# GEORGIA INSTITUTE OF TECHNOLOGY OFFICE OF CONTRACT ADMINISTRATION

# SPONSORED PROJECT INITIATION

Date: \_\_\_\_\_ June 6, 1979

Project Title: Goal and Average Cost Probl State Spaces	ems in Decision Processes with Finite
Project No: G-37-612 Green	card
Project Director: Dr. Theodore P. Hill	
Sponsor: Air Force Office of Scientific	Research; Bolling AFB, DC 20332
Agreement Period: From <u>6/15/</u>	Until 9/30/80(Performance Period)
Type Agreement: Contract No. F49620-79-0	C-0123
Amount: \$18,303 AFOSR NOTE 4,578 GIT(G-37-322) \$22,881 TOTAL	Partially funded through 9/30/79: \$ 8,866 AFOSR 2,211 GIT \$11,077 TOTAL
Reports Required: Annaul Technical Report	t; Final Technical Report
Sponsor Contact Person (s):	
Technical Matters Program Manager: Dr. I. N. Shimi Merle M. Andrew Director of Mathematical & Information Air Force Office of Scientific Research ATTN: NM Bldg. 410 Bolling AFB, DC 20332	Contractual Matters (thru OCA) Lt. ParsonsSciencesAir Force Office of Sci. Res. Bldg. 410 Bolling AFB, DC 20332 202/767-4959Marion R. Harrington, Major, USAF Contracting Officer
Defense Priority Rating: DO-C9 under DMS Reg.	L The second
Assigned to: <u>Mathematics</u>	(School/Laboratory)
COPIES TO:	
Project Director Division Chief (EES) School/Laboratory Director Dean/Director-EES Accounting Office Procurement Office	Library, Technical Reports Section EES Information Office EES Reports & Procedures Project File (OCA) Project Code (GTRI)
Security Coordinator (OCA)	Uther

# GEORGIA INSTITUTE OF TECHNOLOGY OFFICE OF CONTRACT ADMINISTRATION

# SPONSORED PROJECT TERMINATION

Date: 1/12/81

Project Title: Goal and Average Cost Problems in Decision Processes with Finite State Spaces

Project No: G-37-612

Project Director: Dr. Theodore P. Hill

Sponsor: Air Force Office of Scientific Research (#F49620-79-C-0123)

Effective Termination Date: \_\_\_\_\_9/30/80 (Perf. Period)

Clearance of Accounting Charges: Final Report due 11/30/80

Grant/Contract Closeout Actions Remaining:

- Final Invoice and Closing Documents
- x Final Fiscal Report
- x Final Report of Inventions
  - Govt. Property Inventory & Related Certificate
  - Classified Material Certificate
- Other\_

# Assigned to: \_

Mathematics

(School/INDONOTY)

#### COPIES TO:

Project Director Division Chief (EES) School/Laboratory Director Dean/Director—EES Accounting Office Procurement Office Security Coordinator (OCA) Reports Coordinator (OCA) Library, Technical Reports Section EES Information Office Project File (OCA) Project Code (GTRI) Other\_C.E. Smith

DEDODT DOCUMENTATION DACE	and the second
REFORT DOCUMENTATION FAGE	READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER 2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
Goal and average cost problems in decision processes with finite state spaces	<ol> <li>5. TYPE OF REPORT &amp; PERIOD COVERED</li> <li>Final technical 6/79-9/80</li> <li>6. PERFORMING ORG. REPORT NUMBER</li> </ol>
7. AUTHOR(*) Theodore P. Hill	B. CONTRACT OR GRANT NUMBER(*) F49620-79-C-0123
PERFORMING ORGANIZATION NAME AND ADDRESS T. P. Hill School of Mathematics, Georgia Inst. of Technology Atlanta, Georgia 30332	10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
1. CONTROLLING OFFICE NAME AND ADDRESS Air Force Office of Scientific Research	12. REPORT DATE
Air Force Systems Command, USAF Bolling A.F.B., Washington, D. C. 20332	13. NUMBER OF PAGES
4. MONITORING AGENCY NAME & ADDRESS(il different from Controlling Office)	15. SECURITY CLASS, (of this report)
	15a. DECLASSIFICATION/DOWNGRADING SCHEDULE
DISTRIBUTION STATEMENT (of the abstract entered in Block 20, If different from	n Report)
SUPPLEMENTARY NOTES	
SUPPLEMENTARY NOTES	
KEY WORDS (Continue on reverse side if necessary and identify by block number) Decision processes, gambling theory, dynamic prograstationary strategy	camming, Markov processes,
N SUPPLEMENTARY NOTES KEY WORDS (Continue on reverse side if necessary and identify by block number) Decision processes, gambling theory, dynamic progr stationary strategy	ramming, Markov processes,

SECURITY CLASSIFICATION OF THIS PAGE (When Date Entered)

#### SECURITY CLASSIFICATION OF THIS PAGE(When Data Entered)

Investigations of these processes led to results in optimal stopping theory, and in classical probability theory. Universal, best possible constants were found which compared the optimal expected return of a decision maker with the expected supremum of a sequence of independent random variables. A generalization of the classical Borel-Cantelli Lemma was found, as was a very general conditioning principle for strong laws of several forms.

The question of existence of good Markov strategies in finite state decision processes with average reward criteria was addressed, and various partial results were obtained, although the general case was not settled.

#### I. Research Objectives

The objective of the supported research was a continuation of the principal investigator's analysis of decision processes with arbitrary decision sets, with special emphasis on two classical payoff functions. The first was a process with single fixed goal in which the objective is to maximize the probability of reaching the goal, and to minimize the expected time to the goal. A specific objective was to determine whether one can do as well with stationary strategies as he can with strategies which take the whole past into account. The second object of study was the average reward payoff in finite state decision processes, a specific objective being to determine whether or not strategies based only on the current time and state are as good as those which take the whole past into account.

#### II. Status of the Research

A complete, affirmative answer was found to the first question; in every dynamic programming or gambling problem with single fixed goal and finite state space, there exists a stationary strategy which not only uniformly (nearly) maximizes the probability of reaching the goal, but also uniformly (nearly) minimizes the expected time to the goal. Techniques in the proof of this result were considerably generalized to answer several questions about decision processes with arbitrary state spaces and totalcost criteria. It was shown that in a countable state decision process with non-negative costs depending on the current state, the action taken, and the following state, there is always available a Markov strategy which uniformly (nearly) minimizes the expected total cost. If the costs are strictly positive and depend only on the current state, there is even a stationary strategy with the same property.

Investigations of these results led peripherally to several results in optimal stopping theory, and in classical probability theory. Universal, best possible constants were found which compared the optimal expected return of a decision maker with the expected supremum of a sequence of random variables. For example, it was found that for every sequence of independent random variables taking only values between zero and one, the difference between the optimal stop rule expectation and the expected value of the supremum of the random variables is no more than one-fourth. Results in classical probability stemming from this research include a stronger form of the Borel-Cantelli Lemma, and a very general conditioning principle for strong laws which conclude the partial sums converge almost surely.

For the question of existence of good Markov strategies in decision processes with average reward criteria, various partial results have been obtained, including examples showing that the limit of good strategies for the discounted reward payoff is not necessarily average-reward good. This research is still in progress and it is hoped that a complete answer to the finite state case is not far away.

# III. List of Publications

1. "On Reaching a Goal Quickly," Technical Report.

2. "Ratio Comparisons of Supremum and Stop Rule Expectations," (with R. Kertz), submitted to Z. Wahrscheinlichkeitstheorie.

3. "Decision Processes with Total-Cost Criteria," (with S. Demko), accepted for publication in Annals of Probability.

4. "Additive comparisons of Stop Rule and Supremum Expectations of Uniformly Bounded Independent Random Variables," (with R. Kertz), submitted to Proceedings of the A.M.S.

5. "A Stronger Form of the Borel-Cantelli Lemma," submitted to Pacific Journal of Mathematics.

6. "Comparisons of Stop Rule and Supremum Expectations of i.i.d. Random Variables," (with R. Kertz), submitted to Annals of Probability.

7. "Conditional Generalizations of Strong Laws Which Conclude the Partial Sums Coverage Almost Surely," submitted to Annals of Probability.

IV. Spoken Papers

A. Presented

1. "Betting Against a Prophet," seminar in Mathematics Department at University of California at Berkeley, August 1979.

2. "A Stronger Form of the Borel-Cantelli Lemma," seminar in the Mathematics Department at University of California at Berkeley, September 1979.

3. "On the Existence of Good Markov Strategies," Colloquium Presentation, Statistics Department, University of California at Berkeley, October 1979.

4. "Markov Decision Processes, Gambling, and Dynamic Programming," Colloquium Presentation, Mathematics Department, University of Hawaii, April 1980.

5. "Conditional Generalizations of Strong Laws," seminar in the Mathematics Department, University of California at Berkeley, June 1980.

6. , Probability Seminar, Mathematics Department, Georgia Institute of Technology, October 1980.

7. "A Stronger Form of the Borel-Cantelli Lemma," Probability Seminar, Mathematics Department, Georgia Institute of Technology, November 1980.

B. Scheduled

1. "Conditional Generalizations of Strong Laws," Annual American Mathematical Society Meeting, San Francisco, January 1981.

2. "Finite State Decision Processes," Operations Research Seminar, Georgia Institute of Technology, February 1981. Conditional Generalizations of Strong Laws Which Conclude the Partial Sums Converge Almost Surely 9-31-010

6.

T.P. Hill<sup>1</sup>

#### Abstract

Suppose that for every independent sequence of random variables satisfying some hypothesis condition H, it follows that the partial sums converge almost surely. Then it is shown that for every arbitrarily-dependent sequence of random variables, the partial sums converge almost surely on the event where the conditional distributions (given the past) satisfy precisely the same condition H. Thus many strong laws for independent sequences may be immediately generalized into conditional results for arbitrarily-dependent sequences.

AMS(MOS) subject classifications (1970) Primary 60F15; Secondary 60G45.

<sup>1</sup>Partially supported by AFOSR Grant F49620-79-C-0123.

### CONDITIONAL GENERALIZATIONS OF STRONG LAWS

1

### 1. Introduction

If every sequence of independent random variables having property A has property B almost surely, does every arbitrarilydependent sequence of random variables have property B almost surely on the set where the conditional distributions have property A?

Not in general, but comparisons of the conditional Borel-Cantelli Lemmas, the conditional three-series theorem, and many martingale results with their independent counterparts suggest that the answer is affirmative in fairly general situations. The purpose of this note is to prove Theorem 1, which states, in part, that if "property B" is "the partial sums converge", then the answer is *always* affirmative, *hegandless* of "property A". Thus many strong laws for independent sequences (even laws yet undiscovered) may be immediately generalized into conditional results for arbitrarily-dependent sequences.

#### 2. Main Theorem

In this note,  $\Psi = (\Psi_1, \Psi_2, \cdots)$  is a sequence of random variables on a probability triple  $(\Omega, a, P)$ ,  $S_n = \Psi_1 + \Psi_2 + \cdots + \Psi_n$ , and  $F_n$  is the sigma field generated by  $\Psi_1, \cdots, \Psi_n$ . Let  $\pi_n(\cdot, \cdot)$ be a regular conditional distribution for  $\Psi_n$  given  $F_{n-1}$ , and  $\Pi = (\pi_1, \pi_2, \cdots)$ . Let B denote the Borel  $\sigma$ -field on  $\mathbb{R}$ , and  $B^{\infty}$ the product Borel  $\sigma$ -field on  $\mathbb{R}^{\infty}$ ; let  $P(\mathbb{R})$  denote the space of probability measures on  $(\mathbb{R}, \mathbb{B})$ , and let  $C = P(\mathbb{R}) \times P(\mathbb{R}) \times \cdots$ . As a final convention, let L(X) denote the distribution of the random variable X.

Let  $\mathcal{B} \in \mathcal{B}^{\infty}$ . With the above notation, the question this note addresses is: when is the following statement (S) true?

(S) If  $A \in C$  is such that  $(X_1, X_2, \dots) \in B$  a.s. whenever  $X_1, X_2, \dots$ are independent and  $(L(X_1), L(X_2), \dots) \in A$ , then for arbitrary  $\mathbb{Y}$ ,  $\mathbb{Y} \in B$  a.s. on the set where  $\Pi \in A$ .

A partial answer is given by

Theorem 1. (S) holds in the following three cases:

(i)  $B = \{(r_1, r_2, \dots) \in \mathbb{R}^{\infty} : \sum_{j=1}^{n} \text{ converges}\};$ (ii)  $B = \lim \inf_{n \to \infty} \{(r_1, r_2, \dots) : r_n \in A_n\}; \text{ and}$ (iii)  $B = \lim \sup_{n \to \infty} \{(r_1, r_2, \dots) : r_n \in A_n\},$ 

where  $A_n \in B$ ,  $n = 1, 2, \cdots$ ).

# 3. Applications of Theorem 1

As a first application of Theorem 1, consider the two wellknown conditional results: Levy's conditional form of the Borel-Cantelli Lemmas [4, p. 249],

(1) For any sequence of random variables  $Y_1, Y_2, \cdots$  taking only the values 0 and 1,  $\sum_{n=1}^{\infty} Y_n$  is finite (infinite) almost surely where  $\sum_{n=1}^{\infty} E(Y_n | F_{n-1})$  is finite (infinite);

and the conditional three-series theorem [e.g., 5, p. 66],

(2) For any sequence of random variables  $Y_1, Y_2, \cdots$ , the partial sums S<sub>n</sub> converge almost surely on the event where the three series

$$\sum_{n=1}^{\infty} P(|Y_n| \ge c |F_{n-1}), \qquad \sum_{n=1}^{\infty} E[Y_n | (|Y_n| \le c) |F_{n-1}], \text{ and}$$

$$\sum_{n=1}^{\infty} E[Y_n^2 | (|Y_n| \le c) |F_{n-1}] - E^2[Y_n | (|Y_n| \le c) |F_{n-1}] \text{ all converge.}$$

Both results (1) and (2) follow immediately from Theorem 1 and their classical counterparts for independent sequences. Similarly, in many martingale theorems the independent case is also the extremal one. As a second application of Theorem 1, for example, note that the following martingale results of Doob [2, p. 320] and of Chow [1] follow immediately from (i) and the special case of independence:

(3) If  $\{Y_n, F_n n \ge 1\}$  is a martingale difference sequence, then  $S_n$  converges a.s. where  $\sum_{1}^{\infty} \mathbb{E}[Y_n^2|F_{n-1}] < \infty$ ; and

(4) If  $\{Y_n, F_n \ n \ge 1\}$  is a martingale difference sequence and  $\{b_n, n \ge 1\}$  is a sequence of positive constants such that  $\sum_{1}^{\infty} b_n < \infty$ , then  $S_n$  converges almost surely where  $\sum_{1}^{\infty} b_n^{1-p/2} E[|Y_n|^p|F_{n-1}] > \infty$  for some p > 2.

Via Theorem 1(i) one may deduce immediately a conditional generalization of practically *any* result for sequences of independent random variables in which the conclusion is "S<sub>n</sub> converges almost surely." Although the above applications all have hypotheses

involving conditional moments, virtually any hypothesis conditions will carry over. As one final example, consider the well-known fact [e.g., 5, p. 102] that if  $Y_1, Y_2, \cdots$  are independent and  $S_n$  converges in probability, then  $S_n$  converges almost surely. Theorem 1 allows the generalization of this fact given by Theorem 2 below.

<u>Definition</u>. A sequence of probability measures  $(\mu_1, \mu_2, \cdots)$  sums in probability if, for any independent sequence of random variables  $X_1, X_2, \cdots$  with  $L(X_i) = \mu_i$ , it follows that  $X_1 + \cdots + X_n$  converges in probability to some random variable X.

<u>Theorem 2</u>. Let  $Y_1, Y_2, \cdots$  be an arbitrary sequence of random variables. Then  $S_n$  converges almost surely on the set where the conditional distributions I sum in probability.

4. Proof of Theorem 1.

For fixed  $B \in B^{\infty}$ , consider the statement

(S') 
$$P(\{\omega: P_{\Pi(\omega)}(B) = 1\} \cap \Psi \notin B = 0,$$

where  $\mathbb{P}_{\Pi(\omega)}$  is the product measure  $\pi_1(\omega) \times \pi_2(\omega) \times \cdots$  on  $(\mathbb{R}^{\infty}, \mathbb{B}^{\infty})$ .

Without loss of generality, assume  $(\Omega, a, P)$  is complete.

Lemma 1. (S)  $\Leftrightarrow$  (S').

<u>Proof</u>. "=> " Let  $A = \{ \stackrel{\rightarrow}{\mu} \in C : P_{\mu}(B) = 1 \}$ . Then  $\{ \omega : P_{\Pi}(\omega)(B) = 1 \} = \{ \omega : \Pi(\omega) \in A \}$ , so  $P(\{ \omega : P_{\Pi}(\omega)(B) = 1 \} \cap \mathbb{Y} \notin B) = P(\{ \omega : \Pi(\omega) \in A \} \cap \mathbb{Y} \notin B) = 0$ . "<="Since  $\{ \omega : \Pi(\omega) \in A \} \subset \{ \omega : P_{\Pi}(\omega)(B) = 1 \} \in a$ , it follows (by completeness) that  $P(\{ \omega : \Pi(\omega) \in A \} \cap \mathbb{Y} \notin B) = P(\{ \omega : P_{\Pi}(\omega)(B) = 1 \} \cap \mathbb{Y} \notin B) = 0$ .

## Proof of Theorem 1.

For (i), Lemma 1 implies it is enough to show that (S') holds for B = { $(r_1, r_2, \dots) \in \mathbb{R}^{\infty}$ :  $\sum_{j=1}^{n} converges$ }. Let  $(\hat{\Omega}, \hat{a}, \hat{P})$  be a copy of  $(\Omega, a, P)$ , and (enlarging this new space if necessary) for each  $\omega \in \Omega$ , let  $Z_1(\omega)$ ,  $Z_2(\omega)$ ,  $\cdots$  be a sequence of independent random variables on  $(\hat{\Omega}, \hat{a}, \hat{P})$  with  $L(Z_n(\omega)) = \pi_n(\omega)$ , (that is,  $\hat{P}(Z_n(\omega) \in E) = \pi_n(\omega, E) =$  $= P(Y_n \in E | Y_1(\omega), \dots, Y_{n-1}(\omega))$ . Then

(5) 
$$P(\{\omega: P_{\Pi(\omega)}(B)=1\} \cap \Psi \notin B)$$
.  

$$=P(\{\omega: Z_{1}(\omega) + \dots + Z_{n}(\omega) \text{ converges a.s. } (in \hat{\Omega}, \hat{a}, \hat{P})\} \cap \Psi \notin B)$$

$$=P(\{\omega: \text{ the three series } \sum_{1}^{\infty} \hat{P}(|Z_{n}(\omega)|\geq 1), \sum_{1}^{\infty} \hat{E}(Z_{n}(\omega) \cdot I(|Z_{n}|\leq 1), \text{ and}$$

$$\sum_{1}^{\infty} \hat{V}ar(Z_{n}(\omega) \cdot I(|Z_{n}|\leq 1)) \text{ all converge} \cap \Psi \notin B)$$

$$=P(\{\text{event where the three series } \sum_{1}^{\infty} P(|Y_{n}|\geq 1|F_{n-1}),$$

$$\sum_{1}^{\infty} E(Y_{n} \cdot I(|Y_{n}||1)|F_{n-1}), \text{ and } \sum_{1}^{\infty} [E(Y_{n}^{2} \cdot I(|Y_{n}|\leq 1)|F_{n-1}) -$$

where the first equality in (5) follows by the definition of  $Z_n(\omega)$ , the second by Kolmogorov's Three-Series Theorem and independence of the  $\{Z_i(\omega)\}$ , the third by definition of  $Z_n(\omega)$  and  $\pi_n$ , and the last by the conditional three series theorem (2). This completes the proof of (i).

 $- E^{2}(Y_{n}I(|Y_{n}|\leq 1)|F_{n-1})] \text{ all converge} \cap \Psi \notin B) = 0 ,$ 

For (ii) and (iii), application of the same technique using, in place of the three-series theorems, the classical and (Levy's) conditional form (1) of the Borel-Cantelli lemmas yields the desired conclusion.

### 5. Remarks

The class of sets  $B \in B^{\infty}$  for which (S) and (S') hold is not closed under complementation; a counterexample to the converse of the conditional three-series theorem due to Dvoretzky and to Gilat [3] demonstrates that (S) does not hold in general for  $B = "S_n$  does not converge". Whether (S) holds for such useful sets as  $"S_n/n + 0"$ , or "lim sup  $S_n/a_n = 1"$ , is not known to the author.

<u>Acknowledgement</u>. The author is grateful to Professor Lester Dubins for several useful conversations.

#### References

- 1. Chow, Y.S. (1965) Local convergence of martingales and the law of large numbers. Ann. Math. Statist., 36, 552-558.
- 2. Doob, J.L. (1953) "Stochastic Processes". Wiley, New York.
- Gilat, D. (1971) On the nonexistence of a three series condition for series of non-independent random variables. Ann. Math. Statist. 42, 409-410.
- Lévy, P. (1937) Theorie de l'addition des variables aleatoires. Gauthier-Villars, Paris.
- 5. Stout, W.F. (1974) "Almost Sure Convergence". Academic Press, New York.

6 -

Comparisons of Stop Rule and Supremum Expectations of

## i.i.d. Random Variables

(Stop Rule and Supremum Expectations)

by

T.P. Hill<sup>1</sup> Robert P. Kertz

#### Abstract

Implicitly defined (and easily approximated) universal constants  $1.1 < a_n < 1.6$ ,  $n=2,3,\cdots$ , are found so that if  $X_1, X_2, \cdots$  are i.i.d. non-negative random variables and if  $T_n$  is the set of stop rules for  $X_1, \cdots, X_n$ , then  $E(\max\{X_1, \cdots, X_n\}) \leq a_n \sup\{EX_t: t \in T_n\}$ , and the bound  $a_n$  is best possible. Similar universal constants  $0 < b_n < 1/4$  are found so that if the  $\{X_i\}$  are i.i.d. random variables taking values only in [a,b], then  $E(\max\{X_1, \cdots, X_n\}) \leq \sup\{EX_t: t \in T_n\} + b_n(b-a)$ , where again the bound  $b_n$  is best possible. In both situations extremal distributions for which equality is attained (or nearly attained) are given in implicit form.

 Partially supported by AFOSR Grant F49620-79-C-0123 AMS 1980 subject classifications. Primary 60G40, Secondary 62L15, 90C99.

Key Words and Phrases. Optimal Stopping, extremal distributions, inequalities for stochastic processes.

# §1. Introduction.

Let  $T_n$  denote the set of stop rules for random variables  $X_1, \dots, X_n$ . If the  $\{X_i\}$  are independent and non-negative, then it has been shown [4] that

(1) 
$$E(\max\{X_1, \dots, X_n\}) \leq 2 \sup\{EX_t: t \in T_n\}$$
 and

that 2 is the best possible bound, and [2] that in fact strict inequality holds in all but trivial cases. If the  $\{X_i\}$  are independent and take values only in [a,b], then

(2) 
$$E(\max\{X_1, \dots, X_n\}) \leq \sup\{EX_+: t \in T_n\} + (1/4)(b-a),$$

and 1/4 is the best possible bound [3]. Probabilistic interpretations have been given for these results: (1) says that the optimal return of a gambler (player using non-anticipating stop rules) is at least half that of the expected return of a prophet (player with complete foresight) playing the same game; and (2) says that a side payment of 1/8 the game limits, paid by the prophet to the gambler, makes the game at least favorable for the gambler.

If the random variables in question are not only independent, but also identically distributed, then it turns out that the gambler's situation improves, and the constants "2" and "1/4" in (1) and (2) respectively can be improved (lowered). The purpose of this paper is to determine these improvements. Probabilistically, the main results give the minimal odds and side payments, respectively, needed to achieve fairness for a gambler matched against a prophet playing the same game(in which the random variables are independent and identically distributed (i.i.d.)).

Implicitly defined (and easily approximated) universal constants 1.1 <  $a_n$  < 1.6, n=2,3,..., are found (e.g.,  $a_2 = 1.171$ ,  $a_{100} = 1.337$ ,  $a_{10,000} = 1.341$ ) satisfying the first main result,

<u>Theorem A.</u> If n > 1 and  $X_1, X_2, \dots, X_n$  are i.i.d. non-negative random variables, then  $E(\max\{X_1, \dots, X_n\}) \leq a_n \sup\{EX_t: t \in T_n\}$ . Moreover,  $a_n$  is the best possible bound and is not attained except in the trivial cases  $X_1$  is almost surely 0 or has infinite expectation.

Similar universal constants  $0 < b_n < 1/4$  are found (e.g.,  $b_2 = .0625$ ,  $b_{100} \stackrel{\sim}{=} .110$ ,  $b_{10,000} \stackrel{\sim}{=} .111$  satisfying the second main result,

<u>Theorem B.</u> If  $X_1, \dots, X_n$  are i.i.d. random variables taking values only in [a,b], then  $E(\max\{X_1, \dots, X_n\}) \leq \sup\{EX_t: t \in T_n\} + b_n(b-a)$ , (equivalently,  $E(\min\{X_1, \dots, X_n\}) \geq \inf\{EX_t: t \in T_n\} - b_n(b-a)$ ) and  $b_n$  is the best possible **b**ound and is attained.

In Proposition 4.4 actual distributions are given implicitly (but again, in easily approximated form) for which equality in Theorem A nearly holds; Proposition 5.3 likewise gives extremal distributions for which equality in Theorem B holds.

## \$2. Preliminaries.

For random variables X and Y, X v Y denotes the maximum of X and Y,  $X^+ = X v 0$ , and EX denotes the expectation of X. For  $n=1,2,\cdots,E_n(X)=E(X_1 \cdots X_n)$ , and  $V_n(X) = \sup\{EX_t:t \in T_n\}$ , where  $X_1, \cdots, X_n$  are i.i.d. random variables each with distribution that of X. Throughout the remainder of this paper, all random variables will be assumed to have finite expectation.

The first lemma, a special case of [1, p. 50], is included for ease of reference.

Lemma 2.1. (i)  $V_n(X) = E(X \vee V_{n-1}(X))$  for all n > 1; and (ii) if  $t^* \in T_n$  is the stop rule defined by  $t^* = j \iff \{t^* > j-1 \text{ and } X_j \ge V_{n-j}(X)\}$ , then  $EX_{t^*} = V_n(X)$ .

Lemmas 2.4 and 2.5 are probabilistic results which will be used in the proofs of Theorems A and B to restrict attention to simple random variables of special form. In setting up this reduction, a definition and a special case of a result (Lemma 2.2) from [3] are useful.

<u>Definition 2.2</u>. For random variable Y and constants  $0 \le a < b < \infty$ , let  $Y_a^b$  denote a random variable with  $Y_a^b = Y$  if  $Y \notin [a,b]$ , = a with probability  $(b-a)^{-1} \int_{Y \in [a,b]} (b-Y)$ , and = b otherwise.

Lemma 2.3. Let Y be any random variable and  $0 \le a < b < \infty$ . Then EY = EY<sup>b</sup><sub>a</sub>, and if X is any random variable independent of both Y and Y<sup>b</sup><sub>a</sub>, then E(X v Y)  $\le$  E(X v Y<sup>b</sup><sub>a</sub>).

It may be seen that  $Y_a^b$  is the distribution with maximum variance which both coincides with Y off [a,b] and has expectation EY.

Lemma 2.4. Let n > 1 and X be any random variable taking values in [0,1]. Then there exists a simple random variable Y, taking on only the values 0,  $V_1(X)$ ,  $V_2(X)$ ,  $\cdots$ ,  $V_{n-1}(X)$ , and 1, and satisfying both

$$V_j(Y) = V_j(X)$$
 for  $j=1,2,\cdots,n$ , and  $E_n(Y) \ge E_n(X)$ .

Proof. Define Y through Definition 2.2 by

and

 $Y = \left( \cdots \begin{pmatrix} v_1 & x \\ 0 \end{pmatrix} \begin{pmatrix} v_2 & x \\ v_1 & x \end{pmatrix} \right)^1 V_{n-1}(X)$  The conclusion follows easily from Lemmas 2.1 and 2.3.  $\Box$ 

Lemma 2.5. For n > 1, let X be a simple random variable taking values  $0 < V_1(X) < \cdots < V_{n-1}(X) < 1$  with probabilities  $p_0, p_1, \cdots, p_n$ respectively, and let  $s_1 = p_0 + \cdots + p_j$  and  $s_{-1} = 1$ . Then:

(i)  $V_j(x) = V_1(x) [1+s_0+s_0s_1+\cdots+s_0s_1\cdots s_{j-2}], j=2,\cdots,n;$ 

(ii) 
$$V_1(X) = (1-s_{n-1})/[(1-s_{n-1})(1+s_0+s_0s_1+\cdots+s_0s_1\cdots s_{n-3})+s_0s_1\cdots s_{n-2}];$$

(iii) 
$$E_n(X) = V_1(X)[(1+s_0+s_0s_1+\cdots+s_0s_1\cdots s_{n-3})+s_0s_1\cdots s_{n-2}(1+s_{n-1}+\cdots+s_{n-1}^{n-1})]$$
  
-( $s_0^n+s_0s_1^n+\cdots+s_0\cdots s_{n-3}s_{n-2}^n)$ ].

<u>Proof.</u> For (i), observe that by Lemma 2.1,  $V_j(X) = V_j(X)p_j^+$   $V_{j+1}(X) P_{j+1} + \cdots + V_{n-1}(X)p_{n-1}^+ + 1 \cdot p_n^+ + s_{j-1}V_{j-1}(X)$ . Since  $V_j(X)p_j + \cdots + V_{n-1}(X)p_{n-1}^+ + 1 \cdot p_n^- = V_1(X) - [V_1(X)p_1^+ + \cdots + V_{j-1}(X)p_{j-1}]$ , the desired conclusion follows easily by induction on j.

Conclusion (ii) follows since  $V_1(X) = V_1(X)(s_1 - s_0) + \cdots + V_{n-1}(X)(s_{n-1} - s_{n-2}) + (1 - s_{n-1})$  by solving the equations in (i) for  $V_1$  in terms of  $s_0, s_1, \cdots, s_{n-1-1}$ 

For (iii), note that  $E_n(X) = \sum_{j=1}^{n=1} V_j(X) (s_j^n - s_{j-1}^n) + (s_n^n - s_{n-1}^n)$ , and apply (i) and (ii).  $\Box$ 

For the proof of Theorem A the following complements to Definition 2.2. and Lemmas 2.3 and 2.4 are given.

Definition 2.6. For random variable Y and constants  $\alpha > a \ge 0$  satisfying  $\alpha \cdot P(Y \ge a) \ge \int_{Y \ge a} Y$ , let  $Y_{a,\alpha}$  denote a random variable with  $Y_{a,\alpha} = Y$  if  $Y_{\notin}[a,\infty)$ , =a with probability  $(\alpha-a)^{-1} \int_{Y \ge a} (\alpha-Y)$ , and = $\alpha$  otherwise.

Lemma 2.7. Let Y be any random variable and  $0 \le a < \infty$ . Then for all  $\alpha$  sufficiently large, EY=EY<sub>a,  $\alpha$ </sub> and if X is any random variable independent of both Y and Y<sub>a,  $\alpha$ </sub>, then E(X v Y)  $\le$  E(X v Y<sub>a,  $\alpha$ </sub>). This last inequality is strict if and only if P(X > a)  $\cdot$  P(Y > a) > 0.

<u>Proof.</u> That  $EY=EY_{a,\alpha}$  is immediate. For the remainder assume  $P(Y \ge a) > 0$ and fix any X independent of both Y and  $\{Y_{a,\alpha}\}$ . From the definition of  $Y_{a,\alpha}$ , the convexity of the function  $\psi(y) = E(X \lor y)$ , and the independence of X and Y, it follows that  $E(X \lor Y_{a,\alpha})$  is a non-decreasing function of  $\alpha$  and  $\lim_{\alpha \to \infty} E(X \lor Y_{a,\alpha}) = \int_{Y < a} X \lor Y + E(X \lor a)P(Y \ge a) + E(Y-a)^+$ , with the limit being attained if  $P(X > a) \cdot P(Y > a) = 0$ . The conclusion follows from these results and the dichotomy that  $\int_{Y < a} X \lor Y + E(X \lor a) = 0$ , and  $=E(X \lor Y)$  if  $P(X > a) \cdot P(Y > a) = 0$ . The strict inequality in this dichotomy follows since for  $P(X > a) \cdot P(Y > a) > 0$ ,  $\int_{X \ge a, Y \ge a} (X-a+Y-a) - \int_{X \ge a, Y \ge a} [(X-a) \lor (Y-a)] = \int_{X \ge a, Y \ge a} [(X-a) \land (Y-a)] > 0$ .

If P(Y>a)>0, then  $\{Y,\alpha\}$  are random variables which coincide with Y off  $[a,\infty)$ , have expectation EY, and have variances which increase to infinity.

Lemma 2.8. Let n > 1 and X be any non-negative unbounded (ess sup  $X = +\infty$ ) random variable. Then there exists a non-negative bounded random variable. Then there exists a non-negative bounded random variable Y satisfying both  $V_j(Y) = V_j(X)$  for  $j=1,2,\cdots,n$ , and  $E_n(Y) > E_n(X)$ . <u>Proof</u>. Define Y through Definition 2.6 by  $Y = X_{V_{n-1}}(X), \alpha$ . Then the conclusion follows from Lemmas 2.1 and 2.7 for  $\alpha$  sufficiently large.  $\Box$ 

§3. Definition of the constants  $\{a_n\}$  and  $\{b_n\}$ .

The purpose of this section, which is purely analytical (nonprobabilistic) in nature, is to define the constants  $\{a_n\}$  and  $\{b_n\}$ appearing in Theorems A and B, respectively, and to concurrently develop results useful in the proofs of these theorems.

 $\begin{array}{l} \underline{\text{Definition 3.1}} \text{. For } n > 1 \text{ and } w, x \in [0,\infty), \text{ let } \phi_n(w,x) = (n/(n-1)) \text{.} \\ w^{(n-1)/n} + x/(n-1) \text{. For } \alpha \in [0,\infty), \text{ define inductively the functions} \\ \eta_{j,n}, j=0,1,\cdots,n, \text{ by } \eta_{0,n}(\alpha) = \phi_n(0,\alpha), \text{ and } \eta_{j,n}(\alpha) = \phi_n(\eta_{j-1,n}(\alpha),\alpha). \end{array}$ 

Lemma 3.2.  $n_{j,n}$  is continuous, non-negative, strictly increasing and concave for all n > 1, and all  $j=0,1,\cdots,n$ .

<u>Proof</u>. Fix n > 1; proof will be by induction on j. First observe that  $\eta_{0,n}$  is continuous, and for  $\alpha > 0$ ,  $\eta_{0,n}(\alpha) > 0$ ,  $\eta'_{0,n}(\alpha) > 0$ , and  $\eta''_{0,n}(\alpha) = 0$  (where ()' denotes differentiation with respect to  $\alpha$ ). Assume  $\eta_{j-1,n}$  is continuous and for  $\alpha > 0$ , that  $\eta_{j-1,n}(\alpha) > 0$ ,  $\eta'_{j-1}(\alpha) > 0$ , and  $\eta''_{j-1,n}(\alpha) \leq 0$ . Then it is clear that  $\eta_{j,n}$  is continuous, and for

$$\alpha > 0, \eta_{j,n}(\alpha) > 0, \eta'_{j,n}(\alpha) > 0, \text{ and } \eta''_{j,n}(\alpha) = [\eta_{j-1,n}(\alpha)]^{-1/n}.$$

$$[(-n^{-1})(\eta_{j-1,n}(\alpha))^{-1}(\eta'_{j-1,n}(\alpha))^{2} + \eta''_{j-1,n}(\alpha)] \le 0 \quad \Box$$

<u>Definition 3.3</u>. Let  $G_n: [0,\infty) \to \mathbb{R}$  be the function  $G_n(\alpha) = \prod_{n=1,n} (\alpha)$ .

<u>Proposition 3.4</u>. (a) For all  $\alpha \in [0,1]$ ,  $G_n(\alpha) \leq \alpha [(n/(n-1))^n - 1] + [1 - ((n-1)/n)^{n-1}]$ ; and (b) there is a unique number  $\alpha_n > 0$  for which  $G_n(\alpha_n) = 1$ . Moreover,  $\alpha_n < 1$ , and for  $\alpha \in [0, \alpha_n]$ ,  $\alpha [(n/(n-1))^n - 1] \leq G_n(\alpha)$ .

<u>Proof</u>. Let  $\psi_{n}(w,x) = (n/(n-1))w + x/(n-1)$  for  $w,x, \epsilon[0,\infty)$ . For (a), define inductively the functions  $\sigma_{j,n}(\alpha)$ ,  $0 \le j \le n-1$ ,  $\alpha \epsilon[0,1]$ , by  $\sigma_{0,n}(\alpha) = \psi_{n}(0,\alpha)$  and  $\sigma_{j,n}(\alpha) = \psi_{n}(\sigma_{j-1,n}(\alpha) + c_{n}, \alpha)$ , where  $c_{n}=n^{-1}((n-1)/n)^{n-1}$ . It will be shown that  $\eta_{j,n}(\alpha) \le \sigma_{j,n}(\alpha)$ for all  $\alpha \epsilon[0,1]$ . First observe that  $\eta_{0,n}(\alpha) = \alpha/(n-1)$ , and assume  $\eta_{j-1,n}(\alpha) \le \sigma_{j-1,n}(\alpha)$ . Since  $x^{(n-1)/n} \le x + c_{n}$ , it follows that  $\eta_{j,n}(\alpha) = (n/(n-1))(\eta_{j-1,n}(\alpha))^{(n-1)/n} + \alpha/(n-1) \le (n/(n-1)) \cdot$  $(\sigma_{j-1,n}(\alpha))^{(n-1)/n} + \alpha/(n-1) \le (n/(n-1))(\sigma_{j-1,n}(\alpha)+c_{n})+\alpha/(n-1) = \sigma_{j,n}(\alpha)$ . For j=n-1, this yields  $\eta_{n-1,n}(\alpha) = G_{n}(\alpha) \le \sigma_{n-1,n}(\alpha) = \alpha[(n/(n-1))^{n}-1] +$  $[1-((n-1)/n)^{n-1}]$ , completing the proof of (a).

For (b), define inductively the functions  $\mu_{j,n}(\alpha)$ ,  $0 \le j \le n-1$ ,  $\alpha \in [0,1]$ , by  $\mu_{0,n}(\alpha) = \psi_n(0,\alpha)$  and  $\mu_{j,n}(\alpha) = \psi(\mu_{j-1,n}(\alpha),\alpha)$ . It shall first be shown that

(3)  $\mu_{j,n}(\alpha) \leq \eta_{j,n}(\alpha)$ , for  $0 \leq j \leq n-1$  and all  $\alpha \in [0,1]$  with  $G_n(\alpha) \leq 1$ .

Given  $\alpha \in [0,1]$  with  $G_n(\alpha) \leq 1$ , observe that  $\mu_{0,n}(\alpha) = \eta_{0,n}(\alpha) = \alpha/(n-1)$ , and assume that  $\mu_{j-1,n}(\alpha) \leq \eta_{j-1,n}(\alpha)$ . Since  $0 \leq \eta_{0,n}(\alpha) \leq \eta_{1,n}(\alpha) \leq \cdots \leq \eta_{n-1,n}(\alpha) = G_n(\alpha) \leq 1$  and  $x \leq x^{(n-1)/n}$  for  $x \in [0,1]$ , it follows that  $\mu_{j,n}(\alpha) = (n/(n-1)) \ \mu_{j-1,n}(\alpha) + \alpha/(n-1) \leq (n/(n-1)) \ \eta_{j-1,n}(\alpha))^{(n-1)/n} + \alpha/(n-1) = \eta_{j,n}(\alpha)$ , completing the proof of (3).

If  $G_n(\alpha) \leq 1$  for all  $\alpha \in [0,1]$ , then it would follow from (3) that  $G_n(1) = \eta_{n-1,n}(1) \geq \mu_{n-1,n}(1) = (n/(n-1))^n - 1 > e - 1 > 1$ , a contradiction. Thus there exists  $\alpha_n \in (0,1)$  with  $G_n(\alpha_n) = 1$ ; the uniqueness of  $\alpha_n$  follows from the strict monotonicity of  $\eta_{n-1,n}$  proved in Lemma 3.2.  $\Box$ 

Example 3.5. (a) For n=2,  $\phi_2(w,x) = 2\sqrt{w} + x$ ,  $G_2(\alpha) = 2\sqrt{\alpha} + \alpha$ , and  $\alpha_2 = 3 - 2\sqrt{2} \stackrel{\sim}{=} .171$ . (b)  $\alpha_3 \stackrel{\sim}{=} 0.221$ ,  $\alpha_4 \stackrel{\simeq}{=} 0.248$ ,  $\alpha_5 \stackrel{\simeq}{=} 0.264$ ,  $\alpha_{10} \stackrel{\simeq}{=} 0.301$ ,  $\alpha_{100} \stackrel{\simeq}{=} 0.337$ , and  $\alpha_{10,000} \stackrel{\simeq}{=} 0.341$ .

Although the authors believe that the  $\alpha_n$ 's are strictly monotone increasing with limit  $e^{-1}$ , they have established only the general quantitative information about them given in the following proposition.

Proposition 3.6 For all 
$$n > 1$$
,  
(a)  $[(n/(n-1))^{n-1} ((n/(n-1))^{n}-1)]^{-1} \le \alpha_n \le [(n/(n-1))^{n}-1]^{-1};$  and  
(b)  $(3e)^{-1} \le \alpha_n \le (e-1)^{-1}.$ 

<u>Proof</u>. Part (a) follows from Proposition 3.4 with  $\alpha = \alpha_n$ . Part (b) follows from (a) since  $(n/(n-1))^n > e$ , and  $(n/(n-1))^{n-1} e$ .

Definition 3.7. Let  $H_n:[0,1] \rightarrow \mathbb{R}$  be the function  $H_n(\beta) = (n-1) \cdot [\eta_{n,n}(\beta) - \eta_{n-1,n}(\beta)].$ 

<u>Proposition 3.8</u>. For each n > 1 there is a unique number  $\beta_n \in [0,1]$ such that  $H_n(\beta_n) = 1$ . Moreover,  $0 < \beta_n < 1$ .

<u>Proof</u>. Let  $f(x) = (n/(n-1))x^{(n-1)/n} - x$ , let  $g(\beta) = f(\eta_{n-1,n}(\beta))$ , and let u be the linear function  $u(\beta) = (1-\beta)/(n-1)$ . Then  $H_n(\beta)=1$ if and only if

(4) 
$$g(\beta) = u(\beta)$$
.

Let  $\alpha_n$  be as in Proposition 3.4(b). By Lemma 3.2,  $\eta_{n-1,n}$  is strictly increasing from 0 to 1 on  $[0,\alpha_n]$ . Since f is strictly increasing on [0,1], it follows that g is strictly increasing on  $[0,\alpha_n]$ , and since g(0) = 0 and  $g(\alpha_n)=1/(n-1)$ , it follows that (4) has a unique solution in  $[0,\alpha_n]$ . It remains only to show that (4) has no solution on  $[\alpha_n,1]$ . This will be accomplished by exhibiting a function t which lies between g and u on  $[\alpha_n,1]$ , and which has no points in common with u.

Let  $k_n = (n/(n-1))^n - 1$ , let  $d_n = 1 - ((n-1)/n)^{n-1}$ , and let

 $t(\beta) = f(k_n\beta + d_n)$  for  $\beta \in [0,1]$ . Since f is decreasing on  $[1,\infty)$ , in order to show that  $g(\beta) = f(n_{n-1,n}(\beta)) \ge f(k_n\beta + d_n) = t(\beta)$  on  $[\alpha_n, 1]$ , it suffices to show that

(5) 
$$1 \leq \eta_{n-1,n}(\beta) \leq \beta k_n + d_n$$
 for  $\beta \in [\alpha_n, 1]$ .

The first inequality in (5) follows since  $n_{n-1,n}$  is strictly increasing (Lemma 3.2) and since  $n_{n-1,n}(\alpha_n) = 1$ ; and the second by Proposition 3.4(a).

In order to show that t > u on  $[\alpha_n, 1]$ , it is enough to show that t > u on  $[b_n, 1]$ , where  $b_n = k_n^{-1}(1-d_n)$ , since  $b_n \le \alpha_n$  by Proposition 3.6(a). Since  $1 \le e - e^{-1} n/(n-1) \le k_n + d_n \le (n/(n-1))^n$ and f is decreasing on  $[1, \infty)$ , it follows that  $t(1) = f(k_n + d_n) >$ >  $f((n/(n-1))^n) = 0 = u(1)$ . But since  $u(b_n) \le (n-1)^{-1} = t(b_n)$ , and t is concave, it then follows that t > u on  $[b_n, 1]$ , completing the proof.  $\Box$ 

Example 3.9. (a) For n=2,  $H_2(\beta) = 2(2\sqrt{\beta} + \beta)^{1/2} - 2\beta^{1/2}$ , and  $\beta_2 = 1/16$ . (b)  $\beta_3 \stackrel{\sim}{=} .077$ ,  $\beta_4 \stackrel{\sim}{=} .085$ ,  $\beta_5 \stackrel{\sim}{=} .090$ ,  $\beta_{10} \stackrel{\sim}{=} .100$ ,  $\beta_{100} \stackrel{\sim}{=} .110$ ,  $\beta_{10,000} \stackrel{\sim}{=} .111$ .

Definition 3.10. For n > 1, let  $a_n = 1 + \alpha_n$ , and  $b_n = \beta_n$ .

§4. Proof of Theorem A and its extremal distributions.

Definition 4.1. For a random variable X with  $V_n(X) > 0$ , let  $R_n(X) = E_n(X)/V_n(X)$ ,  $n = 1, 2, \cdots$ .

Probabilistically,  $R_n(X)$  is the odds which must be given a gambler playing against a prophet (faced with the same n i.i.d. random variables each with distribution that of X) in order to make the game fair for the gambler.[In terms of  $R_n$ , Theorem A simply states that  $R_n(X) < a_n$  for all distributions X, and that the bound  $a_n$  is the best possible.]

<u>Proof of Theorem A</u>. Fix n > 1. The case where X has infinite expectation is trivial, so assume EX< $\infty$ . First, it shall be shown that it suffices to consider random variables taking values in [0,1] by proving that

(6) for any random variable X, there exists a random variable Y taking values in [0,1] for which  $R_n(X) \leq R_n(Y)$ .

For random variable X, from Lemma 2.8 there exists a bounded random variable Z such that  $R_n(X) \leq R_n(Z)$ . Define Y=Z/(supremum of Z); then Y is a random variable taking its values in [0,1] and  $R_n(X) \leq R_n(Z) = R_n(Y)$ . This establishes (6).

By Lemma 2.4, attention may be further restricted to simple random variables X taking on the values 0,  $V_1(X), \dots, V_{n-1}(X)$ , and 1 (with probabilities  $p_0, p_1, \dots, p_n$  respectively). Let  $s_j = p_0 + \dots + p_j$  for j=0,...,n-1 and let  $s_{-1}=1$ . Now, if  $s_{n-1}=0$  or 1, then X is constant and  $R_n(X)=1$ ; if  $0 < s_{n-1} < 1$ , then  $0 < V_1(X) < \cdots < V_{n-1}(X) < 1$  and from Lemma 2.5  $R_n(X) = R_n(s_0, \cdots, s_{n-1})$  where  $R_n(s_0, \cdots, s_{n-1})$  is the function defined for  $s_j \ge 0$ , j=0,...,n-1, by

(7) 
$$R_{n}(s_{0}, s_{1}, \cdots, s_{n-1}) =$$

$$1 + \frac{\binom{n-1}{j=1}s_{n-1}^{j}s_{0}s_{1}\cdots s_{n-2}-s_{0}^{n}-s_{0}s_{1}^{n}-\cdots-s_{0}\cdots s_{n-3}s_{n-2}^{n}}{1+s_{0}+s_{0}s_{1}+\cdots+s_{0}s_{1}\cdots s_{n-2}}$$

The conclusion of Theorem A follows once it is shown that

(8) there exists a unique point  $(\hat{s}_0, \dots, \hat{s}_{n-1})$  with  $0 < \hat{s}_0 < \dots < \hat{s}_{n-2} < \hat{s}_{n-1} =$ for which  $R_n(s_0, \dots, s_{n-1}) < R_n(\hat{s}_0, \dots, \hat{s}_{n-1}) = a_n$  for all  $(s_0, \dots, s_{n-1})$  with  $0 \le s_0 \le \dots \le s_{n-2} \le s_{n-1} < 1$ ,

where a was given in Definition 3.10.

For each  $(s_0, \dots, s_{n-1})$  with  $0 = s_j \le \dots \le s_{n-1} < 1$ ,  $R_n(s_0, \dots, s_{n-1}) = 1$ , and for each  $(s_0, \dots, s_{n-1})$  with  $0 < s_0 \le s_1 \le \dots \le s_{n-1} < 1$ ,  $R_n(s_0, \dots, s_{n-1}) < R_n(s_0, \dots, s_{n-2}, 1)$ . If the function  $r_n(s_0, \dots, s_{n-2})$ is defined for  $s_j \ge 0$ ,  $j=0, \dots, n-2$ , by  $r_n(s_0, \dots, s_{n-2}) =$  $R_n(s_0, \dots, s_{n-2}, 1)$ , then the proof of (8) follows from showing that (9) there is a unique point  $(\hat{s}_0, \dots, \hat{s}_{n-2})$  with  $0 < \hat{s}_0 < \dots < \hat{s}_{n-2} < 1$ for which  $\max\{r_n(s_0, \dots, s_{n-2}); 0 \le s_0 \le \dots \le s_{n-2} < 1\} =$  $= r_n(\hat{s}_0, \dots, \hat{s}_{n-2}) = a_n.$ 

First, verify that the following four statements are equivalent for  $(s_0, \dots, s_{n-2})$  with  $s_j > 0$  for  $j=0, \dots, n-2$ :

(10a) 
$$\frac{\partial \mathbf{r}_n}{\partial \mathbf{s}_j} (\mathbf{s}_0, \cdots, \mathbf{s}_{n-2}) = 0$$
 for j=0, ..., n-2;

(10b)  $n s_{j+1} \cdots s_{n-2} - n s_{j}^{n-1} + [(1-s_{j+1}^{n}) + s_{j+1}(1-s_{j+2}^{n}) + \cdots + s_{n-2} - n s_{j}^{n-1} + [(1-s_{j+1}^{n}) + s_{j+1}(1-s_{j+2}^{n}) + \cdots + s_{n-2} - n s_{j}^{n-1} + [(1-s_{j+1}^{n}) + s_{j+1}(1-s_{j+2}^{n}) + \cdots + s_{n-2} - n s_{j}^{n-1} + [(1-s_{j+1}^{n}) + s_{j+1}(1-s_{j+2}^{n}) + \cdots + n s_{n-2} - n s_{j}^{n-1} + [(1-s_{j+1}^{n}) + s_{j+1}(1-s_{j+2}^{n}) + \cdots + n s_{n-2} - n s_{j}^{n-1} + [(1-s_{j+1}^{n}) + s_{j+1}(1-s_{j+2}^{n}) + \cdots + n s_{n-2} - n s_{n$ 

$$s_{j+1} \cdots s_{n-3} (1-s_{n-2}^{n}) - r_n (s_0, \cdots, s_{n-2}) (1+s_{j+1}+s_{j+1}s_{j+2}+\cdots + s_{j+1}\cdots s_{n-2}) = 0 \text{ for } 0 \le j \le n-4,$$

$$ns_{n-2} - ns_{n-3}^{n-1} + (1-s_{n-2}^{n}) - r_n(s_0, \dots, s_{n-2}) \cdot (1+s_{n-2}) = 0$$
, and

$$n - n s_{n-2}^{n-1} - r_n(s_0, \cdots, s_{n-2}) = 0;$$

(10c) 
$$(n-1)s_{j+1}^n = ns_j^{n-1} + (n-1)s_0^n$$
 for  $0 \le j \le n-3$ , and

 $n-1 = ns_{n-2}^{n-1} + (n-1)s_0^n, \text{ and at } (s_0, \dots, s_{n-2}) \text{ satisfying these}$  $n-2 \text{ equations, } r_n(s_0, \dots, s_{n-2}) = 1 + (n-1)s_0^n; \text{ and}$ 

(10d) letting 
$$\alpha = (n-1)s_0^n$$
,  $\eta_{j,n}(\alpha) = s_j^n$  for  $0 \le j \le n-2$ ,  
 $l = \eta_{n-1,n}(\alpha) = G_n(\alpha)$ , and at  $(s_0, \dots, s_{n-2})$  satisfying these  
equations,  $r_n(s_0, \dots, s_{n-2}) = 1 + (n-1)s_0^n = 1+\alpha$ .

Let  $B \in \mathbb{R}^{n-1}$  be the region  $B = \{(s_0, \dots, s_{n-2}); s_j \ge 0 \text{ for } j=0, \dots, n-2\}$ . By (10a-d) and Proposition 3.4 there is a unique point  $(\hat{s}_0, \dots, \hat{s}_{n-2})$  in the interior of B at which  $\partial r_n / \partial s_j = 0$  for  $j=0,\dots, n-2$ , and at this point  $r_n(\hat{s}_0,\dots, \hat{s}_{n-2}) = 1 + (n-1)\hat{s}_0^n > 1$ . Thus the maxima and minima for  $r_n$  in B, if they exist, occur at  $(\hat{s}_0,\dots, \hat{s}_{n-2})$  or on the boundary of B. However, if  $s_j=0$  for some  $j=0,\dots, n-2$ , or if  $s_j \neq \infty$  for some or all  $j=0,\dots, n-2$ , then  $r_n(s_0,\dots, s_{n-2}) \le 1$ . Thus the maximum for  $r_n$  in B is at  $(\hat{s}_0,\dots, \hat{s}_{n-2})$ . Since  $0 < \hat{s}_0 < \dots < \hat{s}_{n-2} < 1$  from (10d), Definition 3.1, and Lemma 3.2, and since  $\{(s_0,\dots, s_{n-2}); 0 \le s_0 \le \dots \le s_{n-2} < 1\} \in B$ , it follows that (10d), Proposition 3.4, and Definition 3.10 imply that (9) holds. That the bound  $a_n$  is sharp is clear from the above reasoning (see also Proposition 4.4.).

Example 4.2. Let  $X_1, X_2, \cdots$  be non-negative i.i.d. random variables (with positive finite expectations). Calculations of  $\{a_n\}$  indicate that  $E(X_1 \vee X_2) < 1.172 \sup\{EX_t: t \in T_2\}$ ;  $E(X_1 \vee \cdots \vee X_{100}) < 1.338 \sup\{EX_t: t \in T_{100}\}$ and  $E(X_1 \vee \cdots \vee X_{10,000}) < 1.342 \sup\{EX_t: t \in T_{10,000}\}$ .

<u>Corollary 4.3</u>. Let  $X_1, X_2, \cdots$  be i.i.d. non-negative random variables and let T denote the stop rules for  $X_1, X_2, \cdots$ . Then  $E(\sup X_i) \leq (1+(e-1)^{-1}) \sup\{EX_{\pm}:t \in T\}$ .

Proof. Apply Proposition 3.6(b) to Theorem A.

It is perhaps of some interest to indentify distributions for which equality in Theorem A is nearly attained. For this purpose the following parameters are collected here. Fix n > 1. Let

 $\alpha_{n} \in (0,1)$  be the unique solution of  $G_{n}(\alpha_{n}) = 1$  from Proposition 3.4. For  $j=0, \dots, n-2$ ,  $\hat{s}_{j}$  is given by  $\hat{s}_{j} = (n_{j,n}(\alpha_{n}))^{1/n}$  and  $\hat{p}_{j}$  by  $\hat{p}_{0}=\hat{s}_{0}, \ \hat{p}_{j}=\hat{s}_{j}-\hat{s}_{j-1}$  for  $j=1,\dots, n-2$ , and  $\hat{p}_{n-1}=1-\hat{s}_{n-2}$ .

<u>Proposition 4.4</u>. For each n > 1 and  $\varepsilon > 0$  there exists a simple random variable  $\hat{X} = \hat{X}(n,\varepsilon)$  with  $P(\hat{X}=0)=\hat{p}_0$ ,  $P(\hat{X}=V_j(\hat{X}))=\hat{p}_j$  for  $j=0,\cdots,n-2$ ,  $P(\hat{X}=V_{n-1}(\hat{X})) \in (\hat{p}_{n-1}-\varepsilon,\hat{p}_{n-1})$  and  $P(\hat{X}=1) < \varepsilon$ satisfying  $R_n(\hat{X}) > a_n - \varepsilon$  and hence  $R_n(\hat{X}) > R_n(X) - \varepsilon$  for every non-negative random variable X.

<u>Proof</u>. For  $\varepsilon > 0$  sufficiently small consider the random variables  $X=X(n,\varepsilon)$  taking values  $0 < V_1(X) < \cdots < V_{n-1}(X) < 1$  with probabilities  $\hat{p}_0, \cdots, \hat{p}_{n-2}, \hat{p}_{n-1} - \varepsilon$ ,  $\varepsilon$  respectively; the values  $V_j(X)$ ,  $j=0, \cdots, n-1$ , can be computed from Lemma 2.5 (i,ii). From the proof of Theorem A it is clear that  $R_n(X(n,\varepsilon)) \neq a_n$  as  $\varepsilon > 0$ .

Example 4.5. (a) For n=2,  $(\hat{p}_0, \hat{p}_1) \stackrel{\sim}{=} (0.414, 0.586)$ . Calculations indicate that the random variable  $\hat{x}$  taking values 0, 2.41421 × 10<sup>-5</sup>, and 1 with probabilities 0.41421, 0.58578, and 10<sup>-5</sup> respectively satisfies  $R_2(\hat{x}) > R_2(X) - 10^{-4}$  for every non-negative random variable X. (b) For n=10,  $(\hat{p}_0, \dots, \hat{p}_9) \stackrel{\sim}{=} (0.711925, 0.070190, 0.047863, 0.037426, 0.030936, 0.026304, 0.022730, 0.019837, 0.017423, 0.015367))$ . For  $\epsilon > 0$  small consider the random variables  $\hat{x} = \hat{x}(n, \epsilon)$  taking values 0,  $\epsilon \cdot v_1, \dots, \epsilon \cdot v_9$ , and 1 with probabilities  $\hat{p}_0, \dots, \hat{p}_8$ ,  $\hat{p}_9 - \epsilon$ , and  $\epsilon$  respectively, where  $(v_1, \dots, v_9) \stackrel{\sim}{=} (3.32872, 5.69852, 7.55198, 9.09031, 10.4247, 11.6234, 12.7317, 13.7818, 14.7974)$ . For  $\epsilon > 0$  sufficiently small  $R_{10}(\hat{x}) > R_{10}(X) - 10^{-3}$  for every random variable X. The assumption of non-negativity in Theorem A is essential, as the following example shows.

<u>Example 4.6.</u> Let X be uniformly distributed on [0,1] (so  $E_n(X) > V_n(X)$  for all n > 1). For  $\varepsilon > 0$ , let  $Y_{\varepsilon} = X - V_n(X) + \varepsilon$ . Then  $E_n(Y_{\varepsilon}) = E_n(X) - V_n(X) + \varepsilon$ , and  $V_n(Y_{\varepsilon}) = \varepsilon$ , so  $1 + (E_n(X) - V_n(X))/\varepsilon = R_n(Y_{\varepsilon}) \gg \infty$  as  $\varepsilon \ge 0$ .

§5. Proof of Theorem B and its extremal distributions .

<u>Definition 5.1</u>. For a random variable X taking values in [0,1], let  $D_n(X) = E_n(X) - V_n(X)$ , n=1,2,...

Probabilistically,  $D_n(X)$  is twice the side payment which must be paid to a gambler playing against a prophet (faced with the same n independent random variables each with distribution that of X) in order to make the game fair for the gambler. In terms of  $D_n$ , the conclusion of Theorem B is that  $D_n(X) \leq b_n$  for all n, and that the bound  $b_n$  is the best possible and is attained.

<u>Proof of Theorem B</u>. Without loss of generality (add, or multiply by, suitable constants) a=0 and b=1. By Lemma 2.4, it may be assumed that X is a simple random variable taking on the values 0,  $V_1(X), \dots, V_{n-1}(X)$ , and 1 with probabilities  $p_0, p_1, \dots, p_n$ respectively. Let  $s_j = p_0 + p_1 + \dots + p_j$  for  $0 \le j \le n+1$ , and let  $s_{-1} = 1$ . By Lemma 2.5, for  $0 < s_{n-1} < 1$  (otherwise X is constant and  $D_n(X)$  $D_n(X) = D_n(s_0, s_1, \dots, s_{n-1})$  where  $D_n(s_0, \dots, s_{n-1})$  is the continuous function defined on  $\{(s_0, \dots, s_{n-1}); 0 \le s_0 \le \dots \le s_{n-1} \le 1\} \cup \{(s_0, \dots, s_{n-1}); 0 < s_{n-1} < 1$ and  $s_j > 0$  for  $j=0, \dots, n-2\}$  by

(11) 
$$D_{n}(s_{0},s_{1},\cdots,s_{n-1}) = 0 \text{ if } 0 = s_{0} = \cdots = s_{1} \leq \cdots \leq s_{n-1} = 1,$$
  
and 
$$= \frac{(1-s_{n-1})\left\{\binom{n-1}{j=1}s_{n-1}^{j}\right\}s_{0}s_{1}\cdots s_{n-2}-s_{0}^{n}-s_{0}s_{1}^{n}-\cdots -s_{0}s_{1}\cdots s_{n-3}s_{n-2}^{n}}{(1-s_{n-1})(1+s_{0}+s_{0}s_{1}+\cdots +s_{0}s_{1}\cdots s_{n-3}) + s_{0}s_{1}\cdots s_{n-2}}$$
otherwise.

It remains only to show that

(12) 
$$\max\{D_n(s_0,s_1,\cdots,s_{n-1}); 0 \le s_0 \le s_1 \le \cdots \le s_{n-1} \le 1\} = b_n$$

First observe that the following representations hold for  $(s_0, \dots, s_{n-1})$  with  $s_j > 0$  for  $j=0, \dots, n-2$  and  $0 < s_{n-1} < 1$ :

(13) 
$$\frac{\partial D_n}{\partial s_0} = (\mu_1/s_0)[D_n - (n-1)s_0^n];$$
  

$$s_{j+1} \frac{\partial D_n}{\partial s_{j+1}} - s_j \frac{\partial D_n}{\partial s_j} = \mu_1 s_0 \cdots s_j [D_n + ns_j^{n-1} - (n-1)s_{j+1}^n] \text{ for } 0 \le j \le n-3;$$

$$s_{n-1}(1-s_{n-1}) \frac{\partial D_n}{\partial s_{n-1}} = s_{n-2} \frac{\partial D_n}{\partial s_{n-2}} = \mu_1 s_0 \cdots s_{n-2} [D_n + n s_{n-2}^{n-1} - (n-1) s_{n-1}^{n}]; and$$

$$\frac{\partial D_n}{\partial s_{n-1}} = (-\mu_1 s_0 \cdots s_{n-2} / (1-s_{n-1})^2) [D_n - 1 + n s_{n-1}^{n-1} - (n-1) s_{n-1}^{n}];$$

where  $\mu_1 = V_1(s_0, \dots, s_{n-1})$ , the expression in Lemma 2.5(ii). From (13) it can be deduced that the following three statements are equivalent for  $(s_0, \dots, s_{n-1})$  with  $s_j > 0$  for  $j=0, \dots, n-2$  and  $0 < s_{n-1} < 1$ .

(14a) 
$$\frac{\partial D_n}{\partial s_j} (s_0, \dots, s_{n-1}) = 0$$
 for  $j = 0, \dots, n-1$ ;  
(14a)  $-ns_j^{n-1} - (n-1)s_0^n + (n-1)s_{j+1}^n = 0$  for  $j = 0, \dots, n-2$ ,  
 $-ns_{n-1}^{n-1} - (n-1)s_0^n + (n-1)s_{n-1}^n + 1 = 0$ , and at  $(s_0, \dots, s_{n-1})$  satisfying  
these n equations,  $D_n(s_0, \dots, s_{n-1}) = (n-1)s_0^n$ ; and

(14c) letting  $\beta = (n-1)s_0^n$ , then  $\eta_{j,n}(\beta) = s_j^n$  for  $0 \le j \le n-1$ ,

$$I = (n-1)(n_{n,n}(\beta) - n_{n-1,n}(\beta)) = H_n(\beta), \text{ and at } (s_0, \dots, s_{n-1})$$

satisfying these n equations,  $D_n(s_0, \dots, s_{n-1}) = (n-1)s_0^n = \beta$ .

Let C be the region  $C = \{(s_0, \dots, s_{n-1}); 0 \le s_0 \le \dots \le s_{n-1} \le 1\}$ . Over this region C,  $D_n \le 1$ , as can be seen by considering  $D_n$  as the difference of  $E_n(s_0, \dots, s_{n-1})$  and  $V_n(s_0, \dots, s_{n-1})$ , the expressions in Lemma 2.5 (iii) and (i) respectively. Hence, for  $(s_0, \dots, s_{n-1})$ in C satisfying (14c),  $0 \le D_n(s_0, \dots, s_{n-1}) = \beta \le 1$ , and only solutions of  $H_n(\beta) = 1$  in [0,1] are of interest. From this fact, Proposition 3.8, and (14a-c), there is a unique point  $(s_0, \dots, s_{n-1})$  in the interior of C at which  $\partial D_n / \partial s_j = 0$  for  $j = 0, \dots, n-1$ , and at this point  $D_n(s_0, \dots, s_{n-1})$   $= (n-1)s_0^n > 0$ . Thus the maxima and minima for  $D_n$  in C occur at  $(s_0, \dots, s_{n-1})$  or on the boundary of C.

Consider the behavior of  $D_n$  at and near the boundary of C. If  $s_0=0$  or  $s_{n-1}=1$  (or both), then  $D_n(s_0, \dots, s_{n-1})=0$ . Let  $(s_0, \dots, s_{n-1})$ be a boundary point of C satisfying  $0 < s_0 \leq \dots \leq s_j = s_{j+1} \leq \dots \leq s_{n-1} < 1$ . It can be shown from (13) that either  $D_n(s_0, \dots, s_{n-1}) \leq 0$  or  $(-1,1) \cdot (\frac{\partial D_n}{\partial s_j}, \frac{\partial D_n}{\partial s_{j+1}}) > 0$  if  $0 \leq j \leq n-3$  and  $(-1,1-s_{n-1}) \cdot (\frac{\partial D_n}{\partial s_{n-2}}, \frac{\partial D_n}{\partial s_{n-1}}) > ($ if j=n-2. From this observation one can find a point  $(\overline{s}_0, \dots, \overline{s}_{n-1})$ in the interior of C with  $D_n(\overline{s}_0, \dots, \overline{s}_{n-1}) > D_n(s_0, \dots, s_{n-1})$ . Thus the maximum for  $D_n$  in C is at  $(\widetilde{s}_0, \dots, \widetilde{s}_{n-1})$ , and (12) follows.

That the bound  $b_n$  is best possible is clear from the above reasoning (see also Proposition 5.3).  $\Box$ 

Example 5.2. Let  $X_1, X_2, \dots$  be i.i.d. random variables taking values in [0,1]. Calculations of  $\{b_n\}$  indicate that  $E(X_1 \vee X_2) - \sup\{EX_t: t \in T_2\} \le 0.0625$ ;  $E(X_1 \vee \dots \vee X_{100}) - \sup\{EX_t: t \in T_{100}\} \le 0.1101$ ; and  $E(X_1 \vee \dots \vee X_{10,000}) - \sup\{EX_t: t \in T_{10,000}\} \le 0.113$ .

In the present (additive comparison) case, unique extremal distributions (for which equality in Theorem B holds) can be given explicitly. For this purpose the following parameters are collected here. Fix n > 1. Let  $\beta_n \in (0,1)$  satisfy  $H_n(\beta_n)=1$  as in Proposition 3.8. For  $j=0,\cdots,n-1$ ,  $\hat{s}_j$  is given by  $\hat{s}_j=(\eta_{j,n}(\beta_n))^{1/n}$  and  $\hat{p}_j$  by  $\hat{p}_0=\hat{s}_0, \quad \hat{p}_j=\hat{s}_j-\hat{s}_{j-1}$  for  $j=1,\cdots,n-1$ , and  $\hat{p}_n=1-\hat{s}_{n-1}$ .

<u>Proposition 5.3</u>. For each n > 1, let  $\tilde{Y} = \tilde{Y}(n)$  be the simple random variable taking values 0,  $V_1(\tilde{Y}), \dots, V_{n-1}(\tilde{Y})$ , and 1 with probabilities  $\tilde{p}_0, \dots, \tilde{p}_n$  respectively. Then  $D_n(\tilde{Y}) = b_n$ .

Note that the values  $V_1(\tilde{Y}_1), \dots, V_{n-1}(\tilde{Y})$  can be computed from Lemma 2.5 (i,ii) through  $\tilde{s}_0, \dots, \tilde{s}_{n-1}$ .

Example 5.4. (a)  $\mathring{Y}(2)=0, 1/2$ , and 1 with probabilities 1/4, 1/2, and 1/4 respectively, and  $D_2(\mathring{Y}(2))=b_2=1/16$ .

(b)  $\tilde{\Upsilon}(10) \cong 0$ , .166, .272, .347, .404, .449, .486, .517, .545, .570, 1 with probabilities  $\cong$  .638, .067, .048, .039, .033, .029, .026, .023, .021, .019, .054 respectively and  $D_{10}(\tilde{\Upsilon}(10)) = b_{10} \cong .100$ . §6. Remarks.

It is easy to see that for any fixed distribution X,  $R_n(X) \rightarrow 1$  and  $D_n(X) \rightarrow 0$  as  $n \rightarrow \infty$ , that is,  $\lim_{n \rightarrow \infty} E(X_1 \lor \cdots \lor X_n) = \lim_{n \rightarrow \infty} \sup\{EX_t : t \in T_n\}$  where  $X_1, X_2, \cdots$  are independent random variables each with distribution that of X.

The parenthetical conclusion in Theorem B that  $E(\min\{X_1, \dots, X_n\}) \ge \inf\{EX_t : t \in T_n\} - b_n(b-a)$  is immediate by symmetry. In contrast, no corresponding universal constant exists for ratio comparisons of  $E(\min\{X_1, \dots, X_n\})$  and  $\inf\{EX_t : t \in T_n\}$ . See example 4.1 in [3].

Although the authors believe that the constants  $\{a_n\}$ and  $\{b_n\}$  are monotonically increasing, and hence convergent, they have not been able to demonstrate this nor identify the limits.

<u>Acknowledgement</u>. The authors would like to thank Professor M.J. Christensen for assistance with the numerical approximations of the constants, and Professors I. Aharoni and L. Karlovitz for several useful conversations related to analysis of the functions  $G_n$  and  $H_n \cdot$ 

# References

- Y.S. Chow, H. Robbins, and D. Siegmund. <u>Great Expectations</u>: The Theory of Optimal Stopping, Houghton Mifflin, Boston (1971).
- 2. T.P. Hill and R.P. Kertz, "Ratio Comparisons of Supremum and Stop Rule Expectations," to appear.
- 3. T.P. Hill and R.P. Kertz, "Additive Comparisons of Stop Rule and Supremum Expectations of Uniformly Bounded Independent Random Variables," to appear.
- U. Krengel and L. Sucheston, "On Semiamarts, Amarts, and Processes with Finite Value," Advances in Probability, Vol. 4 (1978), 197-266.