

On Optimal Stopping Rules

By

Y. S. CHOW and HERBERT ROBBINS*

1. Introduction

Let y_1, y_2, \dots be a sequence of random variables with a given joint distribution. Assume that we can observe the y 's sequentially but that we must stop some time, and that if we stop with y_n we will receive a payoff $x_n = f_n(y_1, \dots, y_n)$. What stopping rule will maximize the expected value of the payoff?

In this paper we attempt to give a reasonably general theory of the existence and computation of optimal stopping rules, previously discussed to some extent in [1] and [12]. We then apply the theory to two particular cases of interest in applications. One of these belongs to the general domain of dynamic programming; the other is the problem of showing the Bayesian character of the WALD sequential probability ratio test.

2. Existence of an optimal rule

Let (Ω, \mathcal{F}, P) be a probability space with points ω , let $\mathcal{F}_1 \subset \mathcal{F}_2 \subset \dots$ be a non-decreasing sequence of sub- σ -algebras of \mathcal{F} , and let x_1, x_2, \dots be a sequence of random variables defined on Ω with $E|x_n| < \infty$ and such that $x_n = x_n(\omega)$ is measurable (\mathcal{F}_n). A sampling variable (s.v.) is a random variable (r.v.) $t = t(\omega)$ with values in the set of positive integers (not including $+\infty$) and such that $\{t(\omega) = n\} \in \mathcal{F}_n$ for each n , where by $\{\dots\}$ we mean the set of all ω for which the indicated relation holds. For any s.v. t we may form the r.v. $x_t = x_{t(\omega)}(\omega)$. We shall be concerned with the problem of finding a s.v. t which maximizes the value of $E(x_t)$ in the class of all s.v.'s for which this expectation exists.

We shall use the notation $x^+ = \max(x, 0)$, $x^- = \max(-x, 0)$, so that $x = x^+ - x^-$. To simplify matters we shall suppose that $E(\sup_n x_n^+) < \infty$; then for any s.v. t , $x_t \leq \sup_n x_n^+$, and hence $-\infty \leq E(x_t) \leq E(\sup_n x_n^+) < \infty$. Denoting by C the class of all s.v.'s, it follows that $E(x_t)$ exists for all $t \in C$ but may have the value $-\infty$.

In what follows we shall occasionally refer to [1] for the details of certain proofs.

Definition. A s.v. t is *regular* if for all $n = 1, 2, \dots$

$$(1) \quad t > n \Rightarrow E(x_t | \mathcal{F}_n) > x_n.$$

Note that if t is any regular s.v. then

$$E(x_t) = \int_{\{t=1\}} x_t + \int_{\{t>1\}} x_t \geq \int_{\{t=1\}} x_1 + \int_{\{t>1\}} x_1 = E(x_1) > -\infty.$$

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Lemma 1. *Given any s.v. t , define*

$$t' = \text{first integer } j \geq 1 \text{ such that } E(x_t | \mathcal{F}_j) \leq x_j.$$

Then t' is a s.v. and has the following properties:

- (a) t' is regular,
- (b) $t' \leq t$,
- (c) $E(x_{t'}) \geq E(x_t)$.

Proof. If $t = n$ then $E(x_t | \mathcal{F}_n) = x_n$, so that $t' \leq n$. Thus $t' \leq t < \infty$, and hence (b) holds. For any $A \in \mathcal{F}_n$,

$$(2) \quad \int_{A\{t' \geq n\}} x_{t'} = \sum_{j=n}^{\infty} \int_{A\{t'=j\}} x_j \geq \sum_{j=n}^{\infty} \int_{A\{t'=j\}} E(x_t | \mathcal{F}_j) = \int_{A\{t' \geq n\}} x_t.$$

Putting $n = 1$ and $A = \Omega$, (2) yields the inequality (c). Finally, from (2) and the definition of t' .

$$t' > n \Rightarrow E(x_{t'} | \mathcal{F}_n) \geq E(x_t | \mathcal{F}_n) > x_n,$$

which proves (a).

Lemma 2. *Let t_1, t_2, \dots be any sequence of regular s.v.'s and define*

$$\tau_i = \max(t_1, \dots, t_i), \quad \tau = \sup_i \tau_i = \lim_{i \rightarrow \infty} \tau_i.$$

Then the τ_i are regular s.v.'s, $\tau_1 \leq \tau_2 \leq \dots$, and

$$(3) \quad \max(E x_{t_1}, \dots, E x_{t_i}) \leq E(x_{\tau_i}) \leq E(x_{\tau_{i+1}}) \leq \dots.$$

Moreover, if $P(\tau < \infty) = 1$ then τ is a regular s.v. and

$$(4) \quad E x_{\tau} \geq \lim_{i \rightarrow \infty} E(x_{\tau_i}) \geq \sup E x_{t_i}.$$

Proof. For any $i, n = 1, 2, \dots$ and any $A \in \mathcal{F}_n$ we have

$$\int_{A\{\tau_i \geq n\}} x_{\tau_i} = \sum_{j=n}^{\infty} \left(\int_{A\{\tau_i=j \geq t_{i+1}\}} x_{\tau_{i+1}} + \int_{A\{\tau_i=j < t_{i+1}\}} x_j \right) \leq \sum_{j=n}^{\infty} \left(\int_{A\{\tau_i=j \geq t_{i+1}\}} x_{\tau_{i+1}} + \int_{A\{\tau_i=j < t_{i+1}\}} x_{t_{i+1}} \right) = \int_{A\{\tau_i \geq n\}} x_{\tau_{i+1}}.$$

Hence, since $\tau_1 \leq \tau_2 \leq \dots$, it follows that

$$(5) \quad \tau_i \geq n \Rightarrow E(x_{\tau_i} | \mathcal{F}_n) \leq E(x_{\tau_{i+1}} | \mathcal{F}_n) \leq E(x_{\tau_{i+2}} | \mathcal{F}_n) \leq \dots.$$

Since t_1 is regular and $\tau_1 = t_1$, it follows that

$$t_1 > n \Rightarrow x_n < E(x_{t_1} | \mathcal{F}_n) = E(x_{\tau_1} | \mathcal{F}_n) \leq E(x_{\tau_2} | \mathcal{F}_n) \leq \dots.$$

By symmetry,

$$t_j > n \Rightarrow E(x_{\tau_i} | \mathcal{F}_n) > x_n, \quad j = 1, \dots, i,$$

and hence

$$\tau_i > n \Rightarrow E(x_{\tau_i} | \mathcal{F}_n) > x_n,$$

so that each τ_i is regular. Setting $n = 1$ in (5) we obtain

$$(6) \quad E(x_{t_1} | \mathcal{F}_1) = E(x_{\tau_1} | \mathcal{F}_1) \leq E(x_{\tau_2} | \mathcal{F}_1) \leq \dots,$$

so that

$$E(x_{t_1}) \leq E(x_{\tau_1}) \leq E(x_{\tau_2}) \leq \dots,$$

and by symmetry

$$E(x_{t_i}) \leq E(x_{\tau_i}), \quad j = 1, \dots, i,$$

which proves (3).

Turning our attention to τ we observe that since $x_\tau = \lim_{i \rightarrow \infty} x_{\tau_i}$, and since

$$E(\sup_i x_{\tau_i}) \leq E(\sup_n x_n^+) < \infty,$$

we have by Fatou's lemma for conditional expectations [2, p. 348] that

$$(7) \quad E(x_\tau | \mathcal{F}_n) \geq \limsup_{i \rightarrow \infty} E(x_{\tau_i} | \mathcal{F}_n).$$

Hence by (5) and (7),

$$\begin{aligned} \tau > n \Rightarrow \tau_i > n \text{ for some } i \Rightarrow x_n < E(x_{\tau_i} | \mathcal{F}_n) &\leq E(x_{\tau_{i+1}} | \mathcal{F}_n) \leq \dots \\ \Rightarrow \limsup_{i \rightarrow \infty} E(x_{\tau_i} | \mathcal{F}_n) > x_n \Rightarrow E(x_\tau | \mathcal{F}_n) > x_n, \end{aligned}$$

so that τ is regular. Finally, from (6) and (7) we have

$$E(x_\tau | \mathcal{F}_1) \geq E(x_{\tau_i} | \mathcal{F}_1),$$

so that (4) holds.

Corollary 1. *Let t_0 be any s.v., and let $C(t_0)$ denote the class of all s.v.'s t such that $t \leq t_0$. Then there exists a s.v. $\tau \in C(t_0)$ such that*

$$(8) \quad E(x_\tau) = \sup_{t \in C(t_0)} E(x_t).$$

Proof. Take any sequence t_1, t_2, \dots of s.v.'s in $C(t_0)$ such that

$$\sup_i E(x_{t_i}) = \sup_{t \in C(t_0)} E(x_t).$$

By Lemma 1 we may assume that the t_i are regular. Set $\tau = \sup_i t_i$; then $\tau \in C(t_0)$ and the conclusion follows from Lemma 2.

Corollary 2. *Suppose there exists a s.v. τ_0 such that*

$$(9) \quad E(x_{\tau_0}) = \sup_{t \in C} E(x_t).$$

Choose any sequence t_1, t_2, \dots of regular s.v.'s such that

$$(10) \quad \sup_i E(x_{t_i}) = \sup_{t \in C} E(x_t),$$

and set $\tau = \sup_i t_i$. Then

$$(11) \quad \tau \leq \tau_0,$$

so that τ is a s.v., and

$$(12) \quad E(x_\tau) = \sup_{t \in C} E(x_t).$$

The s.v. τ thus defined does not depend on the particular choice of τ_0, t_1, t_2, \dots , since by (11) and (12) it is the minimal s.v. τ such that (12) holds.

Proof. By Lemma 1 of [I], $t_i \leq \tau_0$ for each i , so that (11) holds, and (12) then follows from Lemma 2.

Lemma 3. *Assume that*

$$(13) \quad x_n = x'_n - x''_n$$

where x'_n, x''_n are measurable (\mathcal{F}_n) for each n , and are such that

$$(14) \quad E[\sup_n (x'_n)^+] = B < \infty,$$

$$(15) \quad x''_n \geq 0, \quad \lim_{n \rightarrow \infty} x''_n = \infty.$$

Let t_1, t_2, \dots be any sequence of s.v.'s such that

$$(16) \quad E(x_{t_i}) \geq K > -\infty,$$

and set $\tau = \liminf_{i \rightarrow \infty} t_i$. Then $P(\tau < \infty) = 1$.

Proof. For any integers i and m ,

$$\int_{\{t_i \geq m\}} x_{t_i} = \int_{\{t_i \geq m\}} (x'_{t_i} - x''_{t_i}) \leq \int_{\{t_i \geq m\}} (\sup_n (x'_n)^+ - \inf_{j \geq m} x''_j) \leq B - \int_{\{t_i \geq m\}} w_m,$$

where we have set

$$w_m = \inf_{j \geq m} x''_j.$$

Since

$$\int_{\{t_i < m\}} x_{t_i} \leq B,$$

we have

$$K \leq E(x_{t_i}) \leq 2B - \int_{\{t_i \geq m\}} w_m.$$

Let $A_i = \{\inf_{j \geq i} t_j \geq m\} \subset \{t_i \geq m\}$; then since $w_m \geq 0$,

$$K \leq 2B - \int_{A_i} w_m,$$

and letting $i \rightarrow \infty$ we have

$$K \leq 2B - \int_{\{\tau \geq m\}} w_m \leq 2B - \int_{\{\tau = \infty\}} w_m.$$

Let $m \rightarrow \infty$; then since

$$0 \leq w_1 \leq w_2 \leq \dots \rightarrow \liminf_{n \rightarrow \infty} x''_n = \infty,$$

it follows that

$$\int_{\{\tau = \infty\}} \infty \leq 2B - K < \infty,$$

so that $P(\tau = \infty) = 0$.

Lemma 4. Under the assumptions (13), (14), (15) of Lemma 3, there exists a s.v. τ such that

$$(17) \quad E(x_\tau) = \sup_{t \in C} E(x_t).$$

Proof. Let t_1, t_2, \dots be any sequence of s.v.'s such that

$$(18) \quad \sup_i E(x_{t_i}) = \sup_{t \in C} E(x_t).$$

By Lemma 1 we may suppose that the t_i are regular and therefore that

$$E(x_{t_i}) \geq E(x_1) > -\infty.$$

Set

$$\tau_i = \max(t_1, \dots, t_i), \quad \tau = \sup_i t_i = \lim_{i \rightarrow \infty} \tau_i.$$

By Lemma 2,

$$E(x_{\tau_i}) \geq E(x_{t_i}) \geq E(x_1),$$

and $\tau_1 \leq \tau_2 \leq \dots$. By Lemma 3, $P(\tau < \infty) = 1$. Hence by Lemma 2,

$$(19) \quad E(x_\tau) \geq \sup_i E(x_{t_i}),$$

and (17) follows from (18) and (19).

The main results so far may be summarized in the following theorem.

Theorem 1. *Assume that $E(\sup_n x_n^+) < \infty$.*

(i) *Choose any sequence t_1, t_2, \dots of regular s.v.'s such that*

$$(20) \quad \sup_i E(x_{t_i}) = \sup_{t \in C} E(x_t)$$

(this can always be done), and define the r.v.

$$(21) \quad \tau = \sup_i t_i.$$

Then $P(\tau < \infty) = 1$ if and only if there exists a s.v. τ_0 such that

$$(22) \quad E(x_{\tau_0}) = \sup_{t \in C} E(x_t),$$

and τ is then the minimal s.v. satisfying (22).

(ii) *Assumptions (13), (14), (15) are sufficient to ensure that $P(\tau < \infty) = 1$.*

Proof.

(i) If $P(\tau < \infty) = 1$ then by the argument of Lemma 4,

$$E(x_\tau) = \sup_{t \in C} E(x_t).$$

And if any s.v. τ_0 exists satisfying (22), then $P(\tau < \infty) = 1$ by Corollary 2 of Lemma 2, and $\tau \leq \tau_0$.

(ii) Follows from Lemma 4.

The main defect of Theorem 1 is that it gives no indication of how to choose a sequence of regular s.v.'s t_1, t_2, \dots satisfying (20). We now turn our attention to this problem.

3. The rules s_N and s

Let C_N denote the class of all s.v.'s t for which $t \leq N$. We shall first show (cf. [3]) how to construct a certain regular s.v. s_N in C_N such that

$$(23) \quad E(x_{s_N}) = \sup_{t \in C_N} E(x_t).$$

To do this we define for each $N \geq 1$ a finite sequence of r.v.'s $\beta_1^N, \dots, \beta_N^N$ by recursion backwards, starting with β_N^N , using the formula

$$(24) \quad \beta_n^N = \max[x_n, E(\beta_{n+1}^N | \mathcal{F}_n)], \quad n = 1, \dots, N; \quad \beta_{N+1}^N = -\infty.$$

Thus

$$(25) \quad \beta_N^N = \max[x_N, -\infty] = x_N,$$

and β_n^N is measurable (\mathcal{F}_n). We now define

$$(26) \quad s_N = \text{first } n \geq 1 \text{ such that } \beta_n^N = x_n.$$

Note that

$$(27) \quad \beta_{s_N}^N = x_{s_N},$$

and, since $\beta_N^N = x_N$,

$$(28) \quad s_N \leq N,$$

so that $s_N \in C_N$. Moreover,

$$(29) \quad s_N > n \Rightarrow E(\beta_{n+1}^N | \mathcal{F}_n) = \beta_n^N > x_n,$$

and

$$(30) \quad E(\beta_{n+1}^N | \mathcal{F}_n) \leq \beta_n^N, \quad \text{all } n = 1, \dots, N.$$

From [1, Lemmas 1, 2, 3] applied to the finite sequence $\beta_1^N, \dots, \beta_N^N$ it follows that s_N is regular, since

$$(31) \quad s_N > n \Rightarrow E(x_{s_N} | \mathcal{F}_n) = E(\beta_{s_N}^N | \mathcal{F}_n) \geq \beta_n^N > x_n,$$

and that

$$(32) \quad E(x_{s_N}) = E(\beta_{s_N}^N) \geq E(\beta_t^N) \geq E(x_t) \quad \text{all } t \in C_N.$$

Thus the sequence s_1, s_2, \dots has the following properties:

$$(33) \quad s_N \text{ is regular, } s_N \leq N, \quad (23) \text{ holds,}$$

and, since $C_1 \subset C_2 \subset \dots$, it follows that

$$(34) \quad E(x_1) = E(x_{s_1}) \leq E(x_{s_2}) \leq \dots \rightarrow \lim_{N \rightarrow \infty} E(x_{s_N}).$$

It is easy to show by induction from (24) and (25) that

$$(35) \quad x_N = \beta_N^N \leq \beta_N^{N+1} \leq \dots.$$

Hence from (26) we have

$$(36) \quad 1 = s_1 \leq s_2 \leq \dots,$$

and we define

$$(37) \quad s = \sup_N s_N = \lim_{N \rightarrow \infty} s_N \leq +\infty.$$

Lemma 5. *If $P(s < \infty) = 1$, then*

$$(38) \quad E(x_s) \geq \lim_{N \rightarrow \infty} E(x_{s_N}).$$

Proof. By (33) and Lemma 2 applied to the sequence s_1, s_2, \dots .

Lemma 6. *If t is any s.v. such that*

$$(39) \quad \liminf_{n \rightarrow \infty} \int_{\{t > n\}} x_n^- = 0$$

then

$$(40) \quad \lim_{N \rightarrow \infty} E(x_{s_N}) \geq E(x_t).$$

Proof. Set

$$(41) \quad t_N = \min(t, N) \in C_N.$$

Then

$$(42) \quad \int_{\{t \leq N\}} x_t = E(x_{t_N}) - \int_{\{t > N\}} x_N \leq E(x_{s_N}) - \int_{\{t > N\}} x_N \leq E(x_{s_N}) + \int_{\{t > N\}} x_N^-.$$

Letting $N \rightarrow \infty$ it follows from (39) that (40) holds.

Corollary. *If $x_n^- \leq cn^\alpha$ for some $c, \alpha \geq 0$, and if $E(t^\alpha) < \infty$, then*

$$\lim_{N \rightarrow \infty} E(x_{s_N}) \geq E(x_t).$$

Proof. From Lemma 6 and the relation

$$\int_{\{t > n\}} x_n^- \leq c \int_{\{t > n\}} n^\alpha \leq c \int_{\{t > n\}} t^\alpha \rightarrow 0.$$

Theorem 2. *Assume that*

$$x_n = x'_n - x''_n = x_n^* - x_n^{**},$$

where all the components are measurable (\mathcal{F}_n) and

$$(43) \quad E[\sup_n (x'_n)^+] = B < \infty,$$

$$(44) \quad 0 \leq x''_1 \leq x''_2 \leq \dots, \quad \lim_{n \rightarrow \infty} x''_n = \infty,$$

$$(45) \quad \text{the } (x_n^*)^- \text{ are uniformly integrable for all } n,$$

and

$$(46) \quad x_n^{**} \leq cx''_n \quad \text{for some } 0 < c < \infty.$$

Then $s = \sup_N s_N$ is a s.v. and

$$E(x_s) = \sup_{t \in C} E(x_t) = \lim_{N \rightarrow \infty} E(x_{s_N}).$$

Proof. For any s.v. t we have from (44) and (46) that for $t > N$,

$$x_N = (x_N^*)^+ - (x_N^*)^- - x_N^{**} \geq -[(x_N^*)^- + cx''_N],$$

so that

$$(47) \quad \int_{\{t > N\}} x_N^- \leq \int_{\{t > N\}} [(x_N^*)^- + cx''_N].$$

Now if $E(x_t) \neq -\infty$ then from (43)

$$E(x_t) = E(x'_t) - E(x''_t) \leq E(x'_t) \leq B < \infty,$$

so that $E(x'_t)$ and hence $E(x''_t)$ is finite. From (47) and (45) it follows that (39) holds. From Lemma 3, $P(s < \infty) = 1$, and hence from Lemmas 5 and 6,

$$E(x_s) \geq \lim_{N \rightarrow \infty} E(x_{s_N}) \geq E(x_t).$$

Since this is trivially true when $E(x_t) = -\infty$ the result follows.

It is of interest to express $E(x_{s_N})$ explicitly. To do this we observe that by the submartingale property (30),

$$\begin{aligned}
 E(x_{s_N}) &= E(\beta_{s_N}^N) = \sum_{n=1}^N \int_{\{s_N=n\}} \beta_n^N = \sum_{n=1}^{N-1} \int_{\{s_N=n\}} \beta_n^N + \int_{\{s_N>N-1\}} \beta_N^N \\
 (48) \quad &\leq \sum_{n=1}^{N-2} \int_{\{s_N=n\}} \beta_n^N + \int_{\{s_N=N-1\}} \beta_{N-1}^N + \int_{\{s_N>N-1\}} \beta_{N-1}^N \\
 &= \sum_{n=1}^{N-2} \int_{\{s_N=n\}} \beta_n^N + \int_{\{s_N>N-2\}} \beta_{N-1}^N \leq \cdots \leq \int_{\{s_N>0\}} \beta_1^N = E(\beta_1^N).
 \end{aligned}$$

But since $E(\beta_{s_N}^N) \geq E(\beta_1^N)$ it follows that

$$(49) \quad E(x_{s_N}) = E(\beta_1^N).$$

Thus under the conditions on the x_n of Theorem 2,

$$(50) \quad E(x_s) = \lim_{N \rightarrow \infty} E(x_{s_N}) = \lim_{N \rightarrow \infty} E(\beta_1^N).$$

From (35) the limits

$$(51) \quad \beta_n = \lim_{N \rightarrow \infty} \beta_n^N$$

exist. By the theorem of monotone convergence for conditional expectations [2, p. 348] it follows from (35) that

$$(52) \quad E(\beta_n^n | \mathcal{F}_n) \leq E(\beta_n^{n+1} | \mathcal{F}_n) \leq \cdots \rightarrow E(\beta_n | \mathcal{F}_n),$$

and hence from (24) that the β_n satisfy the relations

$$(53) \quad \beta_n = \max[x_n, E(\beta_{n+1} | \mathcal{F}_n)], \quad n = 1, 2, \dots$$

Define for the moment

$$(54) \quad s^* = \text{first } i \geq 1 \text{ such that } x_i = \beta_i.$$

We shall show that

$$(55) \quad s^* = \sup_N s_N = s.$$

For if $s^* = n$, then by (54) $x_i < \beta_i$ for $i = 1, \dots, n-1$, and hence for sufficiently large N , $x_i < \beta_i^N$ for $i = 1, \dots, n-1$, so that $s_N \geq n$. Hence $s \geq n$ and therefore $s \geq s^*$. Conversely, if $s = n$ then for sufficiently large N , $s_N = n$, and hence $x_i < \beta_i^N$ for $i = 1, \dots, n-1$ so that $x_i < \beta_i$ for $i = 1, \dots, n-1$ and therefore $s^* \geq n$. Thus $s^* \geq s$.

We may now restate Theorem 2 in the following form.

Theorem 2'. *Assume that the hypotheses on the x_n of Theorem 2 are satisfied. For each $N \geq 1$ define $\beta_1^N, \beta_2^N, \dots, \beta_N^N$ by (24) and set*

$$(56) \quad s = \text{first } i \geq 1 \text{ such that } x_i = \beta_i = \lim_{N \rightarrow \infty} \beta_i^N.$$

Then s is a s.v. and

$$(57) \quad E(x_s) = \lim_{N \rightarrow \infty} E(\beta_1^N) = \sup_{t \in C} E(x_t).$$

This generalizes a theorem of ARROW, BLACKWELL, and GIRSHICK [3].

4. The monotone case

If the sequence of r.v.'s x_1, x_2, \dots is such that for every $n = 1, 2, \dots$,

$$(58) \quad E(x_{n+1} | \mathcal{F}_n) \leq x_n \Rightarrow E(x_{n+2} | \mathcal{F}_{n+1}) \leq x_{n+1},$$

we shall say that we are in the *monotone case* (to which [I] is devoted). In this case the calculation of the s_N defined by (26), and of $s = \sup_N s_N$, become much simpler.

Lemma 7. *In the monotone case we may compute s_N and s by the formulas*

$$(59) \quad s_N = \min[N, \text{first } n \geq 1 \text{ such that } E(x_{n+1} | \mathcal{F}_n) \leq x_n],$$

and

$$(60) \quad s = \sup_N s_N = \text{first } n \geq 1 \text{ such that } E(x_{n+1} | \mathcal{F}_n) \leq x_n.$$

Proof. (a) we begin by proving that in the monotone case, for $n = 1, 2, \dots, N-1$,

$$(61) \quad E(x_{n+1} | \mathcal{F}_n) \leq x_n \Rightarrow E(\beta_{n+1}^N | \mathcal{F}_n) \leq x_n.$$

For $n = N-1$ this is trivial, since $\beta_N^N = x_n$. Assume therefore that (61) is true for $n = j+1$. Then

$$\begin{aligned} E(x_{j+1} | \mathcal{F}_j) \leq x_j &\Rightarrow E(x_{j+2} | \mathcal{F}_{j+1}) \leq x_{j+1} \Rightarrow \\ E(\beta_{j+2}^N | \mathcal{F}_{j+1}) &\leq x_{j+1} \Rightarrow \beta_{j+1}^N = x_{j+1} \Rightarrow \\ E(\beta_{j+1}^N | \mathcal{F}_j) &= E(x_{j+1} | \mathcal{F}_j) \leq x_j, \end{aligned}$$

which establishes (61) for $n = j$.

(b) Recall that by (26),

$$(62) \quad s_N = \text{first } n \geq 1 \text{ such that } \beta_n^N = x_n.$$

Define for the moment

$$(63) \quad s'_N = \min[N, \text{first } n \geq 1 \text{ such that } E(x_{n+1} | \mathcal{F}_n) \leq x_n].$$

(c) Suppose $s'_N = n < N$. Then by (61), $E(\beta_{n+1}^N | \mathcal{F}_n) \leq x_n$, so that $\beta_n^N = x_n$ and hence $s_N \leq n = s'_N$. If $s'_N = N$ then also $s_N \leq s'_N$. Thus $s_N \leq s'_N$ always.

(d) Suppose $s_N = n \leq N$. Then $E(\beta_{n+1}^N | \mathcal{F}_n) \leq x_n$. Since $\beta_{n+1}^N \geq x_{n+1}$ it follows that $E(x_{n+1} | \mathcal{F}_n) \leq x_n$. Hence $s'_N \leq n$ and therefore $s'_N \leq s_N$.

It follows from (c) and (d) that $s'_N = s_N$, which proves (59), and (60) is immediate.

5. An example

Let y, y_1, y_2, \dots be independent r.v.'s with a common distribution, let \mathcal{F}_n be the σ -algebra generated by y_1, \dots, y_n , and let

$$(64) \quad x_n = \max(y_1, \dots, y_n) - a_n,$$

where we assume to begin with only that the a_n are constants such that

$$(65) \quad 0 \leq a_1 < a_2 < \dots$$

and that $E y^+ < \infty$. Set

$$(66) \quad m_n = \max(y_1, \dots, y_n), \quad b_n = a_{n+1} - a_n > 0.$$

Then

$$x_{n+1} = m_{n+1} - a_{n+1} = m_{n+1} - a_n - b_n = x_n + (y_{n+1} - m_n)^+ - b_n.$$

Hence

$$(67) \quad E(x_{n+1} | \mathcal{F}_n) - x_n = E[(y - m_n)^+] - b_n.$$

Define constants γ_n by the relation

$$(68) \quad E[(y - \gamma_n)^+] = b_n$$

(graphically, b_n is the area in the z, y -plane to the right of $y = \gamma_n$ and between $z = 1$ and $z = F(y)$). Then it is easy to see from (67) and (68) that

$$(69) \quad E(x_{n+1} | \mathcal{F}_n) \leq x \quad \text{if and only if} \quad m_n \geq \gamma_n.$$

We are in the monotone case when

$$(70) \quad b_1 \leq b_2 \leq \dots.$$

For if (70) holds, and if $E(x_{n+1} | \mathcal{F}_n) \leq x_n$, then by (68), $m_n \geq \gamma_n$ and hence $m_{n+1} \geq m_n \geq \gamma_n \geq \gamma_{n+1}$, so that $E(x_{n+2} | \mathcal{F}_{n+1}) \leq x_{n+1}$. We can therefore assert that when (70) holds

$$(71) \quad s_N = \min[N, \text{first } n \geq 1 \text{ such that } m_n \geq \gamma_n],$$

and

$$(72) \quad s = \sup_N s_N = \text{first } n \geq 1 \text{ such that } m_n \geq \gamma_n.$$

An example of the monotone case is given by choosing $a_n = cn^\alpha$ with $c > 0$, $\alpha \geq 1$. When $\alpha = 1$ all the γ_n coincide and have the value γ given by

$$(73) \quad E[(y - \gamma)^+] = c.$$

For $0 < \alpha < 1$ we are not in the monotone case and no simple evaluation of s_N and s is possible.

It is interesting to note that if we set

$$(74) \quad \tilde{x}_n = y_n - a_n$$

instead of (64), then, setting $\mu = Ey$,

$$(75) \quad E(x_{n+1} | \mathcal{F}_n) - \tilde{x}_n = \mu - b_n - y_n,$$

and we are never in the monotone case. However, for $a_n = cn$ we have by the above,

$$(76) \quad \begin{aligned} s &= \text{first } n \geq 1 \text{ such that } m_n \geq \gamma \\ &= \text{first } n \geq 1 \text{ such that } y_n \geq \gamma. \end{aligned}$$

Thus

$$(77) \quad x_s = m_s - cs = y_s - cs = \tilde{x}_s,$$

while for any s.v. t , since $\tilde{x}_n \leq x_n$, we have

$$(78) \quad \tilde{x}_t \leq x_t.$$

It follows that

$$\sup_{t \in \mathcal{C}} E(\tilde{x}_t) \leq \sup_{t \in \mathcal{C}} E(x_t),$$

and that if the distribution of the y_n is such that

$$(79) \quad E(x_s) = \sup_{t \in \mathcal{C}} E(x_t),$$

then also

$$E(\tilde{x}_s) = \sup_{t \in \mathcal{C}} E(\tilde{x}_t).$$

We shall now investigate whether in fact (79) holds, and for this we shall use Theorem 2. Write

$$x_n = \max(y_1, \dots, y_n) - a_n = x'_n - x''_n = x_n^* - x_n^{**}$$

where we have set

$$(80) \quad \begin{cases} x'_n = \max(y_1, \dots, y_n) - a_n/2, & x''_n = a_n/2, \\ x_n^* = \max(y_1, \dots, y_n), & x_n^{**} = a_n. \end{cases}$$

Assume that the constants a_n are such that

$$(81) \quad 0 \leq a_1 \leq a_2 \leq \dots \rightarrow \infty.$$

Then (44) and (46) hold, and to apply Theorem 2 it will suffice to show that

$$(82) \quad E \sup_n [\max(y_1, \dots, y_n) - a_n/2] < \infty$$

and that the r.v.'s

$$(83) \quad [\max(y_1, \dots, y_n)]^- \text{ are uniformly integrable.}$$

The latter relation is trivial as long as $E|y| < \infty$, since

$$[\max(y_1, \dots, y_n)]^- \leq y_1^-.$$

It remains only to verify (82).

To find conditions for the validity of (82) in the case

$$a_n = cn^\alpha, \quad c, \alpha > 0,$$

we shall need the following lemma, the proof of which will be deferred until later.

Lemma 8. *Let w, w_1, w_2, \dots be independent, identically distributed, non-negative r.v.'s and for any positive constants c, α set*

$$z = \sup_n [\max(w_1, \dots, w_n) - cn^\alpha].$$

Then

$$(84) \quad P(z < \infty) = 1 \text{ if and only if } E(w^{1/\alpha}) < \infty,$$

and

$$(85) \quad \text{for any } \beta > 0, \quad E(z^{1/\beta}) < \infty \text{ if and only if } E(w^{1/\alpha+1/\beta}) < \infty.$$

Now suppose that the common distribution of the y_n is such that

$$(86) \quad E|y| < \infty, \quad E[(y^+)^{1+\alpha}] < \infty.$$

Then

$$\sup_n \left[\max(y_1, \dots, y_n) - \frac{cn^\alpha}{2} \right] \leq \sup_n \left[\max(y_1^+, \dots, y_n^+) - \frac{cn^\alpha}{2} \right],$$

so that by (85) for $\beta = 1$, $w = y^+$,

$$E \sup_n \left[\max(y_1, \dots, y_n) - \frac{cn^\alpha}{2} \right] < \infty,$$

verifying (82). Thus, if $a_n = cn^\alpha$ ($c, \alpha > 0$) and if $E|y| < \infty$ and $E[(y^+)^{1+\alpha}] < \infty$, then defining the s.v. s by (56) we have

$$E(x_s) = \sup_{t \in G} E(x_t).$$

This generalizes a result of [I], where it was assumed that $\alpha \geq 1$, to the more general case $\alpha > 0$. See also [5, 6, 7] for the case $\alpha = 1$.

A similar argument holds for the sequence

$$x_n = y_n - cn^\alpha,$$

replacing $\max(y_1, \dots, y_n)$ by y_n in (80).

We may summarize these results in

Theorem 3. *Let y, y_1, y_2, \dots be independent and identically distributed random variables, let c, α be positive constants, and let*

$$x_n = \max(y_1, \dots, y_n) - cn^\alpha, \quad \tilde{x}_n = y_n - cn^\alpha.$$

Then if

$$E|y| < \infty, \quad E[(y^+)^{1+\alpha}] < \infty$$

there exist s.v.'s s and \bar{s} such that

$$E(x_s) = \sup_{t \in G} E(x_t), \quad E(\tilde{x}_{\bar{s}}) = \sup_{t \in G} E(\tilde{x}_t).$$

For $\alpha \geq 1$,

$$s = \text{first } n \geq 1 \text{ such that } \max(y_1, \dots, y_n) \geq \gamma_n,$$

where γ_n is defined by

$$E[(y - \gamma_n)^+] = c[(n+1)^\alpha - n^\alpha].$$

Proof of Lemma 8. If w is any r.v. with distribution function F , then $E(w) < \infty$ is equivalent to $\sum_1^\infty [1 - F(n)] < \infty$, which in turn is equivalent to the convergence of $\prod_1^\infty F(n)$. Hence $E(w^{1/\alpha}) < \infty$ if and only if $\prod_1^\infty F(n^\alpha)$ converges.

Now for $u > 0$ let

$$\begin{aligned} G(u) &= P(z \leq u) = P\left[\bigcap_{n=1}^\infty \bigcap_{i=1}^\infty \{w_i \leq n^\alpha + u\}\right] = P\left[\bigcap_{i=1}^\infty \bigcap_{n=i}^\infty \{w_i \leq n^\alpha + u\}\right] \\ &= P\left[\bigcap_{i=1}^\infty \{w_i \leq n^\alpha + u\}\right] = \prod_1^\infty F(n^\alpha + u). \end{aligned}$$

It follows that $\lim_{u \rightarrow \infty} G(u) = 1$ if and only if $\prod_1^\infty F(n^\alpha)$ converges; thus (84) holds.

To prove (85), we have $E(z) < \infty$ if and only if $\prod_1^\infty G(n)$ converges. Hence [4, p. 223], $E(z^{1/\beta}) < \infty$ is equivalent to

$$(87) \quad \sum_{m=1}^\infty \sum_{n=n_0}^\infty \log F[n^\beta + m^\alpha] > -\infty \quad \text{for some } n_0 \text{ such that } F(n_0^\beta) > 0.$$

Now

$$\int_1^\infty dm \int_{n_0}^\infty \log F(n^\beta + m^\alpha) dn = \int_{1+n_0^\beta}^\infty \log F(u) du \int_{n_0^\beta}^{u-1} \frac{1}{\alpha\beta} v^{1/\beta-1} (u-v)^{1/\alpha-1} dv.$$

Hence (87) is equivalent to

$$-\infty < \int_{n_0^\beta}^\infty \log F(u) du \int_0^u v^{1/\beta-1} (u-v)^{1/\alpha-1} dv = B\left(\frac{1}{\alpha}, \frac{1}{\beta}\right) \int_{n_0}^\infty u^{1/\alpha+1/\beta-1} \log F(u) du,$$

But $E(w^{1/\alpha+1/\beta}) < \infty$ is equivalent to

$$-\infty < \int_{n_0^{1/\alpha+1/\beta}}^\infty \log F(t^{\alpha\beta/\alpha+\beta}) dt = \frac{\alpha+\beta}{\alpha\beta} \int_{n_0^{1/\alpha+1/\beta}}^\infty u^{1/\alpha+1/\beta-1} \log F(u) du,$$

which proves (85).

6. Application to the sequential probability ratio test

The following problem in statistical decision theory has been treated in [8, 9, 3, 10, 11]. We shall consider it here as an illustration of our general method.

Let y_1, y_2, \dots be independent, identically distributed random variables with density function f with respect to some σ -finite measure μ on the line. It is desired to test the hypothesis $H_0: f = f_0$ versus $H_1: f = f_1$ where f_0 and f_1 are two specified densities. The loss due to accepting H_1 when H_0 is true is assumed to be $a > 0$ and that due to accepting H_0 when H_1 is true is $b > 0$; the cost of taking each observation y_i is unity. A sequential decision procedure (δ, N) provides for determining the sample size N and making the terminal decision δ ; the expected loss for (δ, N) is

$$\begin{aligned} & a\alpha_0 + E_0(N) \quad \text{when } H_0 \text{ is true,} \\ & b\alpha_1 + E_1(N) \quad \text{when } H_1 \text{ is true} \end{aligned}$$

where

$$\alpha_0 = P_0(\text{accepting } H_1), \quad \alpha_1 = P_1(\text{accepting } H_0).$$

If there is an a priori probability π that H_0 is true (and hence probability $1 - \pi$ that H_1 is true) the global "risk" for (δ, N) is given by

$$r(\pi, \delta, N) = \pi[a\alpha_0 + E_0(N)] + (1 - \pi)[b\alpha_1 + E_1(N)].$$

For a given sampling variable N it is easy to determine the terminal decision rule δ which minimizes $r(\pi, \delta, N)$ for fixed values of a, b , and π . For the part of

$r(\pi, \delta, N)$ that depends on δ is (omitting symbols like $d\mu(y_1) \dots d\mu(y_n)$)

$$\begin{aligned} \pi a \alpha_0 + (1 - \pi) b \alpha_1 &= \pi a \sum_{n=1}^{\infty} \int_{\{N=n, \text{accept } H_1\}} f_0(y_1) \dots f_0(y_n) + \\ &+ (1 - \pi) b \sum_{n=1}^{\infty} \int_{\{N=n, \text{accept } H_0\}} f_1(y_1) \dots f_1(y_n) \\ &\geq \sum_{n=1}^{\infty} \int_{\{N=n\}} \min[\pi a f_0(y_1) \dots f_0(y_n), (1 - \pi) b f_1(y_1) \dots f_1(y_n)] \\ &= \sum_{n=1}^{\infty} \int_{\{N=n\}} \min[\pi_n a, (1 - \pi_n) b] [\pi f_0(y_1) \dots f_0(y_n) + \\ &+ (1 - \pi) f_1(y_1) \dots f_1(y_n)], \end{aligned}$$

where

$$\pi_n = \pi_n(y_1, \dots, y_n) = \frac{\pi f_0(y_1) \dots f_0(y_n)}{\pi f_0(y_1) \dots f_0(y_n) + (1 - \pi) f_1(y_1) \dots f_1(y_n)}.$$

For the given sampling rule N define δ' by

$$\begin{cases} \text{accept } H_1 \text{ if } N = n & \text{and } \pi_n a \leq (1 - \pi_n) b, \\ \text{accept } H_0 \text{ if } N = n & \text{and } \pi_n a > (1 - \pi_n) b. \end{cases}$$

Then

$$\pi a \alpha_0(\delta, N) + (1 - \pi) b \alpha_1(\delta, N) \geq \pi a \alpha_0(\delta', N) + (1 - \pi) b \alpha_1(\delta', N).$$

Hence to find a pair (δ, N) which for given π minimizes $r(\pi, \delta, N)$ (a "Bayes" decision procedure) amounts to solving the following problem: for given $0 < \pi < 1$ let $y_1, y_2, \dots, y_n, \dots$ have the joint density function for each n equal to

$$\pi f_0(y_1) \dots f_0(y_n) + (1 - \pi) f_1(y_1) \dots f_1(y_n),$$

where f_0, f_1 are given univariate density functions. For given $a, b > 0$ let

$$h(t) = \min[at, b(1 - t)] \quad (0 \leq t \leq 1),$$

$$\begin{cases} \pi_0 = \pi \\ \pi_n = \pi_n(y_1, \dots, y_n) = \frac{\pi f_0(y_1) \dots f_0(y_n)}{\pi f_0(y_1) \dots f_0(y_n) + (1 - \pi) f_1(y_1) \dots f_1(y_n)} \quad (n \geq 1), \\ x_n = x_n(\pi_n) = -h(\pi_n) - n \quad (n \geq 0). \end{cases}$$

We want to find a s. v. s such that $E(x_s) = \text{maximum}$. The problem is trivial if a or b is ≤ 1 since then $h(t) < 1$ and $x_0 < x_n$ for all n , so that $E(x_s) = \text{max.}$ for $s = 0$. We shall therefore assume that $a > 1, b > 1$.

We observe that the assumptions of Theorem 2 are satisfied by setting

$$x_n = x'_n - x''_n = x_n^* - x_n^{**}$$

$$\text{with } \begin{cases} x'_n = x_n^* = -h(\pi_n), & (0 \leq h(\pi_n) \leq \frac{ab}{a+b}), \\ x''_n = x_n^{**} = n, \end{cases}$$

so that $s = \sup_N s_N$ is the desired s.v. Thus Theorem 2 guarantees the existence of a Bayes solution of our decision problem.

To find the (minimal) Bayes sampling variable s requires that we compute the quantities $\beta_0^N, \beta_1^N, \dots, \beta_N^N$ for each $N \geq 0$ (note that in the present context we are allowed to take no observations on the y_i and to decide in favor of H_0 or H_1 with $x_0 = -h(\pi)$). We have

$$\beta_n^N = \max [x, E(\beta_{n+1}^N | \mathcal{F}_n)], \quad n = 0, 1, \dots, N; \quad \beta_{N+1}^N = -\infty,$$

and by Theorem 2'

$$s = \text{first } n \geq 0 \text{ such that } x_n = \beta_n = \lim_{N \rightarrow \infty} \beta_n^N.$$

Observing that

$$\pi_{n+1} = \frac{\pi_n f_0(y_{n+1})}{\pi_n f_0(y_{n+1}) + (1 - \pi_n) f_1(y_{n+1})}$$

it follows easily that

$$\beta_n^N(y_1, \dots, y_n) = \gamma_n^N(\pi_n), \quad n = 0, 1, \dots, N + 1,$$

where

$$\gamma_n^N(t) = \max \left\{ -h(t) - n, \int_{-\infty}^{\infty} \gamma_{n+1}^N \left(\frac{t f_0(y)}{t f_0(y) + (1-t) f_1(y)} \right) [t f_0(y) + (1-t) f_1(y)] \right\}$$

$$(n = 0, 1, \dots, N); \quad \gamma_{N+1}^N(t) = -\infty.$$

Now set

$$g_n^N(t) = -\gamma_n^N(t) - n, \quad n = 0, 1, \dots, N + 1.$$

Then

$$g_n^N(t) = \min [h(t), G_{n+1}^N(t) + 1],$$

where

$$G_n^N(t) = \int_{-\infty}^{\infty} g_{n+1}^N \left(\frac{t f_0(y)}{t f_0(y) + (1-t) f_1(y)} \right) [t f_0(y) + (1-t) f_1(y)]$$

for $n = 0, 1, \dots, N$ with

$$g_{N+1}^N(t) = \infty.$$

Obviously,

$$g_n^N(t) = g_{n+1}^{N+1}(t), \quad g_n^N(t) \geq g_{n+1}^{N+1}(t) \quad \text{for } n = 0, 1, \dots, N + 1,$$

so that

$$\lim_{N \rightarrow \infty} g_n^N(t) = g_n(t) = g(t) \quad \text{exists.}$$

By the Lebesgue theorem of dominated convergence,

$$g(t) = \min [h(t), G(t) + 1]$$

where

$$G(t) = \int_{-\infty}^{\infty} g \left(\frac{t f_0(y)}{t f_0(y) + (1-t) f_1(y)} \right) [t f_0(y) + (1-t) f_1(y)].$$

And

$$\beta_n^N(y_1, \dots, y_n) = \gamma_n^N(\pi_n) = -g_n^N(\pi_n) - n,$$

so that

$$\beta_n = \lim_{N \rightarrow \infty} \beta_n^N = -g(\pi_n) - n$$

and hence

$$s = \text{first } n \geq 0 \text{ such that } g(\pi_n) = h(\pi_n); \quad E(x_s) = \beta_0 = -g(\pi).$$

We shall now investigate the nature of the function $g(t)$ which characterizes s .

If a function $a(t)$ is concave for $0 \leq t \leq 1$ and if

$$A(t) = \int_{-\infty}^{\infty} a \left(\frac{tf_0(y)}{tf_0(y) + (1-t)f_1(y)} \right) [tf_0(y) + (1-t)f_1(y)],$$

then it is an easy exercise to show that $A(t)$ is also concave on $0 \leq t \leq 1$. Since $h(t)$ is concave, $g_N^N(t) = h(t)$ is concave, and hence $G_N^N(t)$ is concave. Hence by induction all the $g_n^N(t)$ and $G_n^N(t)$ are concave, as are therefore $g(t)$ and $G(t)$. Note also that

$$g(0) = G(0) = g(1) = G(1) = 0.$$

Now put

$$\begin{aligned} \alpha_1(t) &= at - G(t) - 1, \\ \alpha_2(t) &= b(1-t) - G(t) - 1, \\ \alpha(t) &= h(t) - G(t) - 1 = \min[\alpha_1(t), \alpha_2(t)]. \end{aligned}$$

Then for $a, b > 1$,

$$\begin{aligned} \alpha_1(0) &= \alpha_2(1) = -1 < 0, \\ \alpha_1(1) &= a - 1 > 0, \\ \alpha_2(0) &= b - 1 > 0. \end{aligned}$$

Since $G(t)$ is concave, $G(0) = G(1) = 0$, and at is linear, there exists a unique number $\pi' = \pi'(a, b)$ such that

$$\alpha_1(t) \begin{cases} < 0 & \text{for } t < \pi' \\ = 0 & \text{for } t = \pi' \\ > 0 & \text{for } t > \pi' \end{cases} \quad \left(\frac{1}{a} \leq \pi' < 1 \right).$$

Similarly, there exists a unique number $\pi'' = \pi''(a, b)$ such that

$$\alpha_2(t) \begin{cases} > 0 & \text{for } t < \pi'' \\ = 0 & \text{for } t = \pi'' \\ < 0 & \text{for } t > \pi'' \end{cases} \quad \left(0 < \pi'' \leq 1 - \frac{1}{b} \right).$$

Hence

$$\begin{aligned} s &= \text{first } n \geq 0 \text{ such that } g(\pi_n) = h(\pi_n) \\ &= \text{first } n \geq 0 \text{ such that } h(\pi_n) \leq G(\pi_n) + 1 \\ &= \text{first } n \geq 0 \text{ such that either } \alpha_1(\pi_n) \text{ or } \alpha_2(\pi_n) \leq 0 \\ &= \text{first } n \geq 0 \text{ such that } \pi_n \leq \pi' \text{ or } \pi_n \geq \pi''. \end{aligned}$$

If $\pi'' \leq \pi'$ then $s \equiv 0$. If $\pi' < \pi''$ then s is the first $n \geq 0$ for which π_n does not lie in the open interval (π', π'') , and the decision procedure is a Wald sequential probability ratio test.

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Dept. of Mathematical Statistics, Columbia University
New York 27, N. Y. (USA)

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