Optimal Sequential Selection of a Monotone Sequence From a Random Sample

Stephen Samuels  
Purdue University

J Michael Steele  
University of Pennsylvania

Follow this and additional works at: http://repository.upenn.edu/statistics_papers  
Part of the Physical Sciences and Mathematics Commons

Recommended Citation  

At the time of publication, author J. Michael Steele was affiliated with Stanford University. Currently, he is a faculty member at the Statistics Department at the University of Pennsylvania.

This paper is posted at ScholarlyCommons. http://repository.upenn.edu/statistics_papers/28  
For more information, please contact repository@pobox.upenn.edu.
Optimal Sequential Selection of a Monotone Sequence From a Random Sample

Abstract
The length of the longest monotone increasing subsequence of a random sample of size $n$ is known to have expected value asymptotic to $2n^{1/2}$. We prove that it is possible to make sequential choices which give an increasing subsequence of expected length asymptotic to $(2n)^{1/2}$. Moreover, this rate of increase is proved to be asymptotically best possible.

Keywords
monotone subsequence, optimal stopping, subadditive process

Disciplines
Physical Sciences and Mathematics

Comments
At the time of publication, author J. Michael Steele was affiliated with Stanford University. Currently, he is a faculty member at the Statistics Department at the University of Pennsylvania.

This journal article is available at ScholarlyCommons: http://repository.upenn.edu/statistics_papers/28
OPTIMAL SEQUENTIAL SELECTION OF A MONOTONE SEQUENCE
FROM A RANDOM SAMPLE\(^1\)

BY STEPHEN M. SAMUELS AND J. MICHAEL STEELE

Purdue University and Stanford University

The length of the longest monotone increasing subsequence of a random
sample of size \(n\) is known to have expected value asymptotic to \(2n^{1/2}\). We
prove that it is possible to make sequential choices which give an increasing
subsequence of expected length asymptotic to \((2n)^{1/2}\). Moreover, this rate of
increase is proved to be asymptotically best possible.

1. Introduction. A central theme in the theory of optimal stopping is that many
stochastic tasks can be performed almost as well by someone unable to foresee the future
as by a prophet. In one classic example, the "secretary problem", the task is to stop at the
largest of \(n\) sequentially observed independent identically distributed observations \(X_1, X_2, \ldots, X_n\). Without clairvoyance one attains \(X_\tau\), where \(\tau\) is some stopping time, but a prophet is always able to attain \(\max_{1\leq i\leq n} X_i\).

That the prophet's advantage is rather modest follows from the well-known fact that no matter how large \(n\) is there is a stopping time \(\tau_n\) for which

\[
P(X_n = \max_{1\leq i\leq n} X_i) > e^{-1},
\]

(see, e.g., Gilbert and Mosteller (1966)).

The stochastic task we consider here is more complex than the secretary problem and
the central theme is illustrated in a different way from (1.1). To set the problem, let \(X_i: 1 \leq i < \infty\), denote independent random variables with continuous distribution \(F\). The basic object of interest is

\[L_n = \max\{k: X_{i_1} > X_{i_2} > \cdots > X_{i_k} \quad \text{with} \quad 1 \leq i_1 < i_2 < \cdots < i_k \leq n\},\]

the length of the longest monotone decreasing subsequence of the sample \(X_1, X_2, \ldots, X_n\). (We could equally well have considered increasing subsequences but the notation will be simpler this way.) The variable \(L_n\) has been studied extensively and it is now known that

\[EL_n \sim 2n^{1/2}.\]

The first result, \(EL_n \sim cn^{1/2}\), was obtained by Hammersley (1972) via an ingenious use
of the planar Poisson process. Baer and Brock (1968) had conjectured earlier on the basis
of computer simulations that \(c = 2\). By a delicate variational argument Logan and Shepp (1977) proved that \(c\) is at least 2 and by a similar method Veršik and Kerov (1977) established that \(c\) equals 2.

How well can one sequentially choose a monotone decreasing subsequence using only
stopping times? Formally, we call a sequence of stopping times \(\tau_1, \tau_2, \ldots\) a policy if (1)
they are adapted to \(X_i: 1 \leq i < \infty\), (2) \(1 \leq \tau_1 < \tau_2 < \cdots\), and (3) \(X_{\tau_k} > X_{\tau_{k+1}} > \cdots\). The class of all policies is denoted by \(\mathcal{S}\) and our main problem is to determine

\[u_n = \sup_{\mathcal{S}} E(\max\{k: \tau_k \leq n\}).\]

The quantity \(u_n\) is the largest expected length of a monotone decreasing subsequence

\[\text{Received April 23, 1979; revised April 23, 1980.}\]

\(^1\) The research was supported in part by Grant N00014-76-C-0475 (Office of Naval Research).


Key words and phrases. Monotone subsequence, optimal stopping, subadditive process.

937
which can be achieved by sequential selection. Although \( u_n \) would \textit{a priori} depend on \( F \), one can easily check that it is the same for all continuous \( F \). Moreover the optimal policy for a given \( F \) can be obtained via the probability integral transform from the policy for the uniform distribution on \([0, 1]\).

Our main result is the following

**Theorem.**

\[
(1.3) \quad u_n \sim (2n)^{1/2}.
\]

The intuitive content of this result is another illustration of the central theme; the prophet asymptotically outperforms the intelligent (but nonclairvoyant) individual by only a factor of \( 2^{1/2} \). One should also note that the naive individual who too eagerly reports each successive record low achieves an expected length of only \( \sum_{k=1}^{n} 1/k \sim \log n \) and thus does much worse than the prophet or intelligent individual.

Our proof that \( u_n \sim (2n)^{1/2} \) begins with a simple algorithm for computing \( u_n \) based on an integral equation obtained by dynamic programming. Standing alone, the integral equation seems to be ineffective, so in Section 3 we prove by a subadditivity argument that \( u_n/n^{1/2} \) has a limit. A sequence of efficient, but suboptimal, policies are then given in Section 4 which show \( \lim u_n/n^{1/2} \geq 2^{1/2} \). The crux of the proof is in Section 5, where the integral equation is finally used to show \( \lim u_n/n^{1/2} \leq 2^{1/2} \) after first establishing an essential regularity property of the solution by a probabilistic argument.

The proof outlined above yields several results \textit{en route}. In particular, we obtain results on optimal selection when the sample size is random. These results as well as comments on a related problem are collected in Section 6.

In the final section we are fortunate to be able to include a result due to Burgess Davis on the sequential selection of a decreasing subsequence from a random permutation. This result teams up with the main theorem of this paper to settle a second conjecture given in the computational paper of Baer and Brock (1968). We would like to thank Professor Davis for his kind suggestion that his result be included in the present paper.

2. **An algorithm for computing the optimal expected length.** First of all, as we remarked in the introduction, we may assume without loss of generality that the common distribution of the observations \( X_1, X_2, \ldots \) is uniform on \((0, 1)\).

Let us define, for each \( t \in (0, 1) \),

\[
(2.1) \quad \mathcal{F}_t = \{ \tau = (\tau_1, \tau_2, \cdots) \in \mathcal{F} : X_{\tau_i} < t, i = 1, 2, \cdots \},
\]

the class of policies which only select observations smaller than \( t \). We also let

\[
(2.2) \quad u_n(t) = \sup_{\tau \in \mathcal{F}_t} \mathbb{E}\{ \max (k : \tau_k \leq n) \}.
\]

Clearly

\[
(2.3) \quad u_n = u_n(1)
\]

and

\[
(2.4) \quad u_1(t) = P(X_1 \leq t) = t.
\]

We also record the trivial fact: \( u_0(t) = 0 \).

Now fix \( t \) and consider \( n + 1 \) available observations. Because of the stationarity of the \( X_i \)'s, the maximal conditional expected subsequence length, given \( X_1 \), will be just \( u_n(t) \) if \( X_1 \) is not selected and \( 1 + u_n(X_1) \) if \( X_1 \) is selected (in which case necessarily \( X_1 < t \)). Since the optimal policy must do whichever maximizes the conditional expectation, we have the algorithm:

\[
(2.5) \quad u_{n+1}(t) = u_n(t) P(X_1 \geq t) + \mathbb{E} \max \{ u_n(t), 1 + u_n(X_1) \} I_{\{X_1 < t\}}
\]

\[= (1 - t)u_n(t) + \int_0^t \max \{ u_n(t), 1 + u_n(s) \} \, ds.\]
It follows easily that for each $n$ and $t$, the policy which achieves $u_n(t)$ is

$$
\tau_1 = \min\{i: X_i < t \text{ and } 1 + u_{n-1}(X_i) \geq u_{n-1}(t)\}
$$

$$
> n \text{ (arbitrary) if no such } i \leq n
$$

$$
\tau_{k+1} = \min\{i > \tau_k : X_i < X_{\tau_k} \text{ and } 1 + u_{n-1}(X_i) \geq u_{n-1}(X_{\tau_k})\}
$$

$$
> n \text{ (arbitrary) if no such } i \leq n \text{ or if } \tau_k > n.
$$

Since (2.4) and (2.5) imply that each $u_n(\cdot)$ is strictly increasing on $(0, 1)$, we can implicitly define the functions $t^*_n(t)$ by the following relations:

$$
u_n(t^*_n(t)) = u_n(t) - 1 \quad \text{if } u_n(t) \leq 1
$$

$$
t^*_n(t) = 0 \quad \text{if } u_n(t) \leq 1.
$$

Equation (2.6) now simplifies to the following:

$$
\tau_1 = \min\{i: t^*_n(t) \leq X_i < t\}
$$

$$
\tau_{k+1} = \min\{i > \tau_k : t^*_n(t) \leq X_i < X_{\tau_k}\}.
$$

One would naturally like to show $u_n \sim (2n)^{1/2}$ directly from (2.5), but this does not seem possible. The integral equation (2.5) becomes effective only after substantial quantitative information about $u_n(t)$ is obtained.

Here we should remark that

$$
u_n(t) = \sum_{k=1}^{n-1} \sum_{j=k}^{n-1} \binom{n}{j} t^j (1-t)^{n-j}
$$

for all $t$ small enough so that the right side of (2.9) is less than or equal to one. This can be shown either directly from the integral equation or by noting that when $u_n(t) \leq 1$ the optimal policy is to select all successive minima among those $X_i$'s, $i = 1, 2, \ldots, n$, which are smaller than $t$. The right side of (2.9) is the expected number of such minima.

3. Existence of the limit. To show that $u_n/n^{1/2}$ has a limit, we shall first prove that a limit exists for an analogous planar Poisson process problem and then show that the two problems are asymptotically similar. The proof is a version of Hammersley's subadditivity idea made somewhat simpler because we deal only with expectations rather than with random variables.

3a. The planar Poisson process problem. Let $Z_1, Z_2, \ldots$, be i.i.d., each exponentially distributed with mean one, and independent of the $X_i$'s which are i.i.d. uniform on $(0, 1)$. Let $\mathcal{F}_2$ be the class of policies $\tau = (\tau_1, \tau_2, \ldots)$ with

(a) each $\tau_i$ adapted to $\{(Z_i, X_i) : 1 \leq i < \infty\}$,

(b) $1 \leq \tau_1 < \tau_2 < \cdots$ and $X_{\tau_i} > X_{\tau_j} > \cdots$;

and let

$$
w(\lambda) = \sup_{\tau \in \mathcal{F}_2} E\{\max k : \sum_{i=1}^{k} Z_i < \lambda\}.
$$

In other words, we observe a Poisson process with arrival rate one, on an interval of length $\lambda$. At each arrival time we are allowed to observe a random variable uniform on $(0, 1)$ and independent of its predecessors, and the object is to select a decreasing subsequence of maximal expected length.

What makes this problem so appealing is the well-known fact that, if we choose $p$ and $t$, each in $(0, 1)$, then the following two processes are also Poisson:

(a) those arrival times in $(0, p\lambda)$ for which the corresponding $X_i$'s are $\geq t$;

(b) those arrival times in $(p\lambda, \lambda)$ for which the corresponding $X_i$'s are $< t$.

Those processes have expected numbers of arrivals $p(1-t)\lambda$ and $(1-p)\lambda\lambda$ respectively. It follows, by considering the subclass of $\mathcal{F}_2$ consisting of those $\tau$'s with

$$
X_1 \geq t \quad \text{if } \sum_{j=1}^{\nu_1} Z_j < p\lambda
$$

$$
< t \quad \text{if } \sum_{j=1}^{\nu_1} Z_j > p\lambda,
$$
that

\[(3.1) \quad w(\lambda) \geq w(p(1 - t)\lambda) + w((1 - p)t\lambda).\]

If we now define

\[\rho(x) = w(x^2)\]

and choose \(\lambda = (r + s)^2, p = 1 - t = r/(r + s),\) (3.1) becomes

\[(3.2) \quad \rho(r + s) \geq \rho(r) + \rho(s).\]

By the elementary lemma on subadditive sequences (Fekete (1923), or Khinchin (1957)), this implies the existence of

\[(3.3) \quad \gamma = \lim_{t \to \infty} \rho(t)/t = \lim \sup \rho(t)/t \geq 1.\]

The finiteness of \(\gamma\) follows from the inequality

\[w(\lambda) \leq \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} E k \leq M \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} k^{1/2} \leq M \lambda^{1/2};\]

the second inequality holds for some constant \(M\) by (1.2). The last inequality is just an application of the familiar inequality \(E|X| \leq (EX^2)^{1/2}\).

Thus we have shown that there is a finite \(\gamma > 0\) such that

\[(3.4) \quad \gamma = \lim_{t \to \infty} w(t^2)/t = \lim_{t \to \infty} w(t)/t^{1/2}.\]

3b. Asymptotic similarity of the two processes. We will now use some elementary estimates to show that \(u_n \sim w(n)\). With the usual notation

\[P(k; \lambda) = \sum_{j=0}^{k} \frac{\lambda^j}{j!} \quad \text{and} \quad \bar{P}(k; \lambda) = 1 - P(k - 1; \lambda)\]

we will prove the inequalities:

\[(3.5) \quad u_{[1-(1-\epsilon)\lambda]} \bar{P}([1 - (1 - \epsilon)\lambda]; \lambda) \leq w(\lambda)\]

and

\[(3.6) \quad w(\lambda) \leq u_{[1+(1+\epsilon)\lambda]} P([1 + (1 + \epsilon)\lambda]; \lambda) + \lambda \bar{P}([1 + (1 + \epsilon)\lambda]; \lambda).\]

The first inequality holds since the optimal policy for \(n = [(1 - \epsilon)\lambda]\) observations used on the Poisson process (paying no heed to the \(Z_i's\)) would yield an expected length of at least \(u_{[(1-\epsilon)\lambda]}\) whenever there are at least \([(1 - \epsilon)\lambda]\) arrivals.

For the second inequality let \(N\) be the number of arrivals and let \(L\) be the subsequence length obtained when the optimal policy in \(\mathcal{F}_2\) is used. We then have

\[w(\lambda) = E(L | N \leq [(1 + \epsilon)\lambda]) P([(1 + \epsilon)\lambda]; \lambda) + E(E(L | N)I_{\{N \leq [(1 + \epsilon)\lambda]\}}).\]

We note \(E(L | N \leq [(1 + \epsilon)\lambda]) \leq u_{[(1+\epsilon)\lambda]}\) and trivially \(E(L | N) \leq N\). Inequality (3.6) then follows since

\[E[N_{I_{\{N > [(1+\epsilon)\lambda]\}}} = \lambda \bar{P}([1 + (1 + \epsilon)\lambda]; \lambda).\]

From the fact (3.4) that \(w(\lambda) \sim \gamma \lambda^{1/2}\) and elementary bounds on the Poisson distribution one now easily deduces from (3.5) and (3.6) that \(u_n \sim \gamma n^{1/2}\).

We remark that it is not hard to extend this result to show that for each \(t \in (0, 1]\) one has \(u_n(t)/(nt)^{1/2} \to \gamma\).
4. A lower bound for the limit. For any constant \( \alpha > 0 \), and for each \( n \), we consider the policy \( \tau(n) = \tau(n; \alpha) \), where

\[
\begin{align*}
\tau_1(n) &= \min \{ j : X_j \geq 1 - \alpha/n^{1/2} \} \\
\tau_{k+1}(n) &= \min \{ j > \tau_k(n) : X_j \in [X_{\tau_k(n)} - \alpha/n^{1/2}, X_{\tau_k(n)}] \}.
\end{align*}
\]

We shall show that for these policies

\[
\liminf_{n \to \infty} E \max \{ k : \tau_k(n) \leq n \} \geq n^{1/2} \min(\alpha, 2/\alpha).
\]

The right side of (4.1) is maximized for \( \alpha = 2^{1/2} \), which shows that \( \liminf_{n \to \infty} u_\alpha/n^{1/2} \geq 2^{1/2} \).

(Of course when we complete the proof of the theorem, (4.1) with \( \alpha = 2^{1/2} \) will imply that the policies \( \tau(n; 2^{1/2}) \) are asymptotically optimal.)

What makes the policies \( \tau(n) \) easy to evaluate is the fact that if \( X_{\tau_k(n)} \geq \alpha/n^{1/2} \), then \( \tau_{k+1}(n) - \tau_k(n) \) and \( X_{\tau_k(n)} - X_{\tau_{k+1}(n)} \) are conditionally independent and independent of \( \{ \tau_1(n), \ldots, \tau_k(n) ; X_{\tau_1(n)}, \ldots, X_{\tau_k(n)} \} \), with geometric \( (p = \alpha/n^{1/2}) \) and uniform on \( (0, \alpha/n^{1/2}) \) distributions respectively. Hence we now let \( \{ Y_k : k = 1, 2, \ldots \} \) and \( \{ Z_k : k = 1, 2, \ldots \} \) be independent sequences of i.i.d. random variables with these geometric and uniform distributions respectively. Also set \( S_n = Y_1 + \cdots + Y_n \) and \( S'_n = Z_1 + \cdots + Z_n \), and define

\[
M_n = \max \{ k : S_k \leq n \text{ and } S'_k \leq 1 - \alpha/n^{1/2} \}.
\]

We first observe

\[
EM_n \leq E \max \{ k : \tau_k(n) \leq n \}.
\]

Now, for any \( \epsilon > 0 \), Chebyshev’s inequality gives

\[
P(S_k \leq n) = 1 + O(n^{-1/2}) \quad \text{if} \quad k \leq (1 - \epsilon)\alpha n^{1/2}
\]

\[
= O(n^{-1/2}) \quad \text{if} \quad k \geq (1 + \epsilon)\alpha n^{1/2}
\]

and

\[
P(S'_k \leq 1 - \alpha/n^{1/2}) = 1 + O(n^{-1/2}) \quad \text{if} \quad k \leq (1 - \epsilon)(2/\alpha)n^{1/2}
\]

\[
= O(n^{-1/2}) \quad \text{if} \quad k \geq (1 + \epsilon)(2/\alpha)n^{1/2}.
\]

The \( O(n^{-1/2}) \) terms are uniformly small in the indicated range, so, by the independence of the two sequences,

\[
EM_n = \sum_{k=1}^n P(S_k \leq n)P(S'_k \leq 1 - \alpha/n^{1/2}) \sim n^{1/2} \min(\alpha, 2/\alpha).
\]

By (4.2), this shows that (4.1) holds, completing the proof.

5. An upper bound for the limit. Now that we know that \( \lim u_\alpha/n^{1/2} \) exists and is at least \( 2^{1/2} \), to complete the proof of the theorem it will suffice to show that

\[
\liminf u_\alpha/n^{1/2} \leq 2^{1/2}.
\]

Our proof of (5.1) hinges on showing that

\[
u_\alpha(t)/t^{1/2} \uparrow \text{ in } t \text{ for each } n.
\]

The derivative of \( u_\alpha(t)/t^{1/2} \) is

\[
t^{-1/2}[u'_\alpha(t) - (2t)^{-1}u_\alpha(t)],
\]

so, to prove (5.2), we must show that for each \( t \in (0, 1) \)

\[
u_\alpha(t + \delta) - u_\alpha(t) > (\frac{1}{2})(\delta/t)u_\alpha(t) + o(\delta) \text{ as } \delta \downarrow 0.
\]

This inequality will be proved by selecting a suboptimal member of \( \mathcal{G}_{t+\delta} \) (as defined in
(2.1)) and showing that this policy improves on the optimal policy in $\mathcal{F}_t$ by an amount equal to the right side of (5.3).

What we actually do is a bit more complicated than this and involves showing that $u_n(t)$ is also the maximal expected subsequence length in a problem where the number of available observations is random with a binomial distribution.

5a. Optimal selection with binomially many observations. Since the policy in $\mathcal{F}_t$ which achieves $u_n(t)$, as given by (2.8), ignores the actual values of all $X_i$'s which are greater than $t$, and since the other $X_i$'s are, conditionally, i.i.d. uniform on $(0, t)$, we could just as well replace the $X_i$'s by a sequence of observable coin tosses with probability $t$ of heads, letting each toss which gives heads be accompanied by the next in a sequence of i.i.d. random variables uniform on $(0, t)$.

To exploit this observation let $Y_1, Y_2, \ldots$ and $X_1, X_2, \ldots$ be independent sequences of i.i.d. random variables, the $Y_i$’s Bernoulli (1), and the $X_i$’s uniform on $(0, 1)$. Let $\mathcal{U}_t$ be the class of policies adapted to the $(Y_i, X_i)$'s which select a monotone decreasing subsequence by selecting only $X_i$’s for which $Y_i = 1$ and which totally ignore all $X_i$’s for which $Y_i = 0$. Then for the $u_n(t)$ defined by (2.2) we have the representation

$$\sup_{p \in \mathcal{U}_t} E \{ \max \{ k : \tau_k \leq n \} \} = u_n(t).$$

Since we have made the $X_i$’s uniform on $(0, 1)$, rather than on $(0, t)$—this is to avoid confusion in what follows—the policy $\tau = (\tau_1, \tau_2, \ldots)$ which achieves $u_n(t)$ becomes

$$\tau_1 = \min \{ i : Y_i = 1 \} \quad \text{and} \quad t_-^{*}(t) \leq tX_i < t,$$

$$\tau_{k+1} = \min \{ i > \tau_k : Y_i = 1 \} \quad \text{and} \quad t_-^{*}(tX_i) \leq tX_i < tX_{\tau_k}.\]$$

Now suppose we introduce a second coin toss at each stage—letting $Y_1', Y_2', \ldots$ be i.i.d. Bernoulli $(p')$ and independent of the $Y_i$’s and the $X_i$’s—and we allow policies adapted to the $(Y_i')$ as well, but maintain the requirement that all $X_i$’s for which $Y_i = 0$ must be ignored. Then clearly what we have introduced is external randomization: those policies which depend in some way on the $(Y_i')$ are simply randomized policies, and, of course, none of these can improve on the best nonrandomized policies. In particular, any policy which ignores all $X_i$’s for which either $Y_i = 0$ or $Y_i' = 0$ is really a policy in $\mathcal{U}_t$; hence the expected length of the subsequence of $X_1, \ldots, X_n$ which it selects is no greater than $u_n(tt')$.

Just such a policy will be needed in proving (5.3).

5b. Monotonicity of $u_n(t)/t^{1/2}$. We now fix $n$ and let the $(Y_i)$ be Bernoulli $(t + \delta)$ and the $(Y_i')$ be Bernoulli $(t/(t + \delta))$. First note that $P(Y_i = Y_i' = 1) = t$. We consider two randomized policies $\tau$ and $\tau'$ in $\mathcal{U}_{t+\delta}$. The first is to be equivalent to the optimal policy (for given $n$) in $\mathcal{U}_t$, while the second is to be a slight modification of the first. Specifically, we let $\tau = (\tau_1, \tau_2, \ldots)$ with

$$\tau_1 = \min \{ i : Y_i = Y_i' = 1 \} \quad \text{and} \quad t_-^{*}(t) \leq tX_i,$$

$$\tau_{k+1} = \min \{ i > \tau_k : Y_i = Y_i' = 1 \} \quad \text{and} \quad t_-^{*}(tX_i) \leq tX_i < tX_{\tau_k}.\]$$

We want $\tau'$ to agree with $\tau$ up to the first $i \leq n$, if any, at which $Y_i = 1$, $Y_i' = 0$, and at which $X_i$ would have been selected by $\tau$ if $Y_i' = 1$ had been 1. We want $\tau'$ to select this $X_i$, but thereafter to continue to behave like $\tau$. We thus define

$$I = \min \{ i : Y_i = 1, Y_i' = 0, t_-^{*}(tX_i) \leq tx_i < tX_i \}$$

$$= \infty \text{ if no such } i \leq n,$$

where

$$\sigma_i = \max \{ \tau_k : \tau_k < i \}$$

$$= 0 \text{ (and } X_0 = 1) \quad \text{if } \tau_1 \geq i.$$
We then let \( \tau' = (\tau'_1, \tau'_2, \ldots) \) where

\[
\begin{align*}
\tau'_h &= \tau_h & \text{if } & \tau_h < I \\
\tau'_h &= I & \text{if } & \tau_h < I < \tau_{h+1} \\
\tau'_{h+1} &= \min\{i > \tau'_h : Y_i = Y'_i = 1 \text{ and } t_{n-i}(tX_{i}) \leq tX_i < tX_{i+1} \} & \text{if } & \tau'_h \geq I.
\end{align*}
\]

Now, for convenience, we let \( L \) and \( L' \) be the lengths of the subsequences of \( X_i, \ldots, X_n \) selected by \( \tau \) and \( \tau' \) respectively. Then \( L = L' \) on \( \{I > 0\} \),

\[
EL = u_n(t),
\]

and

\[
EL' \leq u_n(t + \delta)
\]

so

\[
(5.4) \quad u_n(t + \delta) - u_n(t) \geq E(L' - L \mid I \leq n)P(I \leq n).
\]

Furthermore, from (2.2) and the definitions of \( \tau \) and \( \tau' \),

\[
(5.5) \quad E(L' - L \mid I = i, X_n = x) = 1 + E\{u_n(tX_i) \mid I = i, X_n = x\} - u_n(tx).
\]

(Note: (5.5) is valid even when \( i = n \), since we have set \( u_0(t) = 0 \).)

From (5.4) and (5.5) we see that to establish (3.3) it suffices to prove

\[
(5.6) \quad P(I \leq n) \leq (\delta/t)u_n(t) + o(\delta) \quad \text{as } \delta \downarrow 0
\]

and, for each \( i \leq n \),

\[
(5.7) \quad E\{u_n(tX_i) \mid I = i, X_n = x\} \geq u_{n-i}(tx) - \frac{1}{2}.
\]

To prove (5.6) we first remark that, since \( t/(t + \delta) \to 1 \) as \( \delta \downarrow 0 \), we have

\[
(5.8) \quad P(I \leq n) = \sum_{i=1}^{n} P(Y_i = 1, Y'_i = 0, A_i) + o(\delta)
\]

where \( A_i \) denotes the event \( \{t_{n-i}(tX_i) \leq tX_i < tX_{i+1}\} \). \( A_i \) is independent of \( \{Y_i = 1, Y'_i = 0\} \) so

\[
P(Y_i = 1, Y'_i = 0, A_i) = P(Y_i = 1, Y'_i = 0)P(A_i)
\]

\[
= (\delta/t)P(Y_i = Y'_i = 0, A_i)
\]

\[
= (\delta/t)P(X_i \text{ is selected by } \tau).
\]

Putting this back into (5.8) we have

\[
P(I \leq n) = (\delta/t) \sum_{i=1}^{n} P(X_i \text{ is selected by } \tau) + o(\delta) = (\delta/t)u_n(t) + o(\delta),
\]

which is (5.6).

To prove (5.7), we first remark that the conditional distribution of \( tX_i \), given \( X = i \) and \( X_n = x \) is uniform on \( \langle t_{n-i}(tx), tx \rangle \). Also we note that

\[
(5.9) \quad u_{n-i}(t_{n-i}(tx)) \geq u_{n-i}(tx) - 1
\]

with equality holding unless \( u_{n-i}(tx) < 1 \). Hence if \( u_{n-i}(\cdot) \) were \textit{linear} on the interval \( \langle t_{n-i}(tx), tx \rangle \), (5.7) would hold and would in fact be an \textit{equality} if \( u_{n-i}(tx) \geq 1 \). So the most natural way to establish (5.7) is to prove the following lemma:

\textbf{Lemma 5.2.} \textit{For each } \( n \), \( u_n(\cdot) \) \textit{is concave.}

\textbf{Proof.} We proceed by induction and first note the lemma is true for \( n = 1 \) because \( u_1(t) = t \).
Using (2.7), we rewrite (2.5) as
\[ u_{n+1}(t) = t + (1 - t)u_n(t) + t_n^*(t)(u_n(t) - 1) + \int_{t_n^*(t)}^{t} u_n(s) \, ds. \]
Formally we have
\[ u_{n+1}'(t) = 1 - u_n(t) + (1 - t)u_n'(t) - t_n^*(t)(u_n(t) - 1) \\
+ t_n^*(t)u_n'(t) + u_n(t) - t_n^*(t)u_n(t_n^*(t)). \]
Now \( u_n(t_n^*(t)) = (u_n(t) - 1)^+ \) and \( t_n^*(t) = 0 \) if \( u_n(t) < 1 \). Hence whether or not \( u_n(t) \geq 1 \) we have
\[ u_{n+1}'(t) = 1 + (1 - (t - t_n^*(t)))u_n'(t) \]
and
\[ u_{n+1}''(t) = (1 - (t - t_n^*(t)))u_n''(t) - (t - t_n^*(t))u_n'(t). \]
If \( u_n(\cdot) \) is concave (i.e., \( u_n''(t) < 0 \)), then \( (t - t_n^*(t)) \) is increasing. Since, \( t - t_n^*(t) < 1 \) and \( u_n(\cdot) > 0 \), we conclude that \( u_{n+1}''(t) < 0 \), i.e., \( u_{n+1}(\cdot) \) is concave.

The validity of the foregoing differentiations are also easily established by induction.

To begin note \( u_1(t) = t \) and \( t_n^*(t) = 0 \). Next the differentiability of \( u_n \) and \( u_n' \) implies \( t_n^*(\cdot) \) is differentiable on \( \{t: u_n(t) > 1\} \); in fact, we have \( t_n^*(t) = u_n(t)/u_n'(t_n^*(t)) \). By means of (2.5) one even more easily sees the required differentiability of \( u_n(\cdot) \).

This completes the proof of the lemma, from which we obtain (5.7).

5c. Completion of the proof. At last we are ready to prove (5.1). We define
\[ c_n = u_n/n^{1/2} = u_n(1)/n^{1/2}, \]
and note that it only remains to show \( \liminf \, c_n \leq 2^{1/2} \). By (5.2),
\[ c_n(nt)^{1/2} \geq u_n(t) \quad t \in (0, 1]. \]
Abbreviate
\[ t_n^* = t_n^*(1) \]
and define \( s_n^* \) analogously by
\[ c_n(ns_n^*)^{1/2} = c_n n^{1/2} - 1 \]
so
\[ s_n^* = 1 - 2c_n^{-1}n^{-1/2} + c_n^{-2}n^{-1}. \]
Now (5.10) and (5.11) imply that
\[ s_n^* \leq t_n^* \]
so, rewriting (2.5), with \( t = 1 \), as
\[ u_{n+1} = u_n + \int_{t_n^*}^{1} (u_n(t) - (u_n - 1)) \, dt, \]
we conclude from (5.10), (5.11), and (5.13) that
\[ u_{n+1} \leq c_n n^{1/2} + \int_{s_n^*}^{1} \left( c_n(nt)^{1/2} - (c_n n^{1/2} - 1) \right) \, dt. \]
This is perhaps the central inequality in the proof, and it is made possible by (5.2). The remainder of the proof demands only straightforward analytical manipulation of the right side of (5.14).
Evaluating the right side of (5.14) we get

\[(5.15) \quad c_{n+1} \leq c_n n^{1/2} + (\%_2)c_n n^{1/2}(1 - s^{3/2}_*) - (1 - s^*_n)\left(c_n n^{1/2} - 1\right).\]

Substituting (5.12) and the Taylor series expansion

\[1 - s^{3/2}_* = (\%_2)(1 - s^*_n) - (\%_3)(1 - s^*_n)^2 + O((1 - s^*_n)^3),\]

into the right side of (5.15) gives

\[(5.16) \quad u_{n+1} \leq c_n n^{1/2} + c^{-1}_n n^{-1/4} + O(n^{-1})
= (n + 1)^{1/2} c_n n^{1/2}(n + 1)^{-1/2} + c^{-1}_n n^{-1/2}(n + 1)^{-1/2} + O(n^{-3/2}).\]

Now direct computation shows that

\[n^{1/2}(n + 1)^{-1/2} = 1 - (\%_2 - \delta_n)/n^{1/2}(n + 1)^{1/2}\]

where \(\delta_n > 0\) and \(\delta_n \to 0\) as \(n \to \infty\). Hence (5.16) is

\[u_{n+1} \leq (n + 1)^{1/2} \left[c_n + n^{-1/2}(n + 1)^{-1/2}(c^{-1}_n - \left(\frac{1}{2}\right) c_n + o(1))\right].\]

From (5.10), with \(n + 1\) instead of \(n\), we have

\[(5.17) \quad c_{n+1} \leq c_n + n^{-1/2}(n + 1)^{-1/2}\left[c^{-1}_n - \left(\frac{1}{2}\right) c_n + o(1)\right].\]

This is exactly what we need to show that \(\lim \inf c_n \leq 2^{1/2}\) and thereby complete the proof.

We use the fact that \(c^{-1} - c/2\) is decreasing in \(c\) and zero for \(c = 2^{1/2}\). Choose \(\epsilon > 0\) and \(n_c\), large enough so that for all \(n \geq n_c\), the \(o(1)\) in (5.17) satisfies

\[o(1) < (\%_2) \mid 2^{1/2} + \epsilon - (\%_2)(2^{1/2} + \epsilon) \mid = \delta_c.\]

Then for all \(n \geq n_c\),

\[c_n > 2^{1/2} + \epsilon \implies c_{n+1} < c_n - \delta_n n^{-1/2}(n + 1)^{-1/2}.\]

But

\[\sum n^{-1/2}(n + 1)^{-1/2} = \infty\]

so \(c_{n_0} > 2^{1/2} + \epsilon\) for some \(n_0 \geq n_c\) implies \(c_{n_0+m} < 2^{1/2} + \epsilon\) for some \(m\). Since \(\epsilon > 0\) is arbitrary this shows that \(\lim \inf c_n \leq 2^{1/2}\) as required to complete the proof.

We should remark that exactly the same argument can be used to prove that

\[u_n(t)/(nt)^{1/2} \to 2^{1/2}\]

for every \(t\) in \((0, 1]\).

6. Random sample size and an open problem. As an easy consequence of \(u_n \sim (2n)^{1/2}\) one can obtain several results on subsequence selection when the underlying sample size \(N\) is random. In particular we now define \(u_N\) by

\[(6.1) \quad u_N = \sup_{t \in \mathcal{S}} E \{\max\{k : \tau_k \leq N\}\},\]

where \(\mathcal{S}\) consists of those strategies adapted to \(\{X_i\}_{i=1}^\infty\) but not adapted to \(N\). When \(N\) is Poisson or binomial (with fixed \(p\)) one can easily show that as \(EN \to \infty\) we have

\[(6.2) \quad u_N \sim (2EN)^{1/2}.\]

In fact one can check that the same result holds whenever \(EN \to \infty\) and \(\text{Var} N = O(EN)\). (To compare these results with the asymptotic relations of Sections 3a and 5a one needs to note that the class of policies applied there were quite different from those used in (6.1) since they were also adapted to the relevant Poisson or binomial processes.)

We now consider the next most complex case where \(N\) has the geometrical distribution
\((P(N = k) = p(1 - p)^{k-1}, k = 1, 2, \cdots)\). The condition \(\text{Var } N = O(EN)\) does not hold, so as before the natural analysis begins with dynamic programming.

Analogously to (2.2) we define
\[
u_N(t) = \sup_{s \in \gamma} E \{ \max \{ k : \tau_k \leq N \} \}.
\]
One can easily check in this case that
\[
u_{N(p)}(t) = \nu_{N(p')}(1)
where
\[
p' = p/(p + t(1 - p)).
\]
If we define \(f(p) = u_{N(p)}(1)\) we are led to a single integral equation:
\[
f(p) = (1 - p) \int_0^1 \max(f(p), 1 + f(1/(p + t(1 - p)))) \, dt.
\]
As we similarly noted at the end of Section 2 we can solve the equation for sufficiently extreme values. In this case we know
\[
f(p) = \log(p^{-1}) \quad \text{if} \quad p > e^{-1}.
\]
This observation just says that if \(f(p) \leq 1\) the optimal policy is to select all record values exactly as one does in the fixed sample size problem when \(u_n(t) \leq 1\).

One would like to determine the asymptotic behavior of \(f(p)\) as \(p \to 0\). We conjecture, but have not been able to prove, that as \(p \to 0\)
\[
f(p) \sim cp^{-1/2}
\]
for a constant \(c < 2^{1/2}\).

7. A result of Burgess Davis on selections from permutations. If one considers a random permutation of the set \(\{1, 2, \cdots, n\}\), then the distribution of the length of the longest decreasing subsequence is the same as that in a random sample of size \(n\) from a uniform distribution. In contrast, the length of the optimal sequentially selected decreasing subsequence is stochastically larger in the first case.

We let \(l_n\) denote the expected length of the longest decreasing subsequence which can be chosen sequentially from a random permutation. The main result of this paper immediately implies that
\[
(7.1) \quad \lim \inf l_n/n^{1/2} \geq 2^{1/2}.
\]

Part of the interest of this observation stems from the fact that the study of the \(l_n\)'s was already a primary objective in Baer and Brock (1968), where "natural" is used as a synonym for "sequential." On the basis of substantial computation Baer and Brock even conjectured that \(l_n \sim (2n)^{1/2}\). The truth of this conjecture is an immediate consequence of our main result \(u_n \sim (2n)^{1/2}\) and the previously unpublished theorem due to Burgess Davis which is proved below.

THEOREM. (Burgess Davis).
\[
l_n \sim u_n.
\]

PROOF. First suppose \(X_i, 1 \leq i \leq \infty\), are i.i.d. uniform on \([0, 1]\). For any \(\epsilon > 0\) and \(0 < \delta < 1\), let \(I_k^{(n)}\) denote the interval \([(k - 1)\epsilon/n^{1/2}, k\epsilon/n^{1/2}]\) and let \(Y_k^{(n)}\) denote the cardinality of the set \(\{i : 1 \leq i \leq n, X_i \in I_k^{(n)}\}\). Consider the events
\[
A_n = \{ \min_{1 \leq k \leq n^{1/2}} Y_k^{(n)} \geq (1 - \delta)\epsilon n^{1/2} \}
\]
and note that elementary binomial estimates show \(P(A_n) \to 1\) as \(n \to \infty\).
Now assign "pretend ranks" as follows: if \( X_i \in I_k^{(n)} \) and \( X_i \) is one of the first \( [(1 - \delta)en^{1/2}] \) elements of \( I_k^{(n)} \) we chose its "pretend rank" at random from those integers between \( (k - 1)(1 - \delta)en^{1/2} \) and \( k(1 - \delta)en^{1/2} \) which are not already assigned. We then ignore all \( X_i \)'s in \( I_k^{(n)} \) after the first \( [(1 - \delta)en^{1/2}] \). We note that on \( A_n \) the sequence of "pretend ranks" is simply a permutation on the integers \( \{ k : 1 \leq k \leq (1 - \delta)n \} \).

Now use the optimal random permutation policy on the set of "pretend ranks" to select a subsequence with decreasing pretend ranks. Delete from the subsequence all \( X_i \)'s which are not smaller than all their predecessors in the subsequence. This gives a decreasing subsequence.

We now claim that the expected cardinality of the resulting subsequence is at least 
\[
P(A_n)(l_m - en^{1/2})
\]
with \( m = [(1 - \delta)n] \). First note, on \( A_n \) the expected length before deletions is \( l_m \). Let \( J_i^{(m)} \) denote the interval \( I_i^{(m)} \) which contains the smallest selected element from \( \{ X_1, X_2, \ldots, X_i \} \). For \( X_{i+1} \) to be an observation deleted from the selected subsequence it is necessary that \( X_{i+1} \in J_i^{(m)} \). By Boole's inequality and the independence of \( X_{i+1} \) and \( J_i^{(m)} \) we have that the expected number of deleted observations is at most
\[
\sum_{i=1}^{n-1} P(X_{i+1} \in J_i^{(m)}) = n\frac{e}{n^{1/2}} = en^{1/2}.
\]
This proves \( l_m/n^{1/2} \leq P(A_n)^{-1}u_n/n^{1/2} + \epsilon \). By (7.1) and the arbitrariness of \( \epsilon \) and \( \delta \) the theorem is proved.

REFERENCES


