

## A LAW OF THE ITERATED LOGARITHM FOR THE ROBBINS—MONRO METHOD

by  
P. MAJOR

Let a real number  $\alpha$  and a function  $H(x, y)$  be given which is a distribution function for fixed  $x$  and measurable for fixed  $y$ . Set

$$M(x) = \int_{-\infty}^{\infty} yH(dy, x).$$

Let  $a_n \geq 0$  be a sequence of real numbers for which  $\sum a_n = \infty$ ,  $\sum a_n^2 < \infty$ . Let us define the random variables  $x_1, x_2, \dots, y_1, y_2, \dots$  with the following properties:  $x_1$  is an arbitrary constant  $x_{n+1} = x_n - a_n(y_n - \alpha)$ , and

$$P(y_n < y | x_1, y_1, \dots, y_{n-1}, x_n) = P(y_n < y | x_n) = H(y, x_n).$$

This construction of the  $x_i$ 's and  $y_i$ 's is the Robbins—Monro method [1]. J. R. BLUM proved in [2] that if  $M(x)$  and the root  $\theta$  of the equation  $M(x) = \alpha$  satisfy the following conditions:

- (I)  $|M(x)| \leq A|x| + B$  for all  $x$  and suitable  $A, B$ ;
- (II)  $\inf_{\varepsilon < x - \theta < \frac{1}{\varepsilon}} M(x) > \alpha$  and  $\sup_{-\varepsilon > x - \theta > -\frac{1}{\varepsilon}} M(x) < \alpha$  for every  $\varepsilon > 0$ ;
- (III)  $\int_{-\infty}^{\infty} (y - M(x))^2 H(dy, x) \leq K < \infty$  for every  $x$

then  $x_n \rightarrow \theta$  with probability 1.

We shall deal with the special case, when the errors are bounded, that is  $H(M(x) - K, x) = 0$ ,  $H(M(x) + K, x) = 1$  for every  $x$ , and  $a_n = \frac{1}{n}$  are chosen. In this case, using mainly the idea of J. R. BLUM [2] we can strengthen his result in the following way.

**THEOREM 1.** *Let us suppose that  $M'(\theta) > \frac{1}{2}$ ,  $a_n = \frac{1}{n}$ ,  $M(x)$  is bounded in a neighbourhood of  $\theta$  and  $x_n \rightarrow \theta$  with probability 1. Then there exists a number  $L$  (depending on  $M'(\theta)$  and the bound  $K$  of the error) such that*

$$P\left(\overline{\lim} \sqrt{\frac{n}{\log \log n}} |x_n - \theta| < L\right) = 1.$$

On the other hand, if we suppose that the errors are identically distributed, that is the distribution-function  $H(y-M(x), x)$  does not depend on  $x$  then we can state the following

**THEOREM 2.** *If the errors are bounded having the same distribution and  $M'(\theta) < \infty$ , then there exists an  $L' > 0$  such that*

$$P\left(\overline{\lim} \sqrt{\frac{n}{\log \log n}} |x_n - \theta| > L'\right) = 1.$$

For the sake of simplicity we shall suppose that  $\alpha = \theta = 0$ .

It is easy to see that for  $m > n$

$$(1) \quad x_m = x_n - \sum_{i=n}^{m-1} \frac{1}{i} y_i = x_n - \sum_{i=n}^{m-1} \frac{1}{i} M(x_i) - \sum_{i=n}^{m-1} \frac{1}{i} (y_i - M(x_i)).$$

Let  $F_i = B(x_1, y_1, \dots, x_i, y_i)$  be the smallest  $\sigma$ -algebra with respect to which the random variables  $x_1, y_1, \dots, x_i, y_i$  are measurable. Then the system

$$\left\{ \frac{1}{i} (y_i - M(x_i)), F_i \right\}$$

is a martingale difference series. If the errors are identically distributed then the random variables  $\frac{1}{i} (y_i - M(x_i))$  are even independent. Using these facts we give a sharper bound than that of BLUM and these boundings will enable us to prove our statement. This way we need the following

**LEMMA 1.** *Let  $(\xi_1, F_1) \dots (\xi_n, F_n) \dots$  be martingale difference series with  $P(|\xi_i| \leq K) = 1$ . Then for almost all  $\omega$  and for all  $\varepsilon > 0$  there exists an  $n(\omega) = n(\omega, \varepsilon)$  such that for every  $m > n \geq n(\omega)$*

$$\left| \sum_{i=n}^m \frac{1}{i} \xi_i \right| \leq 2\sqrt{2}K + \varepsilon \sqrt{\frac{\log \log n}{n}}.$$

**PROOF.**

$$\begin{aligned} & P\left(\sup_{N \geq m \geq n} \sum_{i=n}^m \frac{\xi_i}{i} > u \sqrt{\frac{\log \log n}{n}}\right) = \\ & = P\left(\sup_{N \geq m \geq n} \exp f(n) \sum_{i=n}^m \frac{\xi_i}{i} > \exp u \cdot f(n) \sqrt{\frac{\log \log n}{n}}\right) \end{aligned}$$

where  $f(n) \geq 0$  is arbitrary constant.

$$\text{But} \quad \left\{ \exp \sum_{i=n}^m \frac{f(n)}{i} \xi_i, F_m \right\} \quad m = n, n+1, \dots, N$$

is a semimartingale and by the Kolmogorov inequality for semimartingale (see [4] Chapter VII) we get that

$$\begin{aligned} P\left(\sup_{N \geq m \geq n} \sum_{i=n}^m \frac{\xi_i}{i} \geq u \sqrt{\frac{\log \log n}{n}}\right) &\leq \\ &= E\left\{\exp\left(f(n) \sum_{i=1}^N \frac{\xi_i}{i}\right)\right\} \\ &= \frac{E\left\{\exp\left(f(n) \sum_{i=1}^N \frac{\xi_i}{i}\right)\right\}}{\exp\left(u \cdot f(n) \sqrt{\frac{\log \log n}{n}}\right)}. \end{aligned}$$

For  $|x| < \delta(\varepsilon)$  we have  $e^x < 1 + x + \frac{x^2}{2-\varepsilon}$ , and choosing  $f(n) = v \cdot \sqrt{n \log \log n}$  we get that if  $n$  is big enough and  $i \geq n$ , then  $\left|\frac{f(n)\xi_i}{i}\right| \leq \delta(\varepsilon)$ .

Hence

$$\begin{aligned} E \exp \sum_{i=n}^N \frac{f(n)\xi_i}{i} &\leq E\left[\exp \sum_{i=n}^{N-1} \frac{f(n)\xi_i}{i} \cdot \left(1 + \frac{f(n)}{N} \xi_N + \frac{f^2(n)\xi_N^2}{(2-\varepsilon)N^2}\right)\right] \\ &\leq \left(1 + \frac{f^2(n)K^2}{(2-\varepsilon)N^2}\right) \cdot E\left[\exp \sum_{i=n}^{N-1} \frac{f(n)\xi_i}{i}\right] \leq \dots \\ &\leq \prod_{i=n}^N \left(1 + \frac{f^2(n)K^2}{(2-\varepsilon)i^2}\right) \leq \exp \frac{f(n)^2 K^2}{(2-\varepsilon)(n-1)}. \end{aligned}$$

So for large  $n$

$$P\left(\sup_{N \geq m \geq n} \sum_{i=n}^m \frac{\xi_i}{i} \geq u \sqrt{\frac{\log \log n}{n}}\right) \leq \exp\left[\frac{f^2(n)K^2}{(2-\varepsilon)(n-1)} - u \cdot f(n) \sqrt{\frac{\log \log n}{n}}\right].$$

Tending with  $N$  to infinity, for large  $n$

$$\begin{aligned} P\left(\sup_{m \geq n} \sum_{i=n}^m \frac{\xi_i}{i} \geq u \sqrt{\frac{\log \log n}{n}}\right) &\leq \exp\left\{\left[v^2 \left(1 + \frac{1}{n-1}\right) \frac{K^2}{2-\varepsilon} - uv\right] \log \log n\right\} \\ &\leq \frac{1}{(\log n)^{1+\varepsilon}} \text{ if we choose } u = \frac{2(1+\varepsilon)}{\sqrt{2-\varepsilon}} K, v = \frac{\sqrt{2-\varepsilon}}{K}. \end{aligned}$$

Using the Borel—Cantelli lemma for arbitrary  $\theta > 1$

$$\sum_{n=1}^{\infty} P\left(\sup_{m \geq \theta^n} \sum_{i=\theta^n}^m \frac{\xi_i}{i} \geq 2 \frac{(1+\varepsilon)}{\sqrt{2-\varepsilon}} K \sqrt{\frac{\log \log \theta^n}{\theta^n}}\right) \leq C + \frac{1}{\log \theta} \sum_{n=1}^{\infty} \frac{1}{n^{1+\varepsilon}} < \infty$$

so for almost all  $\omega$  there is an  $n(\omega)$  such that for every

$$m \geq \theta^k \geq n(\omega) \sum_{i=\theta^k}^m \frac{\xi_i}{i} \leq (\sqrt{2}K + \varepsilon) \sqrt{\frac{\log \log \theta^k}{\theta^k}}.$$

In the same way

$$\sum_{i=\theta^k}^m \frac{\xi_i}{i} \cong -(\sqrt{2K} + \varepsilon) \sqrt{\frac{\log \log \theta^k}{\theta^k}}.$$

Let  $m > n > n(\omega)$  and  $n(\omega) \cong \theta^k < \theta^{k+1}$ . Then

$$\begin{aligned} \left| \sum_{i=n}^m \frac{\xi_i}{i} \right| &\cong \left| \sum_{i=\theta^k}^n \frac{\xi_i}{i} \right| + \left| \sum_{i=\theta^k}^m \frac{\xi_i}{i} \right| \cong \\ &\cong 2(\sqrt{2K} + \varepsilon) \sqrt{\frac{\log \log \theta^k}{\theta^k}} \cong \frac{2(\sqrt{2K} + \varepsilon)}{\theta} \sqrt{\frac{\log \log n}{n}}. \end{aligned}$$

Since  $\varepsilon$  and  $\theta$  can be chosen as near to 0 and to 1, respectively as we want, our lemma is proved.

PROOF of Theorem 1. First we prove that  $P\left(\overline{\lim} \sqrt{\frac{n}{\log \log n}} |x_n| < \infty\right) = 1$ . We shall prove this relation for every  $\omega$  for which  $y_i(\omega) - M(x_i(\omega))$  satisfies the lemma and  $x_n(\omega) \rightarrow 0$  as  $n \rightarrow \infty$ . Let us choose an  $\varepsilon > 0$  in such a way that

$$(2) \quad |M(y)| > \beta|y| \quad \text{and} \quad |M(y)| < a \quad \text{if} \quad |y| < \varepsilon$$

where  $\beta > \frac{1}{2}$ ,  $a > 0$  are constants. Let us choose a number  $c$   $0 < c < 1$  such that  $2\beta c > 1$ .

Then it is easy to see that

$$\lim_{\delta \rightarrow 0} \left[ \frac{\beta \sqrt{1+\delta} \log(1+c\delta)}{\sqrt{1+\delta}-1} - \sqrt{1+\delta} \right] = 2\beta c - 1 > 0.$$

Let us choose a  $\delta > 0$  so, that

$$(3) \quad \frac{\beta \sqrt{1+\delta} \log(1+c\delta)}{\sqrt{1+\delta}-1} - \sqrt{1+\delta} = u > 0.$$

Let us choose an  $n_0 = n_0(\omega)$  so large, that

$$(4) \quad |x_n(\omega)| < \varepsilon \quad \text{for} \quad n \cong n_0$$

$$(5) \quad \left| \sum_{i=n}^m \frac{1}{i} (y_i - M(x_i)) \right| \cong 3K \sqrt{\frac{\log \log n}{n}} \quad \text{for} \quad m \cong n \cong n_0$$

$$(6) \quad \frac{K+a}{\sqrt{n_0}} \cong 3K \frac{1+\delta}{(\sqrt{1+\delta}-1)n}.$$

Let us define

$$L(\omega) = \max \left\{ 3K \sqrt{1+\delta} \frac{1+\delta+u(\sqrt{1+\delta}-1)}{u(\sqrt{1+\delta}-1)}, \max_{n_0 \cong n \cong n_0(1+\delta)} \sqrt{\frac{n}{\log \log n}} |x_n| \right\}.$$

We state that

$$(7) \quad |x_n| \leq L(\omega) \sqrt{\frac{\log \log n}{n}} \quad \text{for every } n \geq n_0.$$

For  $n_0 \leq n \leq n_0(1+\delta)$  (7) follows from the definition of  $L(\omega)$ . As a first step we prove that the validity of (7) for an  $n \geq n_0$  implies its validity for every  $n(1+c\delta) \leq \tilde{n} \leq (1+\delta)n$ . Our statement is a straight consequence of this fact.

In order to prove this we introduce the following notation:

$$L^* = \frac{u(\sqrt{1+\delta}-1)}{\sqrt{1+\delta}[1+\delta+u(\sqrt{1+\delta}-1)]} L(\omega) \quad \text{and} \quad d = L^* \frac{1+\delta}{(\sqrt{1+\delta}-1)u}.$$

Obviously  $L^* \geq 3K$  and  $d \leq L(\omega)$ . Let us consider two different cases:

*First case:*  $x_j > d \sqrt{\frac{\log \log n}{n}}$  for every  $n \leq j < \tilde{n}$ .

Since (7) is true for  $n$  by (1), (2) and (5) in this case we have

$$\begin{aligned} x_{\tilde{n}} &= x_n + \sum_{j=n}^{\tilde{n}-1} \frac{1}{j} [y_j - M(x_j)] - \sum_{j=n}^{\tilde{n}-1} \frac{1}{j} M(x_j) \leq \\ &\leq L(\omega) \sqrt{\frac{\log \log n}{n}} + L^* \sqrt{\frac{\log \log n}{n}} - \beta d \sum_{j=n}^{\tilde{n}-1} \frac{1}{j} \sqrt{\frac{\log \log n}{n}}. \end{aligned}$$

Thus by the definition of  $d$  and by (3) and finally using the definition of  $L^*$  we get

$$\begin{aligned} x_{\tilde{n}} &\leq \sqrt{\frac{\log \log n}{n}} [L(\omega) + L^* - \beta d \log(1+\delta c)] = \\ &= \sqrt{\frac{\log \log n}{n}} \left( L(\omega) + L^* - L^* \sqrt{1+\delta} - L^* \frac{1+\delta}{n} \right) = \frac{L(\omega)}{\sqrt{1+\delta}} \sqrt{\frac{\log \log n}{n}} \leq \\ &\leq L(\omega) \sqrt{\frac{\log \log \tilde{n}}{\tilde{n}}}. \end{aligned}$$

*Second case:* There is a  $j, n \leq j < \tilde{n}$  for which  $x_j < \sqrt{\frac{\log \log n}{n}} d$ . In this case either  $x_{\tilde{n}-1} < 0$  and

$$x_{\tilde{n}} \leq \frac{K+a}{\tilde{n}-1} \leq d \frac{1}{\sqrt{\tilde{n}-1}} \leq L(\omega) \sqrt{\frac{\log \log \tilde{n}}{\tilde{n}}}$$

because of (6) or there is a  $n \leq j^* < \tilde{n}$  for which  $0 \leq x_{j^*} \leq d \sqrt{\frac{\log \log n}{n}}$  and  $x_i \geq 0$  for every  $j^* \leq i < \tilde{n}$  also because of (6). So  $M(x_i) \geq 0$  for these  $i$ -s. Therefore

$$x_{\tilde{n}} \leq x_{j^*} + \left| \sum_{i=j^*}^{\tilde{n}-1} \frac{1}{i} (y_i - M(x_i)) \right| \leq d \sqrt{\frac{\log \log n}{n}} + L^* \sqrt{\frac{\log \log n}{n}} =$$

$$= \sqrt{\frac{\log \log n}{n} \frac{L(\omega)}{\sqrt{1+\delta}}} \leq L(\omega) \sqrt{\frac{\log \log \tilde{n}}{\tilde{n}}}$$

In the same way it can be proved that  $x_n > -L(\omega) \sqrt{\frac{\log \log n}{n}}$ . By a little modification the original statement can be proved too.

Actually we proved the following: There is a constant  $L$

$$\left( \text{explicitly } L = 3K\sqrt{1+\delta} \left( 1 + \frac{1+\delta}{u(\sqrt{1+\delta}-1)} \right) \right),$$

such that if  $|x_n| \leq K_n \sqrt{\frac{\log \log n}{n}}$  for an  $n \geq n_0(\omega)$  and an appropriate number  $K_n$

then  $x_{\tilde{n}} \leq \max(K_n, L) \sqrt{\frac{\log \log n(1+\delta)}{n(1+\delta)}}$  for  $n(1+c\delta) < \tilde{n} \leq n(1+\delta)$ . But choosing a  $c < \varrho < 1$  constant we get that  $x_{\tilde{n}} \leq \sqrt{\frac{1+\delta\varrho}{1+\delta}} \max(L, K_n) \sqrt{\frac{\log \log \tilde{n}}{\tilde{n}}}$  for

$n(1+c\delta) \leq \tilde{n} \leq n(1+\delta\varrho)$ ; If the relation

$$x_n \leq L(\omega) \sqrt{\frac{\log \log n}{n}}$$

were true only for  $L(\omega) > L$  if  $n_0 \leq n < n_0(1+\delta)$  then the inequality  $|x_n| \leq$

$$\leq \sqrt{\frac{1+\delta\varrho}{1+\delta}} L(\omega) \sqrt{\frac{\log \log n}{n}}$$

would be true for  $n_0(1+\varrho\delta) \leq n \leq n_0(1+\varrho\delta)^2$ .

Iterating this result we get our statement.

By an affine transformation we get the following corollary.

COROLLARY. Let  $a_n = \frac{c}{n}$ ,  $2M'(\theta) > c$  and the other conditions of the theorem be fulfilled. Then there is an  $L$  such that

$$P \left( \overline{\lim} \sqrt{\frac{n}{\log \log n}} |x_n - \theta| < L \right) = 1.$$

Remark: If  $M'(\theta) = \beta \leq \frac{1}{2}$ ,  $a_n = \frac{1}{n}$  the same argument gives that

$$P(\lim n^{\beta-\varepsilon} (x_n - \theta) = 0) = 1.$$

The simplest case is when  $M(x) = \beta \cdot x$  we look for the root of  $M(x) = 0$  and there is no error. In this case

$$x_n = (1-\beta) \left( 1 - \frac{\beta}{2} \right) \cdot \left( 1 - \frac{\beta}{n-1} \right) x_0 = x_0 \exp \sum_{i=1}^{n-1} \log \left( 1 - \frac{\beta}{i} \right) \sim C \cdot n^{-\beta}$$

with a constant  $C$  that is

$$P(\lim n^{\beta} (x_n - \theta) = c) = 1.$$

and this shows that the exponent can not be improved.

To prove theorem 2 we need the following lemma.

LEMMA 2. Let  $\xi_1, \xi_2, \dots, \xi_n, \dots$  be independent identically distributed random variables, so that  $P(|\xi_i| \leq K) = 1$  for a constant  $K$  and  $E\xi_i = 0$ .

Then there is a  $\theta > 1$  and  $t > 0$  so that

$$\sum_{i=\theta^{n+1}}^{\theta^{n+1}} \frac{1}{i} \xi_i > t \sqrt{\frac{\log \log \theta^n}{\theta^n}}$$

for infinitely many  $n$  with probability 1.

PROOF. Let us denote  $D\xi_i$  by  $D$ . Clearly

$$\sum_{i=\theta^{n+1}}^{\theta^{n+1}} \frac{1}{i} \xi_i = \sum_{i=\theta^{n+1}}^{\theta^{n+1}} \frac{1}{\theta^n} \xi_i + \sum_{i=\theta^{n+1}}^{\theta^{n+1}} \left( \frac{1}{i} - \frac{1}{\theta^n} \right) \xi_i.$$

To estimate the first member of the sum we need the inequality  $1 - \Phi(x) \cong \frac{1}{\sqrt{2\pi}} \left( \frac{1}{x} - \frac{1}{x^3} \right) e^{-\frac{x^2}{2}}$  ( $\Phi(x)$  is the normal distribution) and the theorem of large deviation for equal components (see [3] p. 517)

$$\begin{aligned} P \left( \sum_{i=\theta^{n+1}}^{\theta^{n+1}} \frac{1}{\theta^n} \xi_i > C_1 D \sqrt{\frac{\log \log \theta^n}{\theta^n}} \right) &= P \left( \frac{\sum_{i=1}^{\theta^n(\theta-1)} \xi_i}{D \sqrt{\theta^n(\theta-1)}} > C_1 \sqrt{\frac{\log \log \theta^n}{\theta^n}} \right) \cong \\ &\cong 1 - \Phi \left[ (C_1 + \varepsilon) \sqrt{\frac{\log \log \theta^n}{\theta-1}} \right] \cong \exp \left[ -(C_1 + \varepsilon)^2 \frac{\log \log \theta^n}{2(\theta-1)} \right] = (n \log \theta)^{-\frac{(C_1 + \varepsilon)^2}{2(\theta-1)}}. \end{aligned}$$

So by the Borel—Cantelli lemma (the sums for different  $n$ 's are independent) for arbitrary  $\varepsilon > 0$

$$(8) \quad \sum_{i=\theta^{n+1}}^{\theta^{n+1}} \frac{1}{\theta^n} \xi_i > \sqrt{(2-\varepsilon)(\theta-1)} D \sqrt{\frac{\log \log \theta^n}{\theta^n}}$$

infinitely many times with probability 1.

Estimating the second member of the sum by the same method as in Lemma 1 we get with  $f(n) = \gamma \sqrt{\theta^n \log \log \theta^n}$ .

$$\begin{aligned} P \left( \sum_{i=\theta^{n+1}}^{\theta^{n+1}} \left( \frac{1}{\theta^n} - \frac{1}{i} \right) \xi_i \cong C_2 \sqrt{\frac{\log \log \theta^n}{\theta^n}} \right) &= \\ &= P \left( \exp f(n) \sum_{i=\theta^{n+1}}^{\theta^{n+1}} \left( \frac{1}{\theta^n} - \frac{1}{i} \right) \xi_i \cong \exp C_2 f(n) \sqrt{\frac{\log \log \theta^n}{\theta^n}} \right) \cong \\ &\cong \prod_{i=\theta^{n+1}}^{\theta^{n+1}} E \left( \exp f(n) \left( \frac{1}{\theta^n} - \frac{1}{i} \right) \xi_i \right) E \left[ \exp \left( -C_2 f(n) \sqrt{\frac{\log \log \theta^n}{\theta^n}} \right) \right] \cong \\ &\cong \exp \left\{ \frac{D^2}{2-\varepsilon} \gamma^2 \sum_{i=\theta^{n+1}}^{\theta^{n+1}} \left( \frac{1}{\theta^n} - \frac{1}{i} \right)^2 \log \log \theta^n - C_2 \gamma \log \log \theta^n \right\} \end{aligned}$$

for sufficiently large  $n$ 's ( $\varepsilon > 0$  is fixed).

But

$$\sum_{i=\theta^{n+1}}^{\theta^{n+1}} \left( \frac{1}{\theta^n} - \frac{1}{i} \right)^2 \leq \frac{\sum_{i=1}^{\theta^{n+1}-\theta^n} i^2}{\theta^{4n}} \leq (1+\varepsilon) \frac{(\theta^{n+1}-\theta^n)^3}{3\theta^{4n}} = \frac{(\theta-1)^3}{3\theta^n} (1+\varepsilon).$$

So by a little calculation, using the Borel—Cantelli lemma we get that

$$(9) \quad \sum_{i=\theta^n}^{\theta^{n+1}} \left( \frac{1}{\theta^n} - \frac{1}{i} \right) \zeta_i \leq \left[ \frac{\sqrt{6}}{3} D(\theta-1)^{\frac{3}{2}} - \varepsilon \right] \sqrt{\frac{\log \log \theta^n}{\theta^n}} \text{ for}$$

sufficiently large  $n$  with probability 1.

Since we can choose  $\theta$  and  $\varepsilon$  as near to 1, and to 0, respectively as we want, Lemma 2 follows from (8) and (9).

Using lemma 2 theorem 2 can be proved easily.

PROOF of theorem 2. Apply lemma 2 for the sequence  $y_i - M(x_i)$  and suppose that the statement of the theorem does not hold. Let  $|M(x)| < \beta|x|$  if  $|x| < \delta$  where  $\beta$  is a positive constant. Then with probability 1 for large  $k$   $|x_k(\omega)| \leq \delta$  and  $|x_k(\omega)| \leq L' \sqrt{\frac{\log \log k}{k}}$  with a constant  $L'$  such that  $L'(2+\beta \log \theta) < t$ . But then

$$\begin{aligned} |x_{\theta^{n+1}+1} - x_{\theta^n+1}| &\leq 2L' \sqrt{\frac{\log \log \theta^n}{\theta^n}} \\ \left| \sum_{i=\theta^{n+1}}^{\theta^{n+1}} \frac{1}{i} M(x_i) \right| &\leq L' \sqrt{\frac{\log \log \theta^n}{\theta^n}} \sum_{i=\theta^{n+1}}^{\theta^{n+1}} \frac{\beta}{i} \leq L' \beta \sqrt{\frac{\log \log \theta^n}{\theta^n}} \log \theta \\ \sum_{i=\theta^{n+1}}^{\theta^{n+1}} \frac{1}{i} [y_i - M(x_i)] &= -x_{\theta^{n+1}+1} + x_{\theta^n+1} - \sum_{i=\theta^{n+1}}^{\theta^{n+1}} \frac{1}{i} M(x_i) \leq \\ &\leq (2L' + \beta \log \theta) \sqrt{\frac{\log \log \theta^n}{\theta^n}} \end{aligned}$$

for sufficiently large  $n$  contradicting to lemma 2.

#### REFERENCES

- [1] ROBBINS, H. and MONRO, S.: A stochastic approximation method, *Annals of Math. Stat.* **22** (1951), 400—407.
- [2] BLUM, J. R.: Approximation methods which converge with probability one, *Annals of Math. Stat.* **25** (1954), 386—388.
- [3] FELLER, W.: *An introduction to Probability Theory and its Applications*, Vol. II. John Wiley and Sons, 1959.
- [4] DOOB, J. L.: *Stochastic processes*, Wiley, New York, 1953.

*Mathematical Institute of the Hungarian Academy of Sciences, Budapest*

(Received February 10, 1972.)