

Optimal stopping under mixed constraints

F. Thomas Bruss

Département de Mathématique
Université libre de Bruxelles

April 2008, Maresias, Brazil

Present optimal stopping with two kinds of constraints

Present optimal stopping with two kinds of constraints

Problem:

- n fixed;
- X_1, X_2, \dots, X_n , i.i.d. random variables ≥ 0 .
- Sequential observation (**no recall**)

Goal:

We want to select online **at least** r and **in expectation** at least $\mu \geq r$ items with minimal cost!

Goal:

We want to select online **at least** r and **in expectation** at least $\mu \geq r$ items with minimal cost!

- Interest of the problem

Surfing!!!

Sales contracts

Online knapsack problems

.....

Goal:

We want to select online **at least** r and **in expectation** at least $\mu \geq r$ items with minimal cost!

– Interest of the problem

Surfing!!!

Sales contracts

Online knapsack problems

.....

Origin

- Probabilistic setting

- Probabilistic setting
- The hierarchy of constraints

- Probabilistic setting
- The hierarchy of constraints
- Recurrence

- Probabilistic setting
- The hierarchy of constraints
- Recurrence
- Precise solution for total selection cost

- Probabilistic setting
- The hierarchy of constraints
- Recurrence
- Precise solution for total selection cost
- Asymptotic behaviour of total selection cost

2. Problem formulation.

- n fixed; X_1, X_2, \dots, X_n i.i.d. $U[0, 1]$ random variables.

2. Problem formulation.

- n fixed; X_1, X_2, \dots, X_n i.i.d. $U[0, 1]$ random variables.
- Define indicators

If $I_k = 1$ then X_k is *selected*

If $I_k = 0$ then X_k is *refused*.

2. Problem formulation.

- n fixed; X_1, X_2, \dots, X_n i.i.d. $U[0, 1]$ random variables.

- Define indicators

If $I_k = 1$ then X_k is *selected*

If $I_k = 0$ then X_k is *refused*.

$\{I_k = 1\} \in \sigma$ -field \mathcal{F}_k generated by X_k 's and I_k 's together.

Selection rules $T = \{\tau := \tau_n = (I_1, I_2, \dots, I_n)\}$.

Objective:

Find

$$v_{r,\mu}(n) = \min_{\tau \in \mathcal{T}} \mathbb{E} \left(\sum_{k=1}^n I_k X_k \right), \quad n \geq \mu \geq r$$

and

$$\tau^* = \arg \min_{\tau \in \mathcal{T}} \mathbb{E} \left(\sum_{k=1}^n I_k X_k \right)$$

Objective:

Find

$$v_{r,\mu}(n) = \min_{\tau \in \mathcal{T}} \mathbb{E} \left(\sum_{k=1}^n I_k X_k \right), \quad n \geq \mu \geq r$$

and

$$\tau^* = \arg \min_{\tau \in \mathcal{T}} \mathbb{E} \left(\sum_{k=1}^n I_k X_k \right)$$

subject to

$$\sum_{k=1}^n I_k \geq r, \quad 1 \leq r \leq n \quad (\text{D-constraint})$$

and

$$\mathbb{E} \left(\sum_{k=1}^n I_k \right) = \mu, \quad \mu \in \mathbf{R}, \quad \mu \geq r. \quad (\text{E-constraint})$$

- $v_{r,\mu}(n) :=$ optimal value for n with (r, μ) -constraints.

- $v_{r,\mu}(n) :=$ optimal value for n with (r, μ) -constraints.
- $V_{r,\mu}(n|\mathcal{F}_k) := \mathbb{E}(\text{min total cost expectation} \mid \mathcal{F}_k)$.

- $v_{r,\mu}(n) :=$ optimal value for n with (r, μ) -constraints.
- $V_{r,\mu}(n|\mathcal{F}_k) := \mathbb{E}(\text{min total cost expectation} \mid \mathcal{F}_k)$.
- $N_k := I_1 + \dots + I_k = \#$ selections up to k under optimal rule.

- $v_{r,\mu}(n) :=$ optimal value for n with (r, μ) -constraints.
- $V_{r,\mu}(n|\mathcal{F}_k) := \mathbb{E}(\text{min total cost expectation} \mid \mathcal{F}_k)$.
- $N_k := I_1 + \dots + I_k = \#$ selections up to k under optimal rule.

Lemma 1 For all (stopping) times $0 \leq \tau \leq n$:

$$V(n|\mathcal{F}_\tau) = v_{r-N_\tau, \mu-N_\tau}(n-\tau) + \sum_{j=1}^{\tau} I_j X_j \text{ a.s.}$$

$$V_\delta(n) = v_{0,\mu-r}(n-\delta) + \sum_{j=1}^{\delta} l_j X_j \text{ a.s.}$$

with

$$v_{0,\mu-r}(k) = \frac{(\mu-r)^2}{2k}.$$

Sketch of Proof.

- Conditioned on $\delta = d$, ... clear.
- Future variables $X_{\delta+1}, \dots, X_n$ are \mathcal{F}_δ - independent .

Sketch of Proof.

- Conditioned on $\delta = d$, ... clear.
- Future variables $X_{\delta+1}, \dots, X_n$ are \mathcal{F}_δ - independent .
- Conditional expectation.

.....

Sketch of Proof.

- Conditioned on $\delta = d$, ... clear.
- Future variables $X_{\delta+1}, \dots, X_n$ are \mathcal{F}_δ - independent .
- Conditional expectation.

.....

Statement holds unconditionally.

Remains to be shown :

$$v_{0,\mu-r}(k) = (\mu - r)^2/2k.$$

At time δ_+ , we must design a rule which selects in expectation $\mu - r$ from $K = n - \delta$ i.i.d $U[0, 1]$ -random variables.

Threshold rules

— If it is optimal to select $X_j = x$, say, then it is optimal to accept $X_j' < x$.

Threshold rules

- If it is optimal to select $X_j = x$, say, then it is optimal to accept $X_j' < x$.
- If optimal to refuse $X_j = x$, optimal to refuse $X_j' > x$.

Threshold rules

- If it is optimal to select $X_j = x$, say, then it is optimal to accept $X_j' < x$.
 - If optimal to refuse $X_j = x$, optimal to refuse $X_j' > x$.
- \implies Each opt. decision is based on a unique threshold!

$t_1, t_2, \dots, t_K :=$ selection thresholds for $X_{\delta+1}, X_{\delta+2}, \dots, X_n$

$t_1, t_2, \dots, t_K :=$ selection thresholds for $X_{\delta+1}, X_{\delta+2}, \dots, X_n$

Then

$$E(I_{\delta+j} X_{\delta+j}) = t_j E(X | X \leq t_j) = t_j^2 / 2.$$

$t_1, t_2, \dots, t_K :=$ selection thresholds for $X_{\delta+1}, X_{\delta+2}, \dots, X_n$

Then

$$E(l_{\delta+j}X_{\delta+j}) = t_j E(X|X \leq t_j) = t_j^2/2.$$

Minimize

$$\sum_{j=1}^K t_j^2$$

subject to

$$\sum_{j=1}^K E(l_{\delta+j}) = \sum_{j=1}^K t_j = \mu - r.$$

Optimization (e.g. Lagrange multiplier method) yields

Optimization (e.g. Lagrange multiplier method) yields

$$t_j \equiv (\mu - r)/K, \quad j > \delta.$$

Hence

$$v_{0, \mu-r}(K) = K \frac{\mu - r}{K} \times \frac{\mu - r}{2K} = \frac{(\mu - r)^2}{2K}.$$



Theorem 3.1

$$v_{r,\mu}(n) = v_{r,\mu}(n-1) - \frac{1}{2} [v_{r,\mu}(n-1) - v_{r-1,\mu-1}(n-1)]^2,$$

for $n = [\mu]^+, [\mu]^+ + 1, \dots$, with initial conditions

$$v_{r,\mu}([\mu]^+) = \frac{\mu}{2}; \quad v_{0,\mu-r}(n) = \frac{(\mu-r)^2}{2n}, \quad n = 1, 2, \dots$$

Theorem 3.1

$$v_{r,\mu}(n) = v_{r,\mu}(n-1) - \frac{1}{2} [v_{r,\mu}(n-1) - v_{r-1,\mu-1}(n-1)]^2,$$

for $n = [\mu]^+, [\mu]^+ + 1, \dots$, with initial conditions

$$v_{r,\mu}([\mu]^+) = \frac{\mu}{2}; \quad v_{0,\mu-r}(n) = \frac{(\mu-r)^2}{2n}, \quad n = 1, 2, \dots$$

Proof. Suppose it is optimal to select X_1 iff $X_1 \leq t$. Then

$$\tilde{v}_{r,\mu}(n, t) = t[\mathbb{E}(X|X \leq t) + v_{r-1,\mu-1}(n-1)] + (1-t)v_{r,\mu}(n-1).$$

$\mathbb{E}(X|X \leq t) = t/2$, differentiable in t for all

$t \in]0, 1[$ $[\partial \tilde{v}_{r,\mu}(n, t)/\partial t = 0$ with $\partial^2 \tilde{v}_{r,\mu}(n, t)/\partial t^2 > 0$ minimizes $v_{r,\mu}(n, t)$.

solution

$$t^* = v_{r,\mu}(n-1) - v_{r-1,\mu-1}(n-1).$$

We must have

$$\tilde{v}_{r,\mu}(n, t^*) = v_{r,\mu}(n).$$

....insert ... elementary steps....

Initial conditions:

Suppose $\mu \in \mathbf{N}$ and $n = \mu$. The optimal policy must select all observations.... value $\mu/2$. The second initial condition stems from (4), and thus the Theorem is proved. □

Initial conditions:

Suppose $\mu \in \mathbf{N}$ and $n = \mu$. The optimal policy must select all observations.... value $\mu/2$. The second initial condition stems from (4), and thus the Theorem is proved. \square

For all r and μ , $v_{r,\mu}(n) \geq 0$. Hence $(v_{r,\mu}(n))$ decreases in n , whenever the sequence $(v_{r-1,\mu-1}(n))$ decreases in n .
 $(v_{0,\mu-r}(n))$ decreases in n

Hence must converge (to the only possible limit 0.)

Corollary For $\mu \geq 1$ and $n \geq \mu \geq r$ $(v_{r,\mu}(n))_{n \geq \mu}$ is monotone decreasing with limit 0.

Lemma

For n fixed with $n \geq [\mu]^+$ and $\mu \geq r$

$$(i) \quad v_{r,\mu}(n) \geq v_{r-1,\mu-1}(n)$$

$$(ii) \quad v_{r,\mu}(n) \geq v_{r,\mu-1}(n)$$

Proof: $\tilde{v}_{\mu,r}(n) :=$ minimal expected total cost of the optimal strategy for the (r, μ) -constraints under the additional hypothesis, that the r th selection for free. Then $\tilde{v}_{\mu,r}(n) \leq v_{\mu,r}(n)$. However if we play right away optimally under the weaker $(r-1, \mu-1)$ -constraints,

$$v_{r-1,\mu-1}(n) \leq \tilde{v}_{r,\mu}(n).$$

Hence $v_{r,\mu}(n) \geq v_{r-1,\mu-1}$.

Inequality (ii) follows from $v_{0,\mu-r}(\cdot) > v_{0,\mu-1-r}(\cdot)$ uniformly.

4. The optimal rule.

Definition For $s \in \{0, 1, \dots, r\}$ and $k \in \{0, 1, \dots, n\}$ we say we are in *state* (s, k) , if s selections have been made until time $n - k$ included.

(Note that the current E-constraint is implicit for $0 \leq s \leq r$.)

Since the continuation thereafter is, by hypothesis, a fixed selection rule, it becomes irrelevant once the D-constraint is satisfied. Hence we need not list it as a separate state-coordinate.

Recall: Optimal thresholds are all unique.

Computing optimal thresholds and values

The optimal thresholds for each state can be computed recursively.

We have to start with two independent lines of initial conditions, namely for $v_{0,\mu-r}(k)$ with $k \geq \mu - r$ and for $v_{s,k}(k)$ with $k \geq s$.

5.1 Algorithm:

A

Optimal values

$$(A1) \quad v_{0,\mu-r}(k) = (\mu - r)^2 / (2k), \quad k = \mu - r, \dots, n - r.$$

$$(A2) \quad v_{s,k}(k) = k/2, \quad k = \mu - r, \dots, n - r; \quad s = 1, \dots, r.$$

5.1 Algorithm:

A

Optimal values

$$(A1) \quad v_{0,\mu-r}(k) = (\mu - r)^2 / (2k), \quad k = \mu - r, \dots, n - r.$$

$$(A2) \quad v_{s,k}(k) = k/2, \quad k = \mu - r, \dots, n - r; \quad s = 1, \dots, r.$$

(A3) For $s = 1, \dots, r$ and init. cond. (A1), (A2) compute

$$v_{s,\mu-r+s}(k) \\ = v_{s,\mu-r+s}(k-1) - \frac{1}{2} [v_{s,\mu-r+s}(k-1) - v_{s-1,\mu-r+(s-1)}(k-1)]^2,$$

$$k = \mu - r + s, \dots, n - r; \quad s = 1, \dots, r.$$

Optimal thresholds

$$(B1) \quad t_{r,k} = v_{0,\mu-r}(k) = (\mu - r)^2/2, \quad k = \mu - r, \dots, n - r.$$

$$(B2) \quad t_{s,k} = v_{r-s,\mu-s}(k-1) - v_{r-s-1,\mu-s-1}(k-1), \\ s = 0, \dots, r-1$$

5.2 Bounds of $v_{r,\mu}(n)$ for general r and μ .

Motivation ...

5.2 Bounds of $v_{r,\mu}(n)$ for general r and μ .

Motivation ...

Lemma For all $0 \leq s \leq r, s \leq m \leq \mu$ and $\max\{s, m\} \leq k \leq n$

$$v_{r,\mu}(n) \leq v_{s,m}(k) + v_{r-s,\mu-m}(n-k).$$

Proof.

Fix indices s , m and k such that the conditions for the Lemma are fulfilled. This is always possible ...at least (r, μ, n) and $(0, 0, 0)$ are possible (by definition.)

Proof.

Fix indices s , m and k such that the conditions for the Lemma are fulfilled. This is always possible ...at least (r, μ, n) and $(0, 0, 0)$ are possible (by definition.)

Consider a two-legged strategy.

— Leg 1 minimizes the expected total cost of accepting items until time k under the (s, m) constraint.

Proof.

Fix indices s , m and k such that the conditions for the Lemma are fulfilled. This is always possible ...at least (r, μ, n) and $(0, 0, 0)$ are possible (by definition.)

Consider a two-legged strategy.

— Leg 1 minimizes the expected total cost of accepting items until time k under the (s, m) constraint.

— Leg 2 remembers the occurred cost at time k and then minimizes (independently) the additional cost of accepting further items under the constraints $r - s, \mu - m$.

Proof.

Fix indices s , m and k such that the conditions for the Lemma are fulfilled. This is always possible ...at least (r, μ, n) and $(0, 0, 0)$ are possible (by definition.)

Consider a two-legged strategy.

— Leg 1 minimizes the expected total cost of accepting items until time k under the (s, m) constraint.

— Leg 2 remembers the occurred cost at time k and then minimizes (independently) the additional cost of accepting further items under the constraints $r - s, \mu - m$.

This composed strategy is admissible since it fulfills the original constraints, and since $X_{k+1}, X_{k+2} \cdots X_n$ are independent of the past, its value is $v_{s,m}(k) + v_{r-s, \mu-m}(n - k)$. The inequality follows then by sub-optimality.



For the special case $s = r = m$ we obtain

Corollary For $1 \leq r \leq \mu \leq n$: $v_{r,\mu}(2n) \leq v_{r,r}(n) + \frac{1}{2n}(\mu - r)^2$.

Lemma For all $1 \leq r \leq \mu$ there exist constants $\alpha = \alpha(r, \mu)$ and $\beta = \beta(r, \mu)$ such that $\alpha/n \leq v_{r,\mu}(n) \leq \beta/n$ for all $n \geq \mu$, with n sufficiently large.

Proof. We first prove that the existence of a lower bound $\alpha(r, \mu)/n$.

By definition of the D-constraint and E-constraint we have $\mu \geq r$. Since $v_{r,\mu}(\cdot)$ is increasing in μ for fixed r and n , it suffices to show $v_{r,r}(n) \geq \alpha/n$ for some constant α .

By definition of the D-constraint and E-constraint we have $\mu \geq r$. Since $v_{r,\mu}(\cdot)$ is increasing in μ for fixed r and n , it suffices to show $v_{r,r}(n) \geq \alpha/n$ for some constant α .

The optimal strategy for the (r, r) -constraints cannot do better than selecting the r smallest order statistics.

By definition of the D-constraint and E-constraint we have $\mu \geq r$. Since $v_{r,\mu}(\cdot)$ is increasing in μ for fixed r and n , it suffices to show $v_{r,r}(n) \geq \alpha/n$ for some constant α .

The optimal strategy for the (r, r) -constraints cannot do better than selecting the r smallest order statistics.

The expectation of the sum of these is $r(r+1)/(2(n+1)) \geq r^2/(2n)$. Hence $v_{r,\mu}(n) \geq v_{r,r}(n) \geq \alpha/n$ for $\alpha = r^2/2$.

Concerning the upper bound β we see that the statement is true, if it is true for $v_{r,r}(n)$.

Now, $v_{r,r}(rn) \leq v_{r-1,r-1}((r-1)n) + v_{1,1}(n)$, and hence by induction $v_{r,r}(rn) \leq rv_{1,1}(n)$. The sequence $(v_{1,1}(n))$ coincides with Moser's sequence, which is known to satisfy $v_{1,1}(n) \leq c/n$ for all n .

Therefore $v_{r,r}(rn) \leq (cr)/n$. But then, for general n we have $v_{r,r}(n) \leq v_{r,r}([n/r]r)$, where $[x]$ denotes the floor of x . Hence $v_{r,r}(n) \leq cr/[n/r] \leq (cr^2 + \epsilon)/n$ for all $\epsilon > 0$ and n sufficiently large, and the proof is complete. □

Therefore $v_{r,r}(rn) \leq (cr)/n$. But then, for general n we have $v_{r,r}(n) \leq v_{r,r}([n/r]r)$, where $[x]$ denotes the floor of x . Hence $v_{r,r}(n) \leq cr/[n/r] \leq (cr^2 + \epsilon)/n$ for all $\epsilon > 0$ and n sufficiently large, and the proof is complete. □

Example:

Aldous' problem (2006). What is $v_{1,2}(n)$ and what is the behaviour of $nv_{1,2}(n)$?

We have $\mu - r = 1$, $v_{0,1}(k) = (\mu - r)^2 / (2k)$. Initial condition: $v_{1,2}(2) = 1$.

Recurrence:

$$v_{1,2}(k) = v_{1,2}(k-1) - \frac{1}{2} \left(v_{1,2}(k-1) - \frac{1}{2(k-1)} \right)^2, k = 2, 3, \dots, n.$$

— $(v_{1,2}(n))$ is decreasing and bounded below by 0.
 $v_{1,2} = \lim v_{1,2}(n)$ exists and taking limits shows $v_{1,2} = 0$.

— $(v_{1,2}(n))$ is decreasing and bounded below by 0.
 $v_{1,2} = \lim v_{1,2}(n)$ exists and taking limits shows $v_{1,2} = 0$.

What is the asymptotic behaviour of $(nv(n))$?

— $(v_{1,2}(n))$ is decreasing and bounded below by 0.
 $v_{1,2} = \lim v_{1,2}(n)$ exists and taking limits shows $v_{1,2} = 0$.

What is the asymptotic behaviour of $(nv(n))$?

Answer: We will see $(nv_{1,2}(n)) \rightarrow 3/2 + \sqrt{2}$.

Asymptotic behaviour

Asymptotic behaviour

We rewrite for $t \in \mathbf{N}$ and $\epsilon = 1$ as

$$\frac{1}{\epsilon} \left(v_{r,\mu}(t) - v_{r,\mu}(t - \epsilon) \right) = -\frac{1}{2} \left(v_{r,\mu}(t - \epsilon) - v_{r-1,\mu-1}(t - \epsilon) \right)^2$$

with initial condition (6). We fix r and μ and can then simplify the notation by writing $v_{r-1,\mu-1}(t) =: v(t)$ and $v_{r,\mu}(t) =: w(t)$, say. Let $\tilde{v}(t)$ and $\tilde{w}(t)$ be differentiable functions which coincide with $v(t)$ and $w(t)$ for $t \in \mathbf{N}$ with $t \geq \mu$.

It follows from Lemma 5.3 and the mean value theorem that the differential equation

$$\tilde{w}'(t) = -\frac{1}{2} (\tilde{w}(t) - \tilde{v}(t))^2$$

defined for $t \in [\mu, \infty]$ must catch the asymptotic behaviour of $w(t)$ for $t \in \mathbf{N}$.

It follows from Lemma 5.3 and the mean value theorem that the differential equation

$$\tilde{w}'(t) = -\frac{1}{2} (\tilde{w}(t) - \tilde{v}(t))^2$$

defined for $t \in [\mu, \infty]$ must catch the asymptotic behaviour of $w(t)$ for $t \in \mathbf{N}$.

Note that this is a general Riccati differential equation, and the idea is now to show that only exactly one solution of equation (12) is compatible with (11).

Theorem 6.1

If $\tilde{v}(t) = c/t$ for some constant $c \geq 2$ then the unique solution $\tilde{w}(t)$ satisfying $\lim_{t \rightarrow \infty} v_{r,\mu}(t)/\tilde{w}(t) = 1$ is the function

$$\tilde{w}(t) := \tilde{w}_1(t) = \frac{1}{t} \left(1 + c + \sqrt{1 + 2c} \right).$$

Proof: We first prove that $\tilde{w}_1(t) = (1 + c + \sqrt{1 + 2c})/t$ is a particular solution of equation (12). Indeed, there must be a constant, c_1 say, such that c_1/t is a particular solution, because plugging in yields the equation

$$\frac{-c_1}{t^2} = \frac{-1}{2t^2} (c_1^2 - 2cc_1 + c^2)$$

with solutions in $\{1 + c + \sqrt{1 + 2c}\}$.

Only the solution $c_1 = (1 + c + \sqrt{1 + 2c})$ is meaningful because with $c > 0$ we would have $(1 + c - \sqrt{1 + 2c}) < c$ contradicting $\tilde{w}(t) \geq \tilde{v}(t)$. Hence $\tilde{w}_1(t)$ is a particular solution.

From the general theory of Riccati differential equations (see e.g. Grauert und Fischer (1967), 109-112) we know that we can generate a general solution $\{\tilde{w}_2\}$ from a particular solution by solving (substitution $u(t) = 1/(w_2(t) - w_1(t))$) the first order linear equation

$$u'(t) = -(Q(t) + 2R(t)\tilde{w}_1(t))u(t) - R(t)$$

where, in our case, $R(t) = -1/2$ and $Q(t) = c/t$. The set $\{\tilde{w}_2\}$ of solutions is then the set $\{\tilde{w}_2(t) = \tilde{w}_1(t) + u(t)^{-1}\}$ with a single undetermined constant.

Plugging our particular solution $\tilde{w}_1(t)$ into the first order equation yields, after straightforward simplification, the equation $u'(t) = u(t) (1 + \sqrt{1 + 2c}) / t + 1/2$. We solve its associated homogeneous equation and then apply the method of the variation of constants. This yields

Plugging our particular solution $\tilde{w}_1(t)$ into the first order equation yields, after straightforward simplification, the equation $u'(t) = u(t) (1 + \sqrt{1 + 2c}) / t + 1/2$. We solve its associated homogeneous equation and then apply the method of the variation of constants. This yields

Finally we see that all other solutions are **incompatible** with at least one of the precedingly proved properties of $v_{\Sigma, \mu}(n)$ and $v_{0, \mu-r}(n)$

Limiting behaviour:

$$nv_{r,\mu}(n) \rightarrow c_r$$

Limiting behaviour:

$$nv_{r,\mu}(n) \rightarrow c_r$$

where

$$c_0 := \frac{(\mu - r)^2}{2}$$

Limiting behaviour:

$$nv_{r,\mu}(n) \rightarrow c_r$$

where

$$c_0 := \frac{(\mu - r)^2}{2}$$

$$c_k := c_{k-1} + 1 + \sqrt{2c_{k-1} + 1}.$$

Limiting behaviour:

$$nv_{r,\mu}(n) \rightarrow c_r$$

where

$$c_0 := \frac{(\mu - r)^2}{2}$$

$$c_k := c_{k-1} + 1 + \sqrt{2c_{k-1} + 1}.$$

Outlook.

(Aldous, D. , private communication)

Bruss, F. T. and Ferguson T. S. (1997). Multiple buying and selling with vector offers. *J. Appl. Prob.*, **34**, 959-973.

Grauwert und Fischer (1967)

Moser, L. (1956). On a problem of Cayley. *Scripta Math.* **22**, 289-292.