Optimal Sequential Selection Alternating Subsequences: Means, Concentration, and CLTs

J. Michael Steele

University of Pennsylvania The Wharton School Department of Statistics

IWAP and ECM8: Summer 2012

Introduction and Motivation

- Famous combinatorial problems with long mathematical history on sequences of *n* real numbers, or permutations of the integers 1, ..., *n*
 - Erdős and Szekeres (1935): monotone subsequences
 - ► Fan Chung (1980): unimodal subsequences
 - Euler (c.f. Stanley, 2010): alternating permutations

Introduction and Motivation

- Famous combinatorial problems with long mathematical history on sequences of *n* real numbers, or permutations of the integers 1,..., *n*
 - Erdős and Szekeres (1935): monotone subsequences
 - Fan Chung (1980): unimodal subsequences
 - Euler (c.f. Stanley, 2010): alternating permutations
- Probabilistic version (full-information)
 - Longest monotone subsequences: Hammersley (1972), Kingman (1973), Logan and Shepp (1977), Veršik and Kerov (1977), ...
 - Longest Unimodal subsequences: Steele (1981)
 - Longest Alternating subsequences: Widom (2006), Pemantle (c.f. Stanley, 2007), Stanley (2008), Houdré and Restrepo (2010)



Introduction and Motivation

- Famous combinatorial problems with long mathematical history on sequences of *n* real numbers, or permutations of the integers 1, ..., *n*
 - Erdős and Szekeres (1935): monotone subsequences
 - Fan Chung (1980): unimodal subsequences
 - Euler (c.f. Stanley, 2010): alternating permutations
- Probabilistic version (full-information)
 - Longest monotone subsequences: Hammersley (1972), Kingman (1973), Logan and Shepp (1977), Veršik and Kerov (1977), ...
 - Longest Unimodal subsequences: Steele (1981)
 - Longest Alternating subsequences: Widom (2006), Pemantle (c.f. Stanley, 2007), Stanley (2008), Houdré and Restrepo (2010)
- Study the sequential (on-line) version of these problems
 - Objective: maximize the expected length (number of selections) of monotone, unimodal and alternating subsequences



Full-information vs. on-line — Increasing





Full-information vs. on-line — Increasing



Full-information vs. on-line — Increasing



Full-information vs. on-line — Unimodal





Full-information vs. on-line — Unimodal



Full-information vs. on-line — Unimodal



Theorem (On-Line Monotone: The Leading Case)

There is a policy $\pi^* \in \Pi(n)$ such that $\mathbb{E}[I_n^o(\pi^*)] = \sup_{\pi \in \Pi(n)} E[I_n^o(\pi)]$, and for such an optimal policy and all $n \ge 1$ one has

 $\mathbb{E}[I_n^o(\pi^*)]$

Theorem (On-Line Monotone: The Leading Case)

There is a policy $\pi^* \in \Pi(n)$ such that $\mathbb{E}[I_n^o(\pi^*)] = \sup_{\pi \in \Pi(n)} E[I_n^o(\pi)]$, and for such an optimal policy and all $n \ge 1$ one has

 $(2n)^{1/2} - (8n)^{1/4} - 2 < \mathbb{E}[I_n^o(\pi^*)]$

Theorem (On-Line Monotone: The Leading Case)

There is a policy $\pi^* \in \Pi(n)$ such that $\mathbb{E}[I_n^o(\pi^*)] = \sup_{\pi \in \Pi(n)} E[I_n^o(\pi)]$, and for such an optimal policy and all $n \ge 1$ one has

$$(2n)^{1/2} - (8n)^{1/4} - 2 < \mathbb{E}[I_n^o(\pi^*)] < (2n)^{1/2}.$$

Theorem (On-Line Monotone: The Leading Case)

There is a policy $\pi^* \in \Pi(n)$ such that $\mathbb{E}[I_n^o(\pi^*)] = \sup_{\pi \in \Pi(n)} E[I_n^o(\pi)]$, and for such an optimal policy and all $n \ge 1$ one has

$$(2n)^{1/2} - (8n)^{1/4} - 2 < \mathbb{E}[I_n^o(\pi^*)] < (2n)^{1/2}.$$

So, in particular, one has $\mathbb{E}[I_n^o(\pi^*)] \sim (2n)^{1/2}$ as $n \to \infty$.

Theorem (On-Line Monotone: The Leading Case)

There is a policy $\pi^* \in \Pi(n)$ such that $\mathbb{E}[I_n^o(\pi^*)] = \sup_{\pi \in \Pi(n)} E[I_n^o(\pi)]$, and for such an optimal policy and all $n \ge 1$ one has

$$(2n)^{1/2} - (8n)^{1/4} - 2 < \mathbb{E}[I_n^o(\pi^*)] < (2n)^{1/2}.$$

So, in particular, one has $\mathbb{E}[I_n^o(\pi^*)] \sim (2n)^{1/2}$ as $n \to \infty$.

- Asymptotic behavior: Samuels and Steele (1981)
- Upper bound: Bruss and Robertson (1991), Gnedin (1999)
- Lower bound: Rhee and Talagrand (1991)

Theorem (On-Line Monotone: The Leading Case)

There is a policy $\pi^* \in \Pi(n)$ such that $\mathbb{E}[I_n^o(\pi^*)] = \sup_{\pi \in \Pi(n)} E[I_n^o(\pi)]$, and for such an optimal policy and all $n \ge 1$ one has

$$(2n)^{1/2} - (8n)^{1/4} - 2 < \mathbb{E}[I_n^o(\pi^*)] < (2n)^{1/2}.$$

So, in particular, one has $\mathbb{E}[I_n^o(\pi^*)] \sim (2n)^{1/2}$ as $n \to \infty$.

- Asymptotic behavior: Samuels and Steele (1981)
- Upper bound: Bruss and Robertson (1991), Gnedin (1999)
- Lower bound: Rhee and Talagrand (1991)
- Well seasoned results 21 years or older. Can we say something NEW?

Theorem (On-Line Monotone: The Leading Case)

There is a policy $\pi^* \in \Pi(n)$ such that $\mathbb{E}[I_n^o(\pi^*)] = \sup_{\pi \in \Pi(n)} E[I_n^o(\pi)]$, and for such an optimal policy and all $n \ge 1$ one has

$$(2n)^{1/2} - (8n)^{1/4} - 2 < \mathbb{E}[I_n^o(\pi^*)] < (2n)^{1/2}.$$

So, in particular, one has $\mathbb{E}[I_n^o(\pi^*)] \sim (2n)^{1/2}$ as $n \to \infty$.

- Asymptotic behavior: Samuels and Steele (1981)
- Upper bound: Bruss and Robertson (1991), Gnedin (1999)
- Lower bound: Rhee and Talagrand (1991)
- Well seasoned results 21 years or older. Can we say something NEW?

Theorem (Something New – Variance Bounds (Arlotto & Steele, 2011))

For all $n \ge 1$, one has

 $\mathbb{E}[I_n^o(\pi^*)]/3 - 2 \leq \operatorname{Var}[I_n^o(\pi^*)] \leq \mathbb{E}[I_n^o(\pi^*)].$

Theorem (On-Line Monotone: The Leading Case)

There is a policy $\pi^* \in \Pi(n)$ such that $\mathbb{E}[I_n^o(\pi^*)] = \sup_{\pi \in \Pi(n)} E[I_n^o(\pi)]$, and for such an optimal policy and all $n \ge 1$ one has

$$(2n)^{1/2} - (8n)^{1/4} - 2 < \mathbb{E}[I_n^o(\pi^*)] < (2n)^{1/2}.$$

So, in particular, one has $\mathbb{E}[I_n^o(\pi^*)] \sim (2n)^{1/2}$ as $n o \infty.$

- Asymptotic behavior: Samuels and Steele (1981)
- Upper bound: Bruss and Robertson (1991), Gnedin (1999)
- Lower bound: Rhee and Talagrand (1991)
- Well seasoned results 21 years or older. Can we say something NEW?

Theorem (Something New – Variance Bounds (Arlotto & Steele, 2011))

For all $n \ge 1$, one has

 $\mathbb{E}[I_n^o(\pi^*)]/3 - 2 \leq \operatorname{Var}[I_n^o(\pi^*)] \leq \mathbb{E}[I_n^o(\pi^*)].$

• Bin-packing Connection: SMS is cognate to a special bin packing problem, and the proof of this variance bound applies to a *rich class* of these.

Theorem (Arlotto & Steele, 2011)

There is a policy $\pi^* \in \Pi(n)$ such that $\mathbb{E}[U_n^o(\pi^*)] = \sup_{\pi \in \Pi(n)} E[U_n^o(\pi)]$, and for such an

optimal policy and all $n \ge 1$ one has

 $\mathbb{E}[U_n^o(\pi^*)]$

Theorem (Arlotto & Steele, 2011)

There is a policy $\pi^* \in \Pi(n)$ such that $\mathbb{E}[U_n^o(\pi^*)] = \sup_{\pi \in \Pi(n)} E[U_n^o(\pi)]$, and for such an

optimal policy and all $n \ge 1$ one has

$$2n^{1/2} - O(n^{1/4}) < \mathbb{E}[U_n^o(\pi^*)]$$

Theorem (Arlotto & Steele, 2011)

There is a policy $\pi^* \in \Pi(n)$ such that $\mathbb{E}[U_n^o(\pi^*)] = \sup_{\pi \in \Pi(n)} E[U_n^o(\pi)]$, and for such an

optimal policy and all $n \ge 1$ one has

$$2n^{1/2} - O(n^{1/4}) < \mathbb{E}[U_n^o(\pi^*)] < 2n^{1/2}.$$

Theorem (Arlotto & Steele, 2011)

There is a policy $\pi^* \in \Pi(n)$ such that $\mathbb{E}[U_n^o(\pi^*)] = \sup_{\pi \in \Pi(n)} E[U_n^o(\pi)]$, and for such an

optimal policy and all $n \ge 1$ one has

$$2n^{1/2} - O(n^{1/4}) < \mathbb{E}[U_n^o(\pi^*)] < 2n^{1/2}.$$

So, in particular, one has

$$\mathbb{E}[U_n^o(\pi^*)] \sim 2n^{1/2}$$
 as $n \to \infty$.

Theorem (Arlotto & Steele, 2011)

There is a policy $\pi^* \in \Pi(n)$ such that $\mathbb{E}[U_n^o(\pi^*)] = \sup_{\pi \in \Pi(n)} E[U_n^o(\pi)]$, and for such an

optimal policy and all $n \ge 1$ one has

$$2n^{1/2} - O(n^{1/4}) < \mathbb{E}[U_n^o(\pi^*)] < 2n^{1/2}.$$

So, in particular, one has

$$\mathbb{E}[U_n^o(\pi^*)]\sim 2n^{1/2} \quad \text{ as } n o\infty.$$

Theorem (Arlotto & Steele, 2011)

For all $n \ge 1$, one has

$$\operatorname{Var}[U_n^o(\pi^*)] \leq \mathbb{E}[U_n^o(\pi^*)].$$

Theorem (Arlotto & Steele, 2011)

There is a policy $\pi^* \in \Pi(n)$ such that $\mathbb{E}[U_n^o(\pi^*)] = \sup_{\pi \in \Pi(n)} E[U_n^o(\pi)]$, and for such an

optimal policy and all $n \ge 1$ one has

$$2n^{1/2} - O(n^{1/4}) < \mathbb{E}[U_n^o(\pi^*)] < 2n^{1/2}.$$

So, in particular, one has

$$\mathbb{E}[U_n^o(\pi^*)] \sim 2n^{1/2}$$
 as $n \to \infty$.

Theorem (Arlotto & Steele, 2011)

For all $n \ge 1$, one has

$$\operatorname{Var}[U_n^o(\pi^*)] \leq \mathbb{E}[U_n^o(\pi^*)].$$

• MDP Connections: Here we have a second MDP where "the mean bounds the variance." This and further examples promise the beginning of a handy theory that knits all the examples together.

J. M. Steele (Upenn, Wharton)

Theorem (Arlotto, Chen, Shepp, Steele, 2011)

For each $n = 1, 2, ..., there is a policy \pi_n^* \in \Pi$ such that $\mathbb{E}[A_n^o(\pi_n^*)] = \sup_{\pi \in \Pi} \mathbb{E}[A_n^o(\pi)]$, and

for such an optimal policy one has for all $n \ge 1$ that

 $\mathbb{E}[A_n^o(\pi_n^*)]$

Theorem (Arlotto, Chen, Shepp, Steele, 2011)

For each $n = 1, 2, ..., there is a policy \pi_n^* \in \Pi$ such that $\mathbb{E}[A_n^o(\pi_n^*)] = \sup_{\pi \in \Pi} \mathbb{E}[A_n^o(\pi)]$, and

for such an optimal policy one has for all $n \ge 1$ that

$$(2-\sqrt{2})n \leq \mathbb{E}[A_n^o(\pi_n^*)]$$

Theorem (Arlotto, Chen, Shepp, Steele, 2011)

For each $n = 1, 2, ..., there is a policy \pi_n^* \in \Pi$ such that $\mathbb{E}[A_n^o(\pi_n^*)] = \sup_{\pi \in \Pi} \mathbb{E}[A_n^o(\pi)]$, and

for such an optimal policy one has for all $n \ge 1$ that

$$(2-\sqrt{2})n \leq \mathbb{E}[A_n^o(\pi_n^*)] \leq (2-\sqrt{2})n + C,$$

where C is a constant with $C < 11 - 4\sqrt{2} \sim 5.343$.

Theorem (Arlotto, Chen, Shepp, Steele, 2011)

For each $n = 1, 2, ..., there is a policy <math>\pi_n^* \in \Pi$ such that $\mathbb{E}[A_n^o(\pi_n^*)] = \sup_{\pi \in \Pi} \mathbb{E}[A_n^o(\pi)]$, and

for such an optimal policy one has for all $n \ge 1$ that

$$(2-\sqrt{2})n \leq \mathbb{E}[A_n^o(\pi_n^*)] \leq (2-\sqrt{2})n + C,$$

where C is a constant with C $< 11-4\sqrt{2}\sim 5.343.$ In particular, one has

$$\mathbb{E}[A_n^o(\pi_n^*)] \sim (2-\sqrt{2})n \quad \text{as } n o \infty.$$

Theorem (Arlotto, Chen, Shepp, Steele, 2011)

For each n = 1, 2, ..., there is a policy $\pi_n^* \in \Pi$ such that $\mathbb{E}[A_n^o(\pi_n^*)] = \sup_{\pi \in \Pi} \mathbb{E}[A_n^o(\pi)]$, and for such an optimal policy one has for all n > 1 that

$$(2-\sqrt{2})n\leq \mathbb{E}[A_n^o(\pi_n^*)]\leq (2-\sqrt{2})n+C,$$

where C is a constant with C $< 11-4\sqrt{2}\sim 5.343.$ In particular, one has

$$\mathbb{E}[A_n^o(\pi_n^*)] \sim (2-\sqrt{2})n \quad \text{as } n o \infty.$$

Theorem (Arlotto, Chen, Shepp, Steele, 2011)

For each $0 < \rho < 1$, there is a $\pi^* \in \Pi$, such that $\mathbb{E}[A_N^o(\pi^*)] = \sup_{\pi \in \Pi} \mathbb{E}[A_N^o(\pi)]$, and for such an optimal policy one has

$$\mathbb{E}[A_N^o(\pi^*)] = \frac{3 - 2\sqrt{2} - \rho + \rho\sqrt{2}}{\rho(1-\rho)}$$

Theorem (Arlotto, Chen, Shepp, Steele, 2011)

For each n = 1, 2, ..., there is a policy $\pi_n^* \in \Pi$ such that $\mathbb{E}[A_n^o(\pi_n^*)] = \sup_{\pi \in \Pi} \mathbb{E}[A_n^o(\pi)]$, and for such an optimal policy one has for all $n \ge 1$ that

$$(2-\sqrt{2})n \leq \mathbb{E}[A_n^o(\pi_n^*)] \leq (2-\sqrt{2})n+C$$

where C is a constant with C $< 11-4\sqrt{2}\sim 5.343.$ In particular, one has

$$\mathbb{E}[A_n^o(\pi_n^*)] \sim (2-\sqrt{2})n \quad \text{as } n o \infty.$$

Theorem (Arlotto, Chen, Shepp, Steele, 2011)

For each $0 < \rho < 1$, there is a $\pi^* \in \Pi$, such that $\mathbb{E}[A_N^o(\pi^*)] = \sup_{\pi \in \Pi} \mathbb{E}[A_N^o(\pi)]$, and for such an optimal policy one has

$$\mathbb{E}[\mathcal{A}_{\mathcal{N}}^{o}(\pi^{*})] = \frac{3 - 2\sqrt{2} - \rho + \rho\sqrt{2}}{\rho(1-\rho)} \sim (2 - \sqrt{2})(1-\rho)^{-1} \sim (2 - \sqrt{2})\mathbb{E}\mathcal{N} \quad \textit{as} \ \rho \to 1.$$

• Finite-horizon Bellman equation:

$$v_{i,n}(s,r) = \begin{cases} sv_{i+1,n}(s,0) + \int_{s}^{1} \max\{v_{i+1,n}(s,0), 1 + v_{i+1,n}(x,1)\} dx & \text{if } r = 0 \end{cases}$$

• Finite-horizon Bellman equation:

$$v_{i,n}(s,r) = \begin{cases} sv_{i+1,n}(s,0) + \int_{s}^{1} \max\{v_{i+1,n}(s,0), 1 + v_{i+1,n}(x,1)\} dx & \text{if } r = 0\\ (1-s)v_{i+1,n}(s,1) + \int_{0}^{s} \max\{v_{i+1,n}(s,1), 1 + v_{i+1,n}(x,0)\} dx & \text{if } r = 1 \end{cases}$$

• Finite-horizon Bellman equation:

$$v_{i,n}(s,r) = \begin{cases} sv_{i+1,n}(s,0) + \int_{s}^{1} \max\{v_{i+1,n}(s,0), 1 + v_{i+1,n}(x,1)\} dx & \text{if } r = 0\\ (1-s)v_{i+1,n}(s,1) + \int_{0}^{s} \max\{v_{i+1,n}(s,1), 1 + v_{i+1,n}(x,0)\} dx & \text{if } r = 1 \end{cases}$$

• Reflection identity: $v_{i,n}(s,0) = v_{i,n}(1-s,1)$ for all $1 \le i \le n$ and all $s \in [0,1]$.

• Finite-horizon Bellman equation:

$$v_{i,n}(s,r) = \begin{cases} sv_{i+1,n}(s,0) + \int_{s}^{1} \max\{v_{i+1,n}(s,0), 1 + v_{i+1,n}(x,1)\} dx & \text{if } r = 0\\ (1-s)v_{i+1,n}(s,1) + \int_{0}^{s} \max\{v_{i+1,n}(s,1), 1 + v_{i+1,n}(x,0)\} dx & \text{if } r = 1 \end{cases}$$

- Reflection identity: $v_{i,n}(s,0) = v_{i,n}(1-s,1)$ for all $1 \le i \le n$ and all $s \in [0,1]$.
- "Flipped" finite-horizon Bellman equation:

$$v_{i,n}(y) = yv_{i+1,n}(y) + \int_{y}^{1} \max \left\{ v_{i+1,n}(y), \quad 1 + v_{i+1,n}(1-x) \right\} dx.$$

• Finite-horizon Bellman equation:

$$v_{i,n}(s,r) = \begin{cases} sv_{i+1,n}(s,0) + \int_{s}^{1} \max\left\{v_{i+1,n}(s,0), 1 + v_{i+1,n}(x,1)\right\} dx & \text{if } r = 0\\ (1-s)v_{i+1,n}(s,1) + \int_{0}^{s} \max\left\{v_{i+1,n}(s,1), 1 + v_{i+1,n}(x,0)\right\} dx & \text{if } r = 1 \end{cases}$$

- Reflection identity: $v_{i,n}(s,0) = v_{i,n}(1-s,1)$ for all $1 \le i \le n$ and all $s \in [0,1]$.
- "Flipped" finite-horizon Bellman equation:

$$v_{i,n}(y) = yv_{i+1,n}(y) + \int_{y}^{1} \max \left\{ v_{i+1,n}(y), \frac{1 + v_{i+1,n}(1-x)}{1 + v_{i+1,n}(1-x)} \right\} dx.$$

• Finite-horizon Bellman equation:

$$v_{i,n}(s,r) = \begin{cases} sv_{i+1,n}(s,0) + \int_{s}^{1} \max\left\{v_{i+1,n}(s,0), 1 + v_{i+1,n}(x,1)\right\} dx & \text{if } r = 0\\ (1-s)v_{i+1,n}(s,1) + \int_{0}^{s} \max\left\{v_{i+1,n}(s,1), 1 + v_{i+1,n}(x,0)\right\} dx & \text{if } r = 1 \end{cases}$$

- Reflection identity: $v_{i,n}(s,0) = v_{i,n}(1-s,1)$ for all $1 \le i \le n$ and all $s \in [0,1]$.
- "Flipped" finite-horizon Bellman equation:

$$v_{i,n}(y) = yv_{i+1,n}(y) + \int_{y}^{1} \max \left\{ v_{i+1,n}(y), \quad 1 + v_{i+1,n}(1-x) \right\} dx.$$

• "Flipped" infinite-horizon Bellman equation — the "Easy One":

$$v(y) = \rho y v(y) + \int_{y}^{1} \max \{ \rho v(y), 1 + \rho v(1-x) \} dx.$$

• Finite-horizon Bellman equation:

$$v_{i,n}(s,r) = \begin{cases} sv_{i+1,n}(s,0) + \int_{s}^{1} \max\left\{v_{i+1,n}(s,0), 1 + v_{i+1,n}(x,1)\right\} dx & \text{if } r = 0\\ (1-s)v_{i+1,n}(s,1) + \int_{0}^{s} \max\left\{v_{i+1,n}(s,1), 1 + v_{i+1,n}(x,0)\right\} dx & \text{if } r = 1 \end{cases}$$

- Reflection identity: $v_{i,n}(s,0) = v_{i,n}(1-s,1)$ for all $1 \le i \le n$ and all $s \in [0,1]$.
- "Flipped" finite-horizon Bellman equation:

$$v_{i,n}(y) = yv_{i+1,n}(y) + \int_{y}^{1} \max \left\{ v_{i+1,n}(y), \quad 1 + v_{i+1,n}(1-x) \right\} dx.$$

• "Flipped" infinite-horizon Bellman equation — the "Easy One":

$$v(y) = \rho y v(y) + \int_{y}^{1} \max \{ \rho v(y), 1 + \rho v(1-x) \} dx.$$

• Threshold-policy for infinite-horizon: $f^*(y) = \max\{\xi_0, y\}, \xi_0 \in [0, 1/2)$

• Finite-horizon Bellman equation:

$$v_{i,n}(s,r) = \begin{cases} sv_{i+1,n}(s,0) + \int_{s}^{1} \max\left\{v_{i+1,n}(s,0), 1 + v_{i+1,n}(x,1)\right\} dx & \text{if } r = 0\\ (1-s)v_{i+1,n}(s,1) + \int_{0}^{s} \max\left\{v_{i+1,n}(s,1), 1 + v_{i+1,n}(x,0)\right\} dx & \text{if } r = 1 \end{cases}$$

- Reflection identity: $v_{i,n}(s,0) = v_{i,n}(1-s,1)$ for all $1 \le i \le n$ and all $s \in [0,1]$.
- "Flipped" finite-horizon Bellman equation:

$$v_{i,n}(y) = yv_{i+1,n}(y) + \int_{y}^{1} \max \left\{ v_{i+1,n}(y), \quad 1 + v_{i+1,n}(1-x) \right\} dx.$$

• "Flipped" infinite-horizon Bellman equation — the "Easy One":

$$v(y) = \rho y v(y) + \int_{y}^{1} \max \{ \rho v(y), 1 + \rho v(1-x) \} dx.$$

- Threshold-policy for infinite-horizon: $f^*(y) = \max\{\xi_0, y\}, \xi_0 \in [0, 1/2)$
- Solve for $v(\cdot)$ and obtain

$$v(0) = v(\xi_0) = \frac{3 - 2\sqrt{2} - \rho + \rho\sqrt{2}}{\rho(1 - \rho)}$$

• Problem of Interest: The problem that most often interests us in sequential selection is the finite horizon problem where we know we will see *n* values.

- Problem of Interest: The problem that most often interests us in sequential selection is the finite horizon problem where we know we will see *n* values.
- A Slightly Easier Problem: The problem that is easier to solve is most often the problem with geometric discounting, or geometric sample size.

- Problem of Interest: The problem that most often interests us in sequential selection is the finite horizon problem where we know we will see *n* values.
- A Slightly Easier Problem: The problem that is easier to solve is most often the problem with geometric discounting, or geometric sample size.
- The On-going Challenge: It is a challenging task to go back from geometric asymptotics to finite *n* asymptotics. This is the "Tauberian Theory" of MDPs, and it is far less developed than one might hope.

- Problem of Interest: The problem that most often interests us in sequential selection is the finite horizon problem where we know we will see *n* values.
- A Slightly Easier Problem: The problem that is easier to solve is most often the problem with geometric discounting, or geometric sample size.
- The On-going Challenge: It is a challenging task to go back from geometric asymptotics to finite *n* asymptotics. This is the "Tauberian Theory" of MDPs, and it is far less developed than one might hope.
- *Not for the Faint of Heart!* For the time being at least, the passage back to finite *n* is special and technical. For the Alternating Sequence Problem there were *two steps*:

- Problem of Interest: The problem that most often interests us in sequential selection is the finite horizon problem where we know we will see *n* values.
- A Slightly Easier Problem: The problem that is easier to solve is most often the problem with geometric discounting, or geometric sample size.
- The On-going Challenge: It is a challenging task to go back from geometric asymptotics to finite *n* asymptotics. This is the "Tauberian Theory" of MDPs, and it is far less developed than one might hope.
- *Not for the Faint of Heart!* For the time being at least, the passage back to finite *n* is special and technical. For the Alternating Sequence Problem there were *two steps*:
- Finite-horizon *lower bound*: use the infinite-horizon threshold policy.

- Problem of Interest: The problem that most often interests us in sequential selection is the finite horizon problem where we know we will see *n* values.
- A Slightly Easier Problem: The problem that is easier to solve is most often the problem with geometric discounting, or geometric sample size.
- The On-going Challenge: It is a challenging task to go back from geometric asymptotics to finite *n* asymptotics. This is the "Tauberian Theory" of MDPs, and it is far less developed than one might hope.
- *Not for the Faint of Heart!* For the time being at least, the passage back to finite *n* is special and technical. For the Alternating Sequence Problem there were *two steps*:
- Finite-horizon *lower bound*: use the infinite-horizon threshold policy.
- Finite-horizon upper bound: use the finite-horizon optimal threshold functions $\{f_{1,n}^*, \ldots, f_{n-2,n}^*\}$ and regenerate this selection process over an infinite horizon. The value of $\mathbb{E}[A_N^o(\pi^*)]$ then gives the desired upper bound.

	Full Information	Real Time Information	Bonus
Increasing			
Unimodal			
Alternating			

	Full Information	Real Time Information	Bonus
Increasing	$2\sqrt{n}$	$\sqrt{2n}$	29%
Unimodal			
Alternating			

	Full Information	Real Time Information	Bonus
Increasing	$2\sqrt{n}$	$\sqrt{2n}$	29%
Unimodal	$2\sqrt{2n}$	$2\sqrt{n}$	29%
Alternating			

	Full Information	Real Time Information	Bonus
Increasing	$2\sqrt{n}$	$\sqrt{2n}$	29%
Unimodal	$2\sqrt{2n}$	$2\sqrt{n}$	29%
Alternating	2 <i>n</i> /3	$(2 - \sqrt{2})n$	12%

• How Much Better Does a "Prophet" Do?

	Full Information	Real Time Information	Bonus
Increasing	$2\sqrt{n}$	$\sqrt{2n}$	29%
Unimodal	$2\sqrt{2n}$	$2\sqrt{n}$	29%
Alternating	2 <i>n</i> /3	$(2-\sqrt{2})n$	12%

	Full Information	Real Time Information	Bonus
Increasing	$2\sqrt{n}$	$\sqrt{2n}$	29%
Unimodal	$2\sqrt{2n}$	$2\sqrt{n}$	29%
Alternating	2 <i>n</i> /3	$(2-\sqrt{2})n$	12%

- Question: Go Beyond Moments and LLNs? How about CLTs?
- Bruss and Delbaen (2004) proved the CLT for the "Monotone Sequential Selection" (in the Poissonized version). It would be nice to do the "Tauberian" transition to recover a CLT for the finite horizon problem. This is not as easy "as it looks."

• How Much Better Does a "Prophet" Do?

	Full Information	Real Time Information	Bonus
Increasing	$2\sqrt{n}$	$\sqrt{2n}$	29%
Unimodal	$2\sqrt{2n}$	$2\sqrt{n}$	29%
Alternating	2 <i>n</i> /3	$(2-\sqrt{2})n$	12%

- Bruss and Delbaen (2004) proved the CLT for the "Monotone Sequential Selection" (in the Poissonized version). It would be nice to do the "Tauberian" transition to recover a CLT for the finite horizon problem. This is not as easy "as it looks."
- A CLT for "Unimodal Sequential Selection" seems feasible but even in the smooth Poisson version technically difficulties appear at every turn.

• How Much Better Does a "Prophet" Do?

	Full Information	Real Time Information	Bonus
Increasing	$2\sqrt{n}$	$\sqrt{2n}$	29%
Unimodal	$2\sqrt{2n}$	$2\sqrt{n}$	29%
Alternating	2 <i>n</i> /3	$(2-\sqrt{2})n$	12%

- Bruss and Delbaen (2004) proved the CLT for the "Monotone Sequential Selection" (in the Poissonized version). It would be nice to do the "Tauberian" transition to recover a CLT for the finite horizon problem. This is not as easy "as it looks."
- A CLT for "Unimodal Sequential Selection" seems feasible but even in the smooth Poisson version technically difficulties appear at every turn.
- The CLT for "Alternating Sequential Selection" looks like the most direct challenge.

• How Much Better Does a "Prophet" Do?

	Full Information	Real Time Information	Bonus
Increasing	$2\sqrt{n}$	$\sqrt{2n}$	29%
Unimodal	$2\sqrt{2n}$	$2\sqrt{n}$	29%
Alternating	2 <i>n</i> /3	$(2-\sqrt{2})n$	12%

- Bruss and Delbaen (2004) proved the CLT for the "Monotone Sequential Selection" (in the Poissonized version). It would be nice to do the "Tauberian" transition to recover a CLT for the finite horizon problem. This is not as easy "as it looks."
- A CLT for "Unimodal Sequential Selection" seems feasible but even in the smooth Poisson version technically difficulties appear at every turn.
- The CLT for "Alternating Sequential Selection" looks like the most direct challenge.
- Here Alessandro Arlotto and I are happy to have some progress to report.

Theorem (Arlotto & Steele, 2012)

$$\frac{\mathsf{A}_n^{\circ}(\pi_n^*)-n(2-\sqrt{2})}{n\sigma} \Rightarrow \mathsf{N}(0,1).$$

Theorem (Arlotto & Steele, 2012)

There is a constant $\sigma > 0$ such that

$$\frac{A_n^o(\pi_n^*)-n(2-\sqrt{2})}{n\sigma} \Rightarrow N(0,1).$$

• The Mysterious σ ? Its existence is proved but the value is not yet known.

Theorem (Arlotto & Steele, 2012)

$$\frac{A_n^o(\pi_n^*)-n(2-\sqrt{2})}{n\sigma} \Rightarrow N(0,1).$$

- The Mysterious σ ? Its existence is proved but the value is not yet known.
- A Candidate σ ? Yes, but not yet in the bag.

Theorem (Arlotto & Steele, 2012)

$$\frac{A_n^o(\pi_n^*)-n(2-\sqrt{2})}{n\sigma} \Rightarrow N(0,1).$$

- The Mysterious σ ? Its existence is proved but the value is not yet known.
- A Candidate σ ? Yes, but not yet in the bag.
- Path to Proof? $A_n^o(\pi_n^*)$ can be written as a (reverse, inhomogeneous) Markov Additive Functional.

Theorem (Arlotto & Steele, 2012)

$$\frac{A_n^o(\pi_n^*)-n(2-\sqrt{2})}{n\sigma} \Rightarrow N(0,1).$$

- The Mysterious σ ? Its existence is proved but the value is not yet known.
- A Candidate σ ? Yes, but not yet in the bag.
- Path to Proof? $A_{n}^{o}(\pi_{n}^{*})$ can be written as a (reverse, inhomogeneous) Markov Additive Functional.
- Appropriate Tools? Dobrushin (long ago) and Sethuraman and Varadhan (more recently) have an elegant approach to the CLT for inhomogeneous Markov additive process.

Theorem (Arlotto & Steele, 2012)

$$\frac{A_n^o(\pi_n^*)-n(2-\sqrt{2})}{n\sigma} \Rightarrow N(0,1).$$

- The Mysterious σ ? Its existence is proved but the value is not yet known.
- A Candidate σ ? Yes, but not yet in the bag.
- Path to Proof? $A_{n}^{o}(\pi_{n}^{*})$ can be written as a (reverse, inhomogeneous) Markov Additive Functional
- Appropriate Tools? Dobrushin (long ago) and Sethuraman and Varadhan (more recently) have an elegant approach to the CLT for inhomogeneous Markov additive process.
- Conditions to Check? These are surprisingly concrete, even though a kind of alpha mixing is involved.

Theorem (Arlotto & Steele, 2012)

$$\frac{A_n^o(\pi_n^*)-n(2-\sqrt{2})}{n\sigma} \Rightarrow N(0,1).$$

- The Mysterious σ ? Its existence is proved but the value is not yet known.
- A Candidate σ ? Yes, but not yet in the bag.
- Path to Proof? $A_{n}^{o}(\pi_{n}^{*})$ can be written as a (reverse, inhomogeneous) Markov Additive Functional
- Appropriate Tools? Dobrushin (long ago) and Sethuraman and Varadhan (more recently) have an elegant approach to the CLT for inhomogeneous Markov additive process.
- Conditions to Check? These are surprisingly concrete, even though a kind of alpha mixing is involved.
- Source of Juice? We have honestly independent blocks (of random size) and this gives us all the mixing we need.

• Problems of Sequential Selection: Rich in history, connections, problems and techniques

- Problems of Sequential Selection: Rich in history, connections, problems and techniques
- Progress Intermittent but presistent over many years

- Problems of Sequential Selection: Rich in history, connections, problems and techniques
- Progress Intermittent but presistent over many years
- New Vistas? The "Tauberian Problem" and "means that bound variances"

- Problems of Sequential Selection: Rich in history, connections, problems and techniques
- Progress Intermittent but presistent over many years
- New Vistas? The "Tauberian Problem" and "means that bound variances"
- Variance Limits and CLTs Some down, many more to go ...

- Problems of Sequential Selection: Rich in history, connections, problems and techniques
- Progress Intermittent but presistent over many years
- New Vistas? The "Tauberian Problem" and "means that bound variances"
- Variance Limits and CLTs Some down, many more to go ...
- Enough for Today? ... almost certainly, but with some left for tomorrow.

- Problems of Sequential Selection: Rich in history, connections, problems and techniques
- Progress Intermittent but presistent over many years
- New Vistas? The "Tauberian Problem" and "means that bound variances"
- Variance Limits and CLTs Some down, many more to go ...
- Enough for Today? ... almost certainly, but with some left for tomorrow.

• Thank You for Your Attention!

References I

- F. Thomas Bruss and Freddy Delbaen. A central limit theorem for the optimal selection process for monotone subsequences of maximum expected length. *Stochastic Process. Appl.*, 114(2):287–311, 2004.
- F. Thomas Bruss and James B. Robertson. "Wald's lemma" for sums of order statistics of i.i.d. random variables. *Adv. in Appl. Probab.*, 23(3):612–623, 1991.
- F. R. K. Chung. On unimodal subsequences. J. Combin. Theory Ser. A, 29(3):267–279, 1980.
- P. Erdős and G. Szekeres. A combinatorial problem in geometry. *Compositio Math.*, 2: 463–470, 1935.
- Alexander V. Gnedin. Sequential selection of an increasing subsequence from a sample of random size. J. Appl. Probab., 36(4):1074–1085, 1999.
- J. M. Hammersley. A few seedlings of research. In *Proceedings of the Sixth Berkeley* Symposium on Mathematical Statistics and Probability (Univ. California, Berkeley, Calif., 1970/1971), Vol. I: Theory of statistics, pages 345–394, Berkeley, CA, 1972. Univ. California Press.
- C. Houdré and R. Restrepo. A probabilistic approach to the asymptotics of the length of the longest alternating subsequence. *Electron. J. Combin.*, 17(1):Research Paper 168, 1–19, 2010.

References II

- J. F. C. Kingman. Subadditive ergodic theory. Ann. Probability, 1:883–909, 1973. With discussion by D. L. Burkholder, Daryl Daley, H. Kesten, P. Ney, Frank Spitzer and J. M. Hammersley, and a reply by the author.
- B. F. Logan and L. A. Shepp. A variational problem for random Young tableaux. *Advances in Math.*, 26(2):206–222, 1977.
- WanSoo Rhee and Michel Talagrand. A note on the selection of random variables under a sum constraint. J. Appl. Probab., 28(4):919–923, 1991.
- Stephen M. Samuels and J. Michael Steele. Optimal sequential selection of a monotone sequence from a random sample. *Ann. Probab.*, 9(6):937–947, 1981.
- Richard P. Stanley. Increasing and decreasing subsequences and their variants. In *International Congress of Mathematicians. Vol. I*, pages 545–579. Eur. Math. Soc., Zürich, 2007.
- Richard P. Stanley. Longest alternating subsequences of permutations. *Michigan Math. J.*, 57:675–687, 2008. Special volume in honor of Melvin Hochster.
- Richard P. Stanley. A survey of alternating permutations. *Contemp. Math.*, 531:165–196, 2010.
- J. Michael Steele. Long unimodal subsequences: a problem of F. R. K. Chung. *Discrete Math.*, 33(2):223–225, 1981.

References III

- A. M. Veršik and S. V. Kerov. Asymptotic behavior of the Plancherel measure of the symmetric group and the limit form of Young tableaux. *Dokl. Akad. Nauk SSSR*, 233 (6):1024–1027, 1977.
- Harold Widom. On the limiting distribution for the length of the longest alternating sequence in a random permutation. *Electron. J. Combin.*, 13(1):Research Paper 25, 1–7, 2006.