}^{+}} P_{F}(\text{some } n \geq 1, S_{n}(t) \leq b_{n}). \end{split}$$

Using (1.9), we see that if $t \geq \gamma_{p,F}$ then $F(t) \geq p$ and $P_F(\text{some } n \geq 1, S_n(t) \leq b_n) \leq \beta$. Therefore $\lim_{n\to\infty} P_F(U_{2,n} > \gamma_{p,F}) \leq \beta$. By a similar argument,

$$P_F(\text{some } n \geq 1, V_{2,n} < \gamma_{p,F}) = \lim_{t \to \gamma_{p,F}} P_F(\text{some } n \geq 1, S_n(t) \geq a_n) \leq \alpha.$$

The proof of (2.7) is obvious and details are omitted.

3. The expected sample size. In this section it will be convenient to distinguish between the two methods, method one of Section 1 and method two of Section 2. We suppose for the discussion that the same pair of sequences $\{a_n, n \geq 1\}$ and $\{b_n, n \geq 1\}$ are used satisfying (1.6) and (1.9). We let N_1 be the least integer n such that $X_{n,a_n} - X_{n,b_n+1} \leq L$, and N_2 be the least integer n such that $V_{2,n} - U_{2,n} \leq L$. From (2.4) it follows at once that if $N_1 = n$ then either $U_{2,n} = V_{2,n}$ or $\min_{1 \leq i \leq n} X_{i,a_i} - \max_{1 \leq i \leq n} X_{i,b_i+1} \leq X_{n,a_n} - X_{n,b_n+1} \leq L$. Therefore $N_2 \leq N_1$.

A basic theorem is

THEOREM 3.1. Suppose there exists a number δ , $0 < \delta < 1$, such that if $t_{-1} = \gamma_{p,F} - \delta L$ and $t_0 = \gamma_{p,F} + (1 - \delta)L$, then $F(t_{-1}) < p$ and $F(t_0) > p$. Then N_1 has a moment generating function in a neighborhood of 0.

Proof.

$$P_{F}(N_{1} \geq n) \leq P_{F}(\text{all } i, 1 \leq i \leq n, X_{i,b,+1} \leq t_{-1} \text{ or } X_{i,a_{i}} > t_{0})$$

$$\leq P_{F}(X_{n,b_{n}+1} \leq t_{-1} \text{ or } X_{n,a_{n}} > t_{0})$$

$$\leq P_{F}(S_{n}(t_{-1}) > b_{n}) + P_{F}(S_{n}(t_{0}) < a_{n}).$$

Under the hypothesis made, since $S_n(t_1)$ is a sum of independently and identically distributed Bernoulli random variables, $P(S_1(t_{-1}) = 1) = F(t_{-1}) < p$,

and since similarly $P_F(S_1(t_0) = 1) = F(t_0) > p$, and since (1.6) holds, the sequences $\{P_F(S_n(t_{-1}) > b_n), n \ge 1\}$ and $\{P_F(S_n(t_0) < a_n), n \ge 1\}$ decrease at least geometrically. Therefore $\{P_F(N_1 \ge n), n \ge 1\}$ decreases at least geometrically which implies the existence of a moment generating function near zero.

In the remainder of this section we will suppose F is a continuous distribution function. Then from the definition of ϵ_F in (1.10) it follows that for some ρ_0 satisfying $0 < \rho_0 < 1$,

(3.1)
$$\epsilon_F = F(\gamma_{p,F} + \rho_0 L) - p = p - F(\gamma_{p,F} + (\rho_0 - 1)L).$$

We will define numbers

$$(3.2) t_0 = \gamma_{p,F} + \rho_0 L, t_{-1} = \gamma_{p,F} + (\rho_0 - 1)L.$$

The event $N_2 > n$ is the event $V_{2,n} - U_{2,n} > L$ and this implies the event $U_{2,n} < t_{-1}$ or $V_{2,n} > t_0$. Therefore

$$P_{F}(N_{2} > n) \leq P_{F}(U_{2,n} < V_{2,n}, U_{2,n} < t_{-1} \text{ or } V_{2,n} > t_{0})$$

$$\leq P_{F}(\max_{1 \leq i \leq n} X_{i,b_{i}+1} \leq t_{-1}) + P_{F}(\min_{1 \leq i \leq n} X_{i,a_{i}} > t_{0})$$

$$= P_{F}(\text{all } i, 1 \leq i \leq n, S_{i}(t_{-1}) > b_{i})$$

$$+ P_{F}(\text{all } i, 1 \leq i \leq n, S_{i}(t_{0}) < a_{i}).$$

Therefore, if N_a is the least integer n such that $S_n(t_0) \ge a_n$, and N_b is the least integer n such that $S_n(t_{-1}) \le b_n$, we find

$$(3.4) P_{r}(N_{2} > n) \leq P_{r}(N_{a} > n) + P_{r}(N_{b} > n).$$

Summing this expression on n gives

$$(3.5) E_F N_2 \leq E_F N_a + E_F N_b.$$

If $n \ge 1$, $S_n(t)$ is a sum of n independently and identically distributed Bernoulli random variables such that $P(S_1(t) = 1) = F(t)$. We bring to bear the results of Farrell [3]. The sequences $\{a_n, n \ge 1\}$ and $\{b_n, n \ge 1\}$ are chosen so that (1.6) and (1.9) hold.

By Theorem 1 of Farrell, op. cit., the sequences may be chosen in such a way

(3.6)
$$\lim_{\epsilon_{F}\to 0} (\epsilon_{F})^{2} (\log (\log (\epsilon_{F})^{-1}))^{-1} EN_{a} = 2p(1-p)(1-\alpha);$$

 $\lim_{\epsilon_{F}\to 0} (\epsilon_{F})^{2} (\log (\log (\epsilon_{F})^{-1}))^{-1} EN_{b} = 2p(1-p)(1-\beta).$

Therefore the conclusion of Theorem 1.4, Section 1 follows by taking $\alpha = \beta$.

REFERENCES

- [1] FARRELL, R. H. (1959). Sequentially determined bounded length confidence intervals. Ph.D. dissertation, University of Illinois.
- [2] FARRELL, R. H. (1962). Bounded length confidence intervals for the zero of a regression function. Ann. Math. Statist. 33 237-247.
- [3] FARRELL, R. H. (1964). Asymptotic behavior of expected sample size in certain one sided tests. Ann. Math. Statist. 35 36-72.
- [4] FARRELL, R. H. (1966). Bounded length confidence intervals for the p-point of a distribution function, II. Ann. Math. Statist. 37 581-585.