



On Sequences of "Pure Heads"

Author(s): J. Komlos and G. Tusnady

Source: *The Annals of Probability*, Vol. 3, No. 4 (Aug., 1975), pp. 608-617

Published by: [Institute of Mathematical Statistics](#)

Stable URL: <http://www.jstor.org/stable/2959327>

Accessed: 15/07/2013 03:33

Your use of the JSTOR archive indicates your acceptance of the Terms & Conditions of Use, available at
<http://www.jstor.org/page/info/about/policies/terms.jsp>

JSTOR is a not-for-profit service that helps scholars, researchers, and students discover, use, and build upon a wide range of content in a trusted digital archive. We use information technology and tools to increase productivity and facilitate new forms of scholarship. For more information about JSTOR, please contact support@jstor.org.



Institute of Mathematical Statistics is collaborating with JSTOR to digitize, preserve and extend access to *The Annals of Probability*.

<http://www.jstor.org>

ON SEQUENCES OF "PURE HEADS"

BY J. KOMLÓS AND G. TUSNÁDY

Hungarian Academy of Sciences

Statistics connected with the maximum of moving averages of series of i.i.d. random variables are investigated.

1. Introduction. If someone tries to produce (without much thinking) the results of a series of coin tossing, *not* using a coin or any other device generating random numbers, he will carefully check that the rate of "heads" be near to $\frac{1}{2}$, and perhaps in short blocks the "heads" and "tails" will follow each other quite randomly. However, the maximal length of blocks of consecutive heads will surely be far less than would be expected in a real coin tossing situation. Let us denote by ν_n the length of the longest block of consecutive heads (a block of "pure heads") in the first n outcomes in an infinite series of coin tosses. In his book, Rényi (1970) proved that

$$P\left(\lim_{n \rightarrow \infty} \frac{\nu_n}{\log_2 n} = 1\right) = 1.$$

Generally, we may ask for the maximal length of blocks in which the frequency of heads exceeds a fixed x . In case $x > \frac{1}{2}$ the maximal length $\nu_n(x)$ of such blocks is expected still to be around $c \log n$, where c depends on x .

Let $\xi_1, \xi_2, \dots, \xi_m, \dots$ be i.i.d. nondegenerate random variables with distribution function F (left-continuous) having expectation 0. For a fixed m define $\eta_m(i)$ by

$$(1.1) \quad \eta_m(i) = \frac{1}{m} \sum_{j=i}^{i+m-1} \xi_j \quad (i = 1, 2, \dots).$$

For $x > 0$, let $\nu_n(x)$ be the maximum of those m 's for which there exists an $i \leq n$ such that $\eta_m(i) \geq x$, and define $\zeta_n(m)$ by

$$(1.2) \quad \zeta_n(m) = \max_{1 \leq i \leq n} \eta_m(i).$$

For a fixed $x > 0$, the elements of the process

$$(1.3) \quad \tau_m(x, 1), \tau_m(x, 2), \dots, \tau_m(x, k), \dots$$

are the indices i for which $\eta_m(i) \geq x$ (in increasing order). The first term of this process will be denoted by $\tau_m(x)$: $\tau_m(x) = \tau_m(x, 1)$.

Erdős and Rényi (1970) proved that

$$P(\lim_{n \rightarrow \infty} \zeta_n([c \log n]) = h(c)) = 1.$$

Received January 24, 1974; revised October 1, 1974.

AMS 1970 subject classifications. Primary 60F10; Secondary 62G30.

Key words and phrases. Moving average, runs, large deviation, limit theorems for maxima, coin tosses.

The function $h(c)$ is given in Section 4, which contains our main results. In Section 5 the asymptotic behaviour of the process $\tau_m(x, k)$ is investigated. Sections 2 and 3 deal with the necessary preliminaries.

2. Theorems on large deviations. Theorems on large deviations state that the probability of the events

$$(2.1) \quad A_i = \{\eta_m(i) < x\}$$

tends to 1 exponentially, where $\eta_m(i)$ is defined by (1.1). (The events A_i depend on x and on the length m of the blocks, too, but for the sake of simplicity, we do not indicate this dependence in our notations.) The first version of this statement was formulated by Chernoff (1956) in the form

$$\lim_{m \rightarrow \infty} \frac{1}{m} \log P(\bar{A}_1) = \log \rho,$$

where $\rho = \rho(x)$ is the so-called Chernoff function defined in (2.4). This theorem was extended by Bahadur and Ranga Rao (1960). They proved—roughly speaking—that $m^{1/2} \rho^{-m} P(\bar{A}_1)$ tends to some constant. Petrov (1965) proved that this convergence is uniform on closed intervals; we shall state his theorem later in detail.

The finiteness of the moment generating function,

$$(2.2) \quad R(t) = Ee^{t\xi_1} = \int_{-\infty}^{\infty} e^{ty} F(dy)$$

at least for some point $t > 0$, is needed for proving such a theorem. Write a_1 and a_2 for the endpoints (possibly infinite) of the domain of $R(t)$; that is,

$$(2.3) \quad a_1 = \inf \{t: R(t) < \infty\}; \quad a_2 = \sup \{t: R(t) < \infty\}.$$

Denote the open interval (a_1, a_2) by T . It is easy to prove the following three statements:

- i) R is differentiable over T .
- ii) The logarithmic derivative of R ,

$$\phi(t) = \frac{R'(t)}{R(t)}$$

is continuous and monotone increasing. Thus it has an inverse function:

$$\alpha(x) = t \quad \text{if} \quad \phi(t) = x, \quad t \in T,$$

which is also continuous. Note that $\alpha(0) = \phi(0) = 0$, since the expectation of ξ_1 is assumed to be 0.

iii) Denote the interior of the range of ϕ by X : $X = \{\phi(t); a_1 < t < a_2\}$, and the set of positive elements of X by X^+ . For a given $x \in X^+$, the function

$$e^{-tx} R(t) \quad (a_1 < t < a_2)$$

takes its minimum at the point $\alpha = \alpha(x)$. (We shall mostly use the shorter form α for $\alpha(x)$, thus not indicating the parameter x .) Denote this minimal value

by $\rho(x)$:

$$(2.4) \quad \rho(x) = e^{-\alpha x} R(\alpha) = \inf_{a_1 < t < a_2} e^{-tx} R(t).$$

The function ρ is differentiable. In fact, $\rho'(x) = -\alpha\rho(x)$, i.e. the logarithmic derivative of ρ is $-\alpha(x)$, and $\alpha(x)$ in turn is the inverse of the logarithmic derivative of $R(t)$.

The estimation of the probability

$$P(\sum_{i=1}^m \xi_i \geq mx + y)$$

for $x \in X^+$ is usually based on the so-called conjugate distribution. For $\alpha = \alpha(x)$, define the distribution function F_α as

$$F_\alpha(\mu) = \frac{1}{R(\alpha)} \int_{-\infty}^{\mu} e^{\alpha z} F(dz),$$

and let $\tilde{\xi}_1, \tilde{\xi}_2, \dots, \tilde{\xi}_n, \dots$ be i.i.d. random variables with the common distribution F_α . Denote the distribution function of the sum $\sum_{i=1}^m \tilde{\xi}_i$ by G_m .

With these definitions

$$\begin{aligned} P(\sum_{i=1}^m \xi_i \geq mx + y) &= R^m(\alpha) \int_{mx+y}^{\infty} e^{-\alpha z} G_m(dz) \\ &= \rho^m(x) e^{-\alpha y} \int_{mx+y}^{\infty} e^{-\alpha(z-mx-y)} G_m(dz). \end{aligned}$$

The distribution G_m is centered at mx , hence

$$G_m(dz) \sim \frac{dz}{\sigma_\alpha(2\pi m)^{\frac{1}{2}}},$$

which yields the approximation

$$P(\sum_{i=1}^m \xi_i \geq mx + y) \sim \rho^m(x) \cdot e^{-\alpha y} \cdot \frac{1}{\sigma_\alpha(2\pi m)^{\frac{1}{2}}} \cdot \frac{1}{\alpha},$$

where $\sigma_\alpha^2 = \text{Var } \xi_1$.

The only exception is the case when ξ_1 is lattice-valued. Assume that Δ is the largest value such that

$$\sum_{k=-\infty}^{\infty} P(\xi_1 = k\Delta + \omega) = 1.$$

Δ is called the width of the lattice. In this case the distribution G_m is concentrated on the lattice $\mathcal{L}_m = \{k\Delta + m\omega\}_{k=-\infty}^{\infty}$.

THEOREM (V. V. Petrov). *Let $I \subset X^+$ be a closed interval. Then for any $\varepsilon > 0$ there exists a number m_0 such that*

$$\left| P(\sum_{i=1}^m \xi_i \geq mx) - \frac{\rho^m(x)}{b_m(x)m^{\frac{1}{2}}} \right| < \varepsilon \frac{\rho^m(x)}{m^{\frac{1}{2}}}$$

for all $x \in I$ whenever $m > m_0$, where

$$\begin{aligned} b_m(x) &= \alpha \sigma_\alpha(2\pi)^{\frac{1}{2}} && \text{if } \xi_1 \text{ is not lattice-valued} \\ &= \frac{1 - e^{-\alpha\Delta}}{\Delta} e^{-\alpha\Delta x} \sigma_\alpha(2\pi)^{\frac{1}{2}} && \text{if } \xi_1 \text{ is lattice-valued.} \end{aligned}$$

Here Δ denotes the width of the lattice $\mathcal{L}$ of ξ_1 , and

$$\Delta_x = \inf_{v \in \mathcal{L}_m, v \geq mx} (v - mx)$$

is the distance between mx and the first element on the right-hand side of mx of the lattice $\mathcal{L}_m$ of $\sum_{i=1}^m \xi_i$.

COROLLARY. *If $I \subset X^+$ is a closed interval, then there is a constant K_1 and an integer m_0 such that*

$$P(\sum_{i=1}^m \xi_i \geq mx + y \mid \sum_{i=1}^m \xi_i \geq mx) \leq K_1 e^{-\alpha y}$$

for all $m > m_0$, $x \in I$ and arbitrary y .

Note that strictly speaking only the case $x + y/m \in X^+$ is a corollary of the above theorem. The proof, however, is easily extended for arbitrary y . Actually, in case of non-lattice-valued distributions, K_1 could be chosen arbitrarily near to 1.

The fact that the rare event $\bar{A}_1 = \{\sum_{i=1}^m \xi_i \geq mx\}$ occurred has a strong effect on the elements of the whole block $\{\xi_1, \xi_2, \dots, \xi_m\}$. Roughly speaking the elements of a block with a large average are forced to be as near to x as possible. The theoretical background of this phenomenon was investigated by Vincze (1972). It is expressed in the following theorems.

THEOREM (Bárfai). *If $I \subset X^+$ is a closed interval, then*

$$\lim_{m \rightarrow \infty} P(\xi_1 < z \mid \sum_{i=1}^m \xi_i \geq mx) = F_\alpha(z),$$

uniformly in $x \in I$, where $F_\alpha(z)$ is the conjugate distribution defined above.

THEOREM 1. *If $I \subset X^+$ is a closed interval and k is fixed, then*

$$\begin{aligned} \lim_{m \rightarrow \infty} P(\sum_{i=1}^m \xi_i < L_m(mx) + y_0, \xi_1 < y_1, \dots, \xi_k < y_k \mid \sum_{i=1}^m \xi_i \geq mx) \\ = G(y_0) \prod_{i=1}^k F_\alpha(y_i) \end{aligned}$$

uniformly for all $x \in I$, where $L_m(u) = u$ and

$$G(u) = 1 - e^{-\alpha u}, \quad (u \geq 0)$$

if ξ_i is non-lattice valued, otherwise

$$L_m(u) = \min \{v \in \mathcal{L}_m; v \geq u\},$$

and

$$\begin{aligned} G(u) &= 1 - e^{-\alpha k \Delta} & \text{for } (k-1)\Delta < u \leq k\Delta & \quad (k = 1, 2, \dots) \\ &= 0 & \text{for } u \leq 0. \end{aligned}$$

PROOF. This theorem is an extension of the theorem of Bárfai. Since his methods apply in our case, we only sketch the proof.

$$\begin{aligned} P(\sum_{i=1}^m \xi_i \geq L_m(mx) + y_0, \xi_1 < y_1, \dots, \xi_k < y_k \mid \sum_{i=1}^m \xi_i \geq mx) \\ = \int_{-\infty}^{y_1} \dots \int_{-\infty}^{y_k} \frac{P(\sum_{i=k+1}^m \xi_i \geq L_m(mx) + \bar{y}_0 - \sum_{i=1}^k z_i)}{P(\sum_{i=1}^m \xi_i \geq mx)} F(dz_1) \dots F(dz_k), \end{aligned}$$

where $\bar{y}_0 = \inf \{j\Delta : j\Delta \geq y_0\}$ for $y_0 > 0$, and $\bar{y}_0 = 0$ for $y_0 \leq 0$. The sequence of the integrands tends to $R^{-k}(\alpha) \exp\{\alpha \sum_{i=1}^k z_i - \alpha \bar{y}_0\}$ and is dominated by $K(\bar{y}_0, k, x) \exp\{\alpha \sum_{i=1}^k z_i\}$. An application of the Lebesgue theorem completes the proof.

3. A conditional large deviation theorem. Let the events A_i be defined by (2.1) and let $\xi_0, \xi_1, \dots, \xi_k, \dots$ be random variables having the joint distribution given in Theorem 1:

$$P(\xi_0 < y_0, \xi_1 < y_1, \dots, \xi_k < y_k) = G(y_0) \prod_{i=1}^k F_\alpha(y_i).$$

Assume further that the systems $\{\xi_i\}$ and $\{\tilde{\xi}_i\}$ are independent. Denote the probability $P(\xi_1 + \dots + \xi_j > \xi_0 + \xi_1 + \dots + \xi_j; j = 1, 2, \dots, i)$ by $p_i(x)$ and their limit by $p(x) = P(\xi_1 + \dots + \xi_j > \xi_0 + \xi_1 + \dots + \xi_j; j = 1, 2, \dots)$.

Note that the distribution function of the variables ξ_i continuously varies with the parameter x , and hence the function p is continuous.

THEOREM 2. For any $\varepsilon > 0$ and any closed interval $I \subset X^+$ there exist $n_0 = n_0(\varepsilon, I)$ and $m_0 = m_0(\varepsilon, I)$ such that

$$\left| \frac{P(\bar{A}_n | A_1 \dots A_{n-1})}{P(\bar{A}_n)} - p(x) \right| < \varepsilon$$

if $m > m_0$, $n > n_0$ and $x \in I$.

PROOF. Note that

$$\frac{P(\bar{A}_n | A_1 \dots A_{n-1})}{P(\bar{A}_n)} = \frac{P(\bar{A}_1 A_2 \dots A_n)}{P(\bar{A}_1)P(A_2 \dots A_n)} = \frac{P(A_2 \dots A_n | \bar{A}_1)}{P(A_2 \dots A_n)}.$$

Introduce the following events:

$$\begin{aligned} A &= A_1 \\ B &= A_2 \dots A_{k+1} \\ C &= A_{k+2} \dots A_m \\ D_i &= A_{im+1} \dots A_{(i+1)m} & (i = 0, 1, \dots, l) \\ E_i &= A_{im+1} \dots A_n & (i = 0, 1, \dots, l), \end{aligned}$$

where $l < n/m \leq l + 1$, and $k < m_0 < n_0$ will be defined later.

In case $n \leq 3m$ we use the inequalities

$$\begin{aligned} P(B | \bar{A}) &\geq P(A_2 \dots A_n | \bar{A}_1) \geq P(BCD_1 D_2 | \bar{A}) \\ &\geq P(B | \bar{A}) - P(\bar{C} | \bar{A}) - P(\bar{D}_1) - P(\bar{D}_2). \end{aligned}$$

In case $n > 3m$ $A_2 \dots A_n = BCD_1 E_2$, whence

$$\begin{aligned} P(A_2 \dots A_n | \bar{A}_1) &\leq P(BE_2 | \bar{A}) = P(B | \bar{A})P(E_2) \\ P(A_2 \dots A_n | \bar{A}_1) &= P(BE_2 | \bar{A}) - P(BE_2 \bar{C} \bar{D}_1 | \bar{A}) \\ &\geq P(B | \bar{A})P(E_2) - P(\bar{C} | \bar{A})P(E_2) - P(\bar{D}_1)P(E_2). \end{aligned}$$

We shall prove that

- i) for fixed k $P(B|\bar{A})$ tends to p_k as $m \rightarrow \infty$;
- ii) $P(\bar{C}|\bar{A})$ is arbitrarily small if k and m are large enough;
- iii) $P(E_i|E_{i+1})$ is arbitrarily near to 1 for $0 \leq i < l$ if m and n are large enough.

It is easy to see that our theorem is a consequence of these statements.

Part i) is a consequence of Theorem 1. Now we prove ii).

$$\begin{aligned} P(\bar{C}|\bar{A}) &= P(\bigcup_{j=k+2}^m \bar{A}_j | \bar{A}_1) \leq P\left(\eta_m(1) \geq x + \frac{k\delta}{m} \mid \eta_m(1) \geq x\right) \\ &\quad + \sum_{j=k+2}^m P(\eta_{j-1}(1) \leq 2\delta \mid \eta_m(1) \geq x) \\ &\quad + \sum_{j=k+2}^m P(\eta_{j-1}(m+1) \geq \delta) = U + V + W. \end{aligned}$$

The theorem of Bártfai and the corollary of Petrov's theorem imply

$$\begin{aligned} U &\leq K_1 e^{-k\delta\alpha} \\ W &\leq \sum_{j=k+2}^m \rho_1^{j-1} \leq \frac{\rho_1^{k+1}}{1 - \rho_1}, \end{aligned}$$

where $\rho_1 = \rho(\delta)$. The corollary of Petrov's theorem yields

$$\begin{aligned} V &\leq \sum_{j=k+2}^m P(\sum_{i=j}^m \xi_i \geq mx - 2\delta(j-1) \mid \eta_m(1) \geq x) \\ &\leq \sum_{j=k+2}^m \frac{1}{P(\eta_m(1) \geq x)} \cdot P(\sum_{i=j}^m \xi_i \geq (m-j+1)x + (x-2\delta)(j-1)) \\ &\leq K_2 \sum_{j=k+2}^m \rho^{-m} \cdot e^{-(x-2\delta)(j-1)\alpha} \cdot \rho^{m-j+1} \cdot \left(\frac{m}{m-j+1}\right)^{\frac{1}{2}}. \end{aligned}$$

Fortunately $e^{-x\alpha} < \rho(x)$ because

$$\{\int_{-\infty}^{\infty} e^{\alpha z} F(dz) > \exp\{\int_{-\infty}^{\infty} \alpha z F(dz)\} = 1.$$

This inequality assures that V is small enough for a suitably chosen δ and for m and k large enough. This completes the proof of ii), and now we pass to the proof of iii).

From the inequality $P(E_{i+1}) \geq P(E_i) \geq P(E_{i+1}) - P(\bar{D}_i)P(E_{i+2})$ we get

$$1 \geq P(E_i | E_{i+1}) \geq 1 - \frac{P(\bar{D}_i)}{P(E_{i+1} | E_{i+2})}.$$

If m is large enough $P(E_l)$, $P(E_{l-1})$, $P(D_{l-2})$ are close to 1, so we may assume $P(E_{l-1} | E_l) \geq \frac{1}{2}$, $P(D_{l-2}) \geq \frac{3}{4}$.

Step by step we get $P(E_i | E_{i+1}) \geq \frac{1}{2}$ for all $i = 0, 1, \dots, l-1$ (note that the probabilities $P(D_j)$ are equal). Hence $P(E_i | E_{i+1}) \geq 1 - 2P(\bar{D}_i) \geq 1 - 2mP(\bar{A})$. Thus $P(E_i | E_{i+1})$ is arbitrarily close to 1 if m is large enough.

4. The first large block. The investigation of the random variables $\nu_n(x)$, $\tau_n(x)$ and $\zeta_n(m)$ defined in Section 1 is based on the following theorem.

THEOREM 3. For an arbitrary closed interval $I \subset X^+$

$$\begin{aligned} p_{mn}(x) &= P(\tau_m(x) > n) = P(\zeta_n(m) < x) \\ &= \left(1 - (1 + o_{m,n}(1)) \frac{p(x)\rho^m(x)}{b_m(x)m^{\frac{1}{2}}}\right)^n \end{aligned}$$

for all $x \in I$, where $|o_{m,n}(1)|$ is less than $\varepsilon > 0$ if $m > m_1$, and $n > n_1$.

PROOF. The event indicated in the theorem means that there is no block of length m among the first n blocks with an average greater than or equal to x , hence

$$\begin{aligned} p_{mn}(x) &= P(A_1 \cdots A_n) = P(A_1) \prod_{i=2}^n P(A_i | A_1 \cdots A_{i-1}) \\ &= P(A_1) \prod_{i=2}^n (1 - P(\bar{A}_i | A_1 \cdots A_{i-1})). \end{aligned}$$

Theorem 2 implies that $P(\bar{A}_i | A_1 \cdots A_{i-1})$ is near to $p\rho^m b_m^{-1} m^{-\frac{1}{2}}$ if i and m are large enough: $i \geq n_0$, $m \geq m_0$. Since $p(x)$ is continuous and positive, it has a positive lower bound on I . Hence we could write

$$P(\bar{A}_i | A_1 \cdots A_{i-1}) = (1 + o_{m,n}(1)) \frac{p(x)\rho^m(x)}{b_m(x)m^{\frac{1}{2}}}$$

for $i \geq n_0$, $m \geq m_0$. For $i < n_0$ these probabilities tend to 0 as $m \rightarrow \infty$, and so does the term $p\rho^m b_m^{-1} m^{-\frac{1}{2}}$. Hence the given approximation is valid for the whole product.

THEOREM 4. For arbitrary closed interval $I \subset X^+$, and for arbitrary $Z > 0$,

$$P\left(\frac{p(x)\rho^m(x)}{b_m(x)m^{\frac{1}{2}}} \tau_m(x) < z\right) = 1 - e^{-z} + o_m(1),$$

uniformly for all $x \in I$, $0 \leq z \leq Z$, and

$$P(m(\zeta_n(m) - x) < z) = \exp\left\{-\frac{p(x)}{\bar{\alpha}\sigma_\alpha(2\pi)^{\frac{1}{2}}} e^{-\alpha z}\right\} + o_{m,\delta}(1)$$

uniformly for all $x \in I$, $|z| \leq Z$. In the second formula $o_{m,\delta}(1)$ tends to 0 if $m \rightarrow \infty$ and $\delta \rightarrow 0$, where $\delta = |nm^{-\frac{1}{2}}\rho^m(x) - 1|$; moreover in this formula

- i) if ξ_1 is non-lattice valued, then $\bar{\alpha} = \alpha$ and z is arbitrary;
- ii) if ξ_1 is lattice-valued, then $\bar{\alpha} = \Delta^{-1}(1 - e^{-\alpha\Delta})$ and z has to be chosen in such a way that $mx + z \in L_m$.

THEOREM 5. For arbitrary $x \in X^+$,

$$P\left(\lim_{m \rightarrow \infty} \frac{1}{m} \log \tau_m(x) = -\log \rho(x)\right) = 1.$$

$$P\left(\lim_{n \rightarrow \infty} \frac{\nu_n(x)}{\log n} = -\frac{1}{\log \rho(x)}\right) = 1, \quad \text{and}$$

$$P(\lim_{n \rightarrow \infty} \zeta_n(m) = x) = 1.$$

In the third case $m = m(n)$ is an arbitrary sequence with the property $\lim_{n \rightarrow \infty} 1/m \log n = -\log \rho(x)$.

The proof of Theorem 4 is straightforward. The proof of Theorem 5 is based on Theorem 3 and is similar to the proof given by Erdős and Rényi (1970) so we omit the details. Actually the third statement of Theorem 5 is a slight generalization of their theorem. The second statement of Theorem 5 is a generalization of the original theorem of Rényi (1970) on the "pure heads" given in his book. Now the function $h(c)$ mentioned in the introduction is the following: for $1/c = -\log \rho(x)$ the number $h(c)$ is the same as our x . Note that we have no theorem on the limit distribution of $\nu(x)$.

According to Theorem 4 the order of $\tau_m(x)$ is $\rho^{-m}m^{\frac{1}{2}}$, which is also reflected in Theorem 5. This approximation can be refined as follows:

$$P\left(\limsup_{m \rightarrow \infty} \sup_{x \in I} \frac{\log \tau_m(x) + m \log \rho(x) - \frac{1}{2} \log m}{\log \log m} \leq 1\right) = 1,$$

$$P\left(\liminf_{m \rightarrow \infty} \inf_{x \in I} \frac{\log \tau_m(x) + m \log \rho(x) - \frac{1}{2} \log m}{\log m} \geq -2\right) = 1.$$

Note that the term $\log \tau_m(x) + m \log \rho(x) - \frac{1}{2} \log m$ is stochastically bounded by Theorem 4 and hence after division by an arbitrary function tending to infinity, the ratio tends to 0 stochastically.

5. The sequence of indices of large blocks. Fix $x \in I \subset X^+$ and write $\tau_m(x, k)$ for the first index of the k th large block, i.e. $\tau_m(x, k)$ is the first index of the k th of those blocks which have an average greater than or equal to x :

$$\begin{aligned} \eta_m(i) &\geq x && \text{for } i = \tau_m(x, 1), \tau_m(x, 2), \dots \\ \eta_m(j) &< x && \text{for } \tau_m(x, i-1) < j < \tau_m(x, i); \quad i = 1, 2, \dots \end{aligned}$$

where $\tau_m(x, 0) = 0$. In particular $\tau_m(x, 1) = \tau_m(x)$.

Divide the τ 's into groups in the following way. Starting with $\gamma_1 = 1$ we define a sequence of random variables recursively, as follows: $\gamma_k (k \geq 2)$ is the smallest integer for which $\tau_m(x, \gamma_k) - \tau_m(x, \gamma_{k-1}) \geq m$. Denote the set of differences $\{\tau_m(x, j) - \tau_m(x, \gamma_k); j = \gamma_k + 1, \gamma_k + 2, \dots, \gamma_{k+1} - 1\}$ by $\Gamma_m(x, k)$ ($\Gamma_m(x, k)$ is empty if $\gamma_{k+1} = \gamma_k + 1$), and, for the sake of brevity, denote $\Gamma_m(x, 1)$ by $\Gamma_m(x)$. The set $\Gamma_m(x)$ is a random subset of the set of the first $m - 1$ integers: $\Gamma_m(x) \subset \{1, 2, \dots, m - 1\}$. In other words, starting from the first large block and going $j (j < m)$ steps forward we get at a large block if and only if $j \in \Gamma_m(x)$. For determining the limit distribution of the random set $\Gamma_m(x)$ first we present a modification of Theorem 1, in which we investigate the joint distribution of the first variables and the "surplus variable" in the first large block, rather than in an arbitrary large block as done in Theorem 1.

THEOREM 6. *If $I \subset X^+$ is a closed interval, and k is fixed, then*

$$\begin{aligned} \lim_{m \rightarrow \infty} P\left(\sum_{i=\tau_m(x)}^{\tau_m(x)+m-1} \xi_i < L_m(mx) + y_0, \xi_{\tau_m(x)} < y_1, \dots, \xi_{\tau_m(x)+k-1} < y_k\right) \\ = G^*(y_0) \prod_{i=1}^k F_\alpha(y_i) \end{aligned}$$

uniformly for $x \in I$, where $L_m(u)$ is the same as in Theorem 1, and for $u \geq 0$

$$G^*(u) = 1 - e^{-\alpha u} \cdot \frac{P(\sum_{i=1}^j \tilde{\xi}_i > u + \tilde{\xi}_0 + \sum_{i=1}^j \xi_i; j = 1, 2, \dots)}{P(\sum_{i=1}^j \tilde{\xi}_i > \tilde{\xi}_0 + \sum_{i=1}^j \xi_i; j = 1, 2, \dots)}.$$

If ξ_1 is lattice-valued, then we have to replace y_0 in $G^*(y_0)$ by $\tilde{y}_0 = \inf \{j\Delta : j\Delta \geq y_0\}$.

The proof of this theorem is a combination of the methods used in proving Theorems 1 and 2 and so is omitted.

Let ξ_0^* be a random variable with distribution function $G^*(u)$ and let ξ_0^* be independent of the random variables $\{\tilde{\xi}_i\}$, and $\{\xi_i\}$. Define the random subset Γ of the natural numbers as follows: $j \in \Gamma$ if and only if the inequality

$$\sum_{i=1}^j \tilde{\xi}_i \leq \xi_0^* + \sum_{i=1}^j \xi_i$$

holds.

COROLLARY. If $I \subset X^+$ is a closed interval and H is an arbitrary subset of natural numbers, then

$$\lim_{m \rightarrow \infty} P(\Gamma_m(x) = H) = P(\Gamma = H)$$

uniformly for $x \in I$.

THEOREM 7. If $x \in I \subset X^+$ and k is fixed, then the random sets $\Gamma_m(x, 1)$, $\Gamma_m(x, 2)$, $\dots$, $\Gamma_m(x, k)$ have the same asymptotic distribution and they are asymptotically independent. The limit distribution of the normed differences

$$\frac{p(x)\rho^m(x)}{b_m(x)m^{\frac{1}{2}}} [\tau_m(x, \gamma_k) - \tau_m(x, \gamma_{k-1})]$$

is an exponential distribution with parameter $\lambda = 1$.

PROOF. The random variables $\tau_m(x, 1) + m - 1$, $\tau_m(x, \gamma_2) - \tau_m(x, \gamma_1)$, $\dots$, $\tau_m(x, \gamma_k) - \tau_m(x, \gamma_{k-1})$ are independent and identically distributed. Applying Theorem 4 we get the second statement of the theorem. Starting with $\tilde{\gamma}_1 = \gamma_1^* = 1$ define the sequence of random variables $\tilde{\gamma}_k, \gamma_k^*$ recursively as follows: $\tilde{\gamma}_k (k \geq 2)$ is the smallest integer for which $\tau_m(x, \tilde{\gamma}_k) - \tau_m(x, \tilde{\gamma}_{k-1}) \geq 2m$, and $\gamma_k^* (k \geq 2)$ is the smallest integer for which $\tau_m(x, \gamma_k^*) - \tau_m(x, \tilde{\gamma}_{k-1}) \geq m$. Denote by $\tilde{\Gamma}_m(x, k)$ the set of differences $\{\tau_m(x, j) - \tau_m(x, \tilde{\gamma}_k); j = \tilde{\gamma}_k + 1, \tilde{\gamma}_k + 2, \dots, \gamma_{k+1}^* - 1\}$. The random sets $\tilde{\Gamma}_m(x, 1), \tilde{\Gamma}_m(x, 2), \dots, \tilde{\Gamma}_m(x, k)$ are independent and identically distributed. The probability $P(\Gamma_m(x, j) = \tilde{\Gamma}_m(x, j); j = 1, 2, \dots, k) \geq 1 - \sum_{i=2}^k P(\tau_m(x, \gamma_i) < \tau_m(x, \gamma_{i-1}) + 2m)$ tends to 1, and this proves our theorem.

REFERENCES

- [1] BAHADUR, P. R. and RAO, R. RANGA (1960). On deviations of the sample mean. *Ann. Math. Statist.* **31** 1015–1027.
- [2] BÁRTFAI, P. (1972). On a conditional limit theorem. *Prog. Statist.* **1** 85–92. (Budapest).
- [3] CHERNOFF, H. (1956). Large-sample theory: parametric case. *Ann. Math. Statist.* **27** 1–22.
- [4] ERDÖS, P. and RÉNYI, A. (1970). On a new law of large numbers. *J. Analyse Math.* **23** 103–111.

- [5] PETROV, V. V. (1965). On the probabilities of large deviations for sums of independent random variables. *Teor. Verojatnost. i Primenen.* **10** 310-322. *Theor. Probability Appl.* **10** 287-298.
- [6] RÉNYI, A. (1970). *Foundations of Probability*. Holden-Day, San Francisco.
- [7] VINCZE, I. (1972). On the maximum probability principle in statistical physics. *Prog. Statist.* **2** 869-894 (Budapest).

MATHEMATICAL INSTITUTE OF THE
HUNGARIAN ACADEMY OF SCIENCES
1053 BUDAPEST, REÁLTANODA U 13-15
HUNGARY