

## RECONSTRUCTING THE DISTRIBUTION FROM PARTIAL SUMS OF SAMPLES

BY G. HALÁSZ AND P. MAJOR

*Mathematical Institute of the Hungarian  
Academy of Sciences*

Let us observe an infinite sequence  $z_1 = r_1 + \varepsilon_1, z_2 = r_2 + \varepsilon_2, \dots$  where  $r_1, r_2, \dots$  are the partial sums of independent and identically distributed random variables and the sequence of random variables  $\varepsilon_k$  (the errors) is bounded by a function  $f(k)$ . Knowing the sequence  $z_n$  we want to determine the distribution function of the summands. We will show that this problem cannot be solved in general even if  $f(k)$  is constant.

**1. Introduction.** Let a sequence of independent and identically distributed random variables  $\xi_1, \xi_2, \dots$  with an unknown distribution  $F(x)$  be given. Denote the partial sums  $\sum_{i=1}^k \xi_i$  by  $r_k, k = 1, 2, \dots$ . We observe a sequence  $r_k + \varepsilon_k, k = 1, 2, \dots$ , where  $\varepsilon_k$  is some error term. The error is bounded by a function  $f(k)$  i.e.,  $\limsup \varepsilon_k/f(k) \leq 1$  with probability 1, but we know nothing more about it. Can we recognize the unknown distribution  $F(x)$ ? The answer is trivial if  $f(k)$  tends to 0. In that case we know the individual terms  $\xi_i$  with an error tending to zero, thus the empirical distribution functions  $F_n(x)$  based on the first  $n$  terms of the erroneous sample will tend to  $F(x)$ . Now what can be said about larger errors?

The first nontrivial answer was given by P. Bártfai who proved in [1] and [2] that if  $\int \exp(tu) dF(u) < \infty$  for  $|t| < t_0$  and  $f(k) = o(\log k)$ , then the unknown distribution can be recognized from one single realization with probability 1. On the other hand, Remark 1 of [3] implies that even if  $F(x)$  is the standard normal distribution but  $f(k) = \varepsilon \log k$ , then on the basis of the sequence  $r_k + \varepsilon_k$  one cannot decide whether  $F(x)$  is normal or not.

In this paper we deal with the case when the existence of the moment generating function is not assumed. We substitute it by the following condition:

$$(1) \quad F(-x) + [1 - F(x)] < C_1 e^{-u(x)}, x \geq 0.$$

We shall suppose throughout this paper that  $u(x)$  is nonnegative, monotonically increasing, concave (i.e.,  $u'(x)$  is nonincreasing),  $xu'(x) \nearrow \infty$  as  $x \rightarrow \infty$ , and  $u'(x)$  is continuous. ( $xu'(x) \rightarrow \infty$  implies that  $F$  has all moments.)

By a modification of the proof of Bártfai we prove

**THEOREM 1.** *If  $r_1, r_2, \dots, s_1, s_2, \dots$  are sums of i.i.d. rv's with two different*

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distribution functions  $F(x)$  and  $G(x)$  satisfying (1) with an  $u(x)$  such that

$$(2) \quad \int_{\infty} \frac{u(x)}{x^2} dx = \infty$$

then we have with probability 1 with appropriate  $c > 0$  ( $c$  depending only on  $F$  and  $G$ )

$$|r_n - s_n| > \frac{\log n}{(\log \log n)^c}$$

for infinitely many  $n$ .

We do not know whether the  $(\log \log n)^c$  can be omitted in this inequality. A slight modification of the proof would give the following

**THEOREM 1a.** *If  $F(x)$  satisfies (1) with a function  $u(x)$  satisfying (2),*

$$f(n) = o\left(\frac{\log n}{(\log \log n)^k}\right) \quad \text{for all } k > 0$$

then  $F(x)$  can be reconstructed from the sequence  $r_k + \varepsilon_k$ ,  $k = 1, 2, \dots$  with probability 1.

Our Theorem 2 will show that the case  $\int u(x)/x^2 < \infty$  is quite different.

**THEOREM 2.** *If*

$$\int_{\infty} \frac{u(x)}{x^2} dx < \infty$$

then we can find two distributions  $F(x)$  and  $G(x)$ ,  $F(x) \not\equiv G(x)$  and two samples  $\xi_1, \xi_2, \dots$  and  $\eta_1, \eta_2, \dots$  with distributions  $F$  and  $G$  in such a way that  $F(x)$  and  $G(x)$  satisfy (1) and the partial sums  $r_k = \sum_{i=1}^k \xi_i$ ,  $s_k = \sum_{i=1}^k \eta_i$  satisfy the relation

$$|r_n - s_n| \leq 1$$

for all  $n$  with probability 1.

We shall see that this theorem has the following

**COROLLARY.** *For any  $u(x)$ , for which  $\int u(x)/x^2 dx < \infty$  there is a distribution  $F(x)$  satisfying (1) such that  $F(x)$  cannot be recognized even if  $f(k) = C$  whatever the positive constant  $C$  is.*

One may expect that these “hardly recognizable” distributions are pathological. We will show however that there are many pairs of “nice” distributions which satisfy Theorem 2.

Finally, we would like to mention that our investigations concern the situation when nothing is known about the structure of the error. If we know something of it, we may expect better results. The case when the error is caused by rounding off seems to have special interest. Therefore we quote the following result of P. Bártfai.

**THEOREM OF BÁRTFAI [2].** *Let  $\mathcal{F}$  be the class of distribution functions with an*

absolutely continuous density function of bounded variation. Let  $r_1, r_2, \dots$  be the partial sums of i.i.d. rv's with a distribution  $F \in \mathcal{F}$ . Then the unknown distribution  $F$  can be recognized from the sequence  $[r_k], k = 1, 2, \dots$  with probability 1. ( $[\cdot]$  stands for integer part.)

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**2. Proof of the theorems.**

PROOF OF THEOREM 1. Suppose first that the characteristic functions  $\varphi(t)$  and  $\psi(t)$  of our distributions are infinitely differentiable satisfying

$$|a_\nu|, |b_\nu| \leq D_\nu \quad \nu = 1, 2, \dots$$

where

$$\frac{a_\nu}{b_\nu} = ((-i)^\nu / \nu!) \left[ \log \frac{\varphi(t)}{\psi(t)} \right]_{t=0}^{(\nu)}$$

(these are real numbers) and  $D_\nu (\geq 1)$  is logarithmically convex, i.e.,  $D_{\nu+1}/D_\nu$  is nondecreasing. Let

$$f_k(z) = \sum_{\nu=1}^{2k} a_\nu z^\nu .$$

This is to replace the logarithm of the moment generating function, the existence of which is not assumed here, and we try to approximate  $\exp(lf_k(t))$  by

$$(1/m) \sum_{j=1}^m \exp(tR_j)$$

where

$$R_j = \sum_{(j-1)l < i \leq jl} \xi_i \quad j = 1, \dots, m = [n/l] .$$

The integers  $k, l$  and the positive number  $t$  will be given later depending on  $n$  assumed to be large enough.

For  $0 \leq ex/m \leq \frac{1}{2}$

$$\sum_{\nu=m}^{\infty} x^\nu / \nu! \leq \sum_{\nu=m}^{\infty} (ex/\nu)^\nu \leq 1$$

and we have

$$\exp(tR_j) = \sum_{\nu=0}^k (tR_j)^\nu / \nu! + O(1) ,$$

provided that  $|tR_j| \leq k/2e$ . To estimate the probability of this event we use Markov's inequality

$$P(|R_j| > k/2et) \leq (2et/k)^\mu E|R_j|^\mu .$$

Generally, putting

$$\begin{aligned} \exp(lf_k(z)) &= \sum_{\mu=0}^{\infty} d_\mu z^\mu , \\ d_\mu &= (1/\mu!) ER_j^\mu \end{aligned} \quad 0 \leq \mu \leq 2k ,$$

the characteristic function of  $R_j$  being  $\varphi^l(t)$ . By Cauchy's coefficient estimation

$$|d_\mu| \leq (1/r^\mu) \max_{|z|=r} |\exp(lf_k(z))| \leq (1/r^\mu) \exp(l \sum_{\nu=1}^{2k} D_\nu r^\nu)$$

for all  $\mu = 0, 1, \dots$ . Generally, for fixed  $s$  and

$$0 \leq t \leq 1/2D_{2k}^{1/k} \leq 1/2D_{2k}^{1/(2k-s-1)} \quad (k \geq s + 1)$$

$$(3) \quad \sum_{\nu=s+1}^{2k} D_\nu t^\nu \leq t^{s+1} \max_{s+1 \leq \nu \leq 2k} D_\nu (2t)^\nu - s - 1 \sum_{\nu=0}^{\infty} (\frac{1}{2})^\nu \leq c_3 t^{s+1} ,$$

since the maximum here is attained either for  $\nu = s + 1$  or  $\nu = 2k$ , the sequence  $D_\nu(2t)^{\nu-s-1}$  being logarithmically convex. Using this with  $s = 0$  and

$$(4) \quad r = 1/2D_{2k}^{1/k},$$

$$|d_\mu| \leq (1/r^\mu) \exp(c_2lr) \quad \mu = 0, 1, \dots$$

Hence

$$(5) \quad E|R_j|^\mu \leq (\mu!/r^\mu) \exp(c_2lr) \quad \mu \text{ even, } 0 \leq \mu \leq 2k$$

and the Markov inequality gives

$$P(|R_j| > k/2et) \leq (2et/k)^\mu (\mu!/r^\mu) \exp(c_2lr)$$

$$\leq \exp(c_2lr - k)$$

e.g., if  $t \leq 0.1r$  and  $\mu = 2k$ . Since  $j$  takes  $m = [n/l] \leq n$  values, we get

$$(6) \quad \exp(tR_j) = \sum_{\nu=0}^k (tR_j)^\nu / \nu! + O(1)$$

for all  $j = 1, \dots, m$  simultaneously with the exception of an event of probability  $\leq n \exp(c_2lr - k)$ .

Now

$$E \sum_{\nu=0}^k (tR_j)^\nu / \nu! = \sum_{\nu=0}^k d_\nu t^\nu = \exp(lf_k(t)) - \sum_{\nu=k+1}^\infty d_\nu t^\nu$$

$$= \exp(lf_k(t)) + O(1)$$

for  $k \geq c_2lr$ , using again (4) and  $t \leq 0.1r$ . By Cauchy's inequality and (5) we also have

$$E|\sum_{\nu=0}^k (tR_j)^\nu / \nu!|^2 \leq (k + 1) \sum_{\nu=0}^k (t^{2\nu} / \nu!^2) E|R_j|^{2\nu}$$

$$\leq (k + 1) \sum_{\nu=0}^k (t^{2\nu} / \nu!^2) (2\nu)! \exp(c_2lr) / r^{2\nu}$$

$$\leq (k + 1) \exp(c_2lr) \sum_{\nu=0}^\infty (2\nu)! / \nu!^2 10^{2\nu} \leq c_3 k \exp(c_2lr).$$

We are now ready to apply Tchebycheff's inequality for

$$(1/m) \sum_{j=1}^m (\sum_{\nu=0}^k (tR_j)^\nu / \nu!).$$

The  $R_j$ 's being independent, its variance is at most  $c_3 k \exp(c_2lr) / m$  which is thus also an upper bound for the probability that our quantity deviates by more than 1 from its expectation. Taking into account (6) at the same time, we have

$$(1/m) \sum_{j=1}^m \exp(tR_j) = \exp(lf_k(t)) + O(1)$$

with probability at least  $1 - n \exp(c_2lr - k) - c_3 k \exp(c_2lr) / m$ . Choosing  $k = [2 \log n]$ ,  $l = [k/5c_2r]$  this probability is  $\geq 1 - 1/n^k \rightarrow 1$  as  $n \rightarrow \infty$ , if e.g.,

$$(7) \quad r = 1/2D_{2k}^{1/k} \geq 1/k.$$

We proceed the same way with the  $\eta_i$ 's, denoting by  $S_j$  and  $g_k(z)$  quantities corresponding to  $R_j$  and  $f_k(z)$ , respectively. Let

$$M_n = \max_{1 \leq i \leq n} |r_i - s_i|.$$

Then

$$|tR_j - tS_j| \leq t2M_n \leq 2M_n$$

and so

$$(1/m) \sum_{j=1}^m \exp(tR_j) = \exp(O(M_n))(1/m) \sum_{j=1}^m \exp(tS_j).$$

Hence we obtain

$$\exp(lf_k(t)) + O(1) = \exp(lg_k(t) + O(M_n)) + O(\exp(O(M_n)))$$

and in case

$$(8) \quad lg_k(t) \geq c_4(M_n + 1)$$

this yields

$$l(f_k(t) - g_k(t)) = O(M_n + 1).$$

Suppose that  $a_\nu \neq b_\nu$  and let  $\nu = s$  be the first index with  $a_\nu \neq b_\nu$ . Recalling  $|a_\nu|, |b_\nu| \leq D_\nu$  (3) shows that

$$|f_k(t) - g_k(t)| \geq (|a_s - b_s|/2)t^s,$$

if we make the legitimate choice

$$(9) \quad t = c_5/D_{2k}^{1/k}$$

with  $c_5$  sufficiently small, giving

$$(10) \quad M_n + 1 \geq c_6 t^s \geq c_7 k/D_{2k}^{s-1/k}$$

with probability tending to 1. Our choice of  $D_\nu$  will satisfy  $D_{2k}^{1/k} \leq \log^4 k$  for infinitely many  $k$  and so

$$M_n = \max_{1 \leq i \leq n} |r_i - s_i| \geq c_8 \log n / (\log \log n)^{4(s-1)}$$

a.s. for infinitely many  $n$ .

It remains to take care of the assumptions made in the course of the proof.

$D_{2k}^{1/k} \leq \log^4 k$  for our  $k$  guarantees (7).

Without loss of generality we may suppose

$$b_1 = E\eta_i = 0 \quad \text{and} \quad b_2 = E(\eta_i - b_1)^2 > 0.$$

(3) with  $s = 2$  shows that for  $c_8$  in (9) sufficiently small

$$lg_k(t) \geq c_9 t^2$$

and if (8) did not hold, we would get (10) right away with  $s = 2$ .

Turning to  $a_\nu$  and  $b_\nu$ , we first estimate

$$\sup_{-\infty < t < \infty} |\varphi^{(\nu)}(t)| \leq -\int_0^\infty x^\nu dP(|\xi_i| \geq x) \leq \nu \int_0^\infty x^{\nu-1} P(|\xi_i| \geq x) dx,$$

and the same way for  $\psi^{(\nu)}(t)$ . Applying (1) and factoring out

$$x^{\nu-1} \exp(-u(x)/2) \leq c_{10} \max_{x \geq 0} x^\nu \exp(-u(x)/2),$$

we get further

$$\leq c_{10} \nu \max_{x \geq 0} x^\nu \exp(-u(x)/2) \int_0^\infty \exp(-u(x)/2) dx.$$

Differentiation shows that the maximum is taken at  $x = x(\nu) \nearrow +\infty$  defined by

$$\nu = xu'(x)/2$$

since by assumption  $xu'(x) \nearrow +\infty$ . This latter also implies  $u(x)/\log x \rightarrow +\infty$  ( $x \rightarrow \infty$ ), hence the last integral is finite. Putting

$$D_\nu = x^\nu(\nu) \exp(-u(x(\nu))/2)/\nu^\nu$$

we thus have

$$(11) \quad \sup_{-\infty < t < \infty} \frac{|\varphi^{(\nu)}(t)|}{|\psi^{(\nu)}(t)|} \leq c_{11} \nu! \exp(2\nu) D_\nu.$$

The convexity of  $\log D_\nu$  can be checked by considering  $\nu$  as a continuous parameter and calculating

$$\frac{d \log D_\nu}{d\nu} = \log 2/u'(x(\nu)) - 1$$

which is in fact increasing since both  $1/u'(x)$  and  $x(\nu)$  are such. Hence  $\nu! D_\nu$  is also logarithmically convex; and to infer from  $\varphi(t) \not\equiv \psi(t)$   $a_k \not\equiv b_k$ , or what is the same thing  $\varphi^{(\nu)}(0) \not\equiv \psi^{(\nu)}(0)$ , we can apply the Denjoy–Carleman theorem (see [5]) provided that

$$(12) \quad \sum_{\nu=1}^\infty \nu! D_\nu/(\nu + 1)! D_{\nu+1} = \sum_{\nu=1}^\infty D_\nu/(\nu + 1) D_{\nu+1} = +\infty.$$

But,  $D_\nu$  being log-convex even for continuous  $\nu$ , this is easily seen to be equivalent to

$$\begin{aligned} +\infty &= \int_0^\infty \exp(-d \log D_\nu/d\nu) d\nu/\nu = (e/2) \int_0^\infty u'(x(\nu)) d\nu/\nu \\ &= (e/2) \int_0^\infty (u'(x)/xu'(x)) d(xu'(x)) = (e/2) \int_0^\infty du'(x) + (e/2) \int_0^\infty u'(x) dx/x \\ &= O(1) + (e/2) \int_0^\infty (u(x)/x^2) dx \end{aligned}$$

by partial integration and  $u(x) = O(x)$ .

Finally, from (11) (for  $t = 0$ ) it follows the same way as in (3) that the polynomial

$$\pi(z) = \sum_{\mu=1}^\nu \varphi^{(\mu)}(0)z^\mu/\mu! \quad \text{or} \quad \sum_{\mu=1}^\nu \psi^{(\mu)}(0)z^\mu/\mu!$$

satisfies

$$|\pi(z)| \leq \frac{1}{2}$$

for

$$|z| = r = c_{12} \min(1/D_\nu^{1/\nu}, 1)$$

and as  $\pi^{(\mu)}(0) = \varphi^{(\mu)}(0)$  and  $\psi^{(\mu)}(0)$  ( $\mu = 1, 2, \dots, \nu$ ), respectively, we get

$$|a_\nu| \quad \text{or} \quad |b_\nu| = |[\log(1 + \pi(z))]_{z=0}^{(\nu)}|/\nu! \leq \log 2/r^\nu \leq c_{13}^\nu D_\nu$$

by Cauchy’s coefficient estimation, where the right-hand side can be made increasing with  $c_{13}$  large enough and this can play the role of  $D_\nu$  in the proof. (12) and log-convexity implies

$$D_{\nu+1}/D_\nu \leq D_{2k}/D_{2k-1} \leq \log^2 k \quad (\nu \leq 2k - 1)$$

for infinitely many  $k$  and by multiplying these  $D_{2k}^{1/k} \leq c_{14} \log^4 k$  and the proof is completed.

(The above method shows that under the conditions of Theorem 1a the  $a_\nu$ 's can be determined with probability 1. This remark proves Theorem 1a.)

In preparation for the next proof we remark that the Denjoy-Carleman theorem is sharp: If

$$\sum_{\nu=1}^{\infty} D_\nu / (\nu + 1) D_{\nu+1} < +\infty,$$

which we have seen to be equivalent to

$$\int_0^\infty (u(x)/x^2) dx < +\infty,$$

then for any interval  $(\alpha, \beta)$  we can find a function  $h(t)$  vanishing outside  $(\alpha, \beta)$  but not identically such that

$$\sup_{-\infty < t < \infty} |h^{(\nu)}(t)| \leq \nu! D_\nu$$

([5]). If  $(\alpha, \beta) \subset [-\pi, \pi]$ , then, integrating by parts  $\nu$  times, we get for the  $n$ th Fourier coefficient

$$\begin{aligned} |(1/2\pi) \int_\alpha^\beta \exp(-int)h(t) dt| &\leq (1/2\pi|n|^\nu) \int_\alpha^\beta |h^{(\nu)}(t)| dt \\ &\leq \nu! D_\nu / |n|^\nu = \nu! x^\nu(\nu) \exp(-u(x(\nu))/2) / |n|^\nu \\ &\leq c_{15} \exp(-u(|n|/2)/2), \end{aligned}$$

choosing for  $\nu$  an integer with  $|n|/2 \leq x(\nu) \leq |n|$ . This is possible if the variation of  $xu'(x)/2$  is at least 1 over the interval  $[|n|/2, |n|]$ , which, e.g., by adding  $x^2$  to  $u(x)$ , can always be achieved. Replacing  $u(x)$  by  $\alpha u(\beta x)$ , the  $\frac{1}{2}$ 's can, of course, be replaced by any number.

PROOF OF THEOREM 2. The idea is based on the (known) fact that there exists a random variable  $\gamma$  that can be represented in two ways as the sum of two independent identically distributed random variables,  $\gamma = \xi_1 + \xi_2 = \eta_1 + \eta_2$ , say, the two distributions being different. If for  $(\xi_{2l-1}, \xi_{2l}, \eta_{2l-1}, \eta_{2l})$  ( $l = 1, 2, \dots$ ) we choose independent replicas of the quadruple  $(\xi_1, \xi_2, \eta_1, \eta_2)$  then we have defined our sequences with  $r_{2n} = s_{2n}$ . If  $\xi_1 - \eta_1$  can even be made bounded, then  $r_n - s_n$  will also be bounded.

All our variables will take integer values with probabilities

$$\begin{aligned} P(\xi_1 = k) &= P(\xi_2 = k) = p_k, \\ P(\eta_1 = k) &= P(\eta_2 = k) = q_k. \end{aligned}$$

We must have

$$(13) \quad P(\gamma = m) = \sum_{k=-\infty}^{\infty} p_k p_{m-k} = \sum_{k=-\infty}^{\infty} q_k q_{m-k}.$$

$p_k$  and  $q_k$  determine the conditional distributions of  $\xi_1$  and  $\eta_1$ ,

$$\begin{aligned} P_{n,m} &= P(\xi_1 \leq n | \gamma = m) = \sum_{k=-\infty}^n p_k p_{m-k} / P(\gamma = m), \\ Q_{n,m} &= P(\eta_1 \leq n | \gamma = m) = \sum_{k=-\infty}^n q_k q_{m-k} / P(\gamma = m), \end{aligned}$$

but we are at liberty to prescribe their joint conditional distributions, e.g., as

$$(14) \quad P(\xi_1 = i, \eta_1 = j | \gamma = m) \\ = \text{length of the interval } [P_{i-1,m}, P_{i,m}] \cap [Q_{j-1,m}, Q_{j,m}],$$

(This is the so called quantile transformation that has already played an essential role in [2] and [3], [4].) If for each  $n, m$

$$Q_{n-1,m} \leq P_{n,m} \leq Q_{n+1,m}$$

or equivalently

$$(15) \quad -q_n q_{m-n} \leq \sum_{k=-\infty}^n (p_k p_{m-k} - q_k q_{m-k}) \leq q_{n+1} q_{m-n-1},$$

then (14) will be zero unless  $i - j = 1, 0$  or  $-1$ , i.e.,  $P(|\xi_1 - \eta_1| \leq 1) = 1$  and defining  $\xi_2 = \gamma - \xi_1, \eta_2 = \gamma - \eta_1$  the proof will be completed if we can choose  $p_k$  and  $q_k$  with the above properties.

In terms of the characteristic functions

$$\varphi(t) = \sum_{k=-\infty}^{\infty} p_k \exp(ikt), \quad \psi(t) = \sum_{k=-\infty}^{\infty} q_k \exp(ikt) \quad -\pi \leq t \leq \pi$$

condition (13) takes the form  $\varphi^2(t) \equiv \psi^2(t)$ . This will be fulfilled beforehand if we seek our functions as

$$\begin{aligned} \varphi(t) &= f(t) + g(t), & \psi(t) &= f(t) - g(t), \\ f(t) &= \sum_{k=-\infty}^{\infty} a_k \exp(ikt) \quad (\text{with } f(0) = 1) & \text{and} \\ g(t) &= \sum_{k=-\infty}^{\infty} b_k \exp(ikt) \end{aligned}$$

having disjoint support.

According to the remark made after the proof of Theorem 1 there is a Fourier series

$$h_1(t) = \sum_{k=-\infty}^{\infty} d_k \exp(ikt)$$

vanishing for  $\pi/4 \leq |t| \leq \pi$  but not identically (we may suppose  $d_0 \neq 0$ ) such that

$$d_k = O(\exp(-u(|k|))).$$

The convolution

$$h_2(t) = (1/2\pi) \int_{-\pi}^{\pi} h_1(t+z) \overline{h_1(z)} dz$$

has nonnegative coefficients  $|d_k|^2$  and vanishes for  $\pi/2 \leq |t| \leq \pi$ . We define  $f(t)$  by

$$a_k = \sum_{l=-\infty}^{\infty} |d_l|^2 \exp(-u(|k-l|))$$

where we can assume  $\sum_{k=-\infty}^{\infty} a_k = 1$ . The property of vanishing for  $\pi/2 \leq |t| \leq \pi$  is preserved since

$$f(t) = h_2(t) \sum_{k=-\infty}^{\infty} \exp(-u(|k|) + ikt),$$

but we also have

$$a_k \geq |d_0|^2 \exp(-u(|k|))$$

and since  $u(|k-l|) \geq u(|k|) - u(|l|)$ ,  $u(x)$  being increasing and concave,

$$(16) \quad \begin{aligned} a_k &\leq c_{16} \sum_{l=-\infty}^{\infty} \exp(-2u(|l|) - u(|k-l|)) \\ &\leq c_{16} \exp(-u(|k|)) \sum_{l=-\infty}^{\infty} \exp(-u(|l|)) \end{aligned}$$



and so

$$(17) \quad c_{17} \exp(-u(|k|)) \leq a_k \leq c_{18} \exp(-u(|k|)) .$$

Let now

$$h_3(t) = \sum_{k=-\infty}^{\infty} e_k \exp(ikt)$$

be a function vanishing for  $-\pi \leq t \leq \pi/2$  but not identically with

$$e_k = O(\exp(-4u(|k|)))$$

and put

$$g(t) = \delta(h_3(t) + \overline{h_3(-t)}) \quad (\neq 0) .$$

( $\delta$  will be fixed later.) This is zero for  $|t| \leq \pi/2$  and has real coefficients satisfying

$$|b_k| \leq c_{19} \delta \exp(-4u(|k|)) .$$

From (17) it follows that

$$(18) \quad 0 < c_{20} \exp(-u(|k|)) \leq \frac{p_k}{q_k} = \frac{a_k + b_k}{a_k - b_k} \leq c_{21} \exp(-u(|k|))$$

for  $\delta$  small enough.

Turning to condition (15) we see from the last estimations and the fact  $|u(|k + 1|) - u(|k|)| \leq u(1)$  that it is equivalent to

$$(19) \quad |\sum_{k=-\infty}^n (b_k a_{m-k} + b_{m-k} a_k)| \leq |\sum_{k=-\infty}^n b_k a_{m-k}| + |\sum_{k=m-n}^{\infty} b_k a_{m-k}| \\ \leq c_{22} \exp(-u(|n|) - u(|m - n|)) .$$

Note that,  $f(t)$  and  $g(t)$  having disjoint support,  $f(t)g(t) \equiv 0$ , hence

$$\sum_{k=-\infty}^{\infty} b_k a_{m-k} = 0 .$$

This means that we can replace, in the case of the first sum,  $\sum_{k=-\infty}^n$  by  $\sum_{n+1}^{\infty}$ . We do so if  $n \geq 0$  but leave it in the original form if  $n < 0$ . In any case

$$|\sum_{k=-\infty}^n b_k a_{m-k}| \leq c_{23} \delta \sum_{|k| \geq n} \exp(-4u(|k|) - u(|m - k|)) \\ \leq c_{23} \delta \exp(-2u(|n|)) \sum_{k=-\infty}^{\infty} \exp(-2u(|k|) - u((m - k))) ,$$

and as in (16) we get further

$$\leq c_{24} \delta \exp(-2u(|n|) - u(|m|)) \leq c_{24} \delta \exp(-u(|n|) - u(|m - n|))$$

using again  $u(|m|) \geq u(|m - n|) - u(|n|)$ .

The second sum in (19) coincides with the first for  $n$  replaced by  $m - n - 1$  and we see that (19) holds for  $\delta$  sufficiently small. From (18) we get for the tail probabilities the upper bound

$$c_{21} \sum_{|k| \geq x} \exp(-u(|k|)) \leq c_{21} \exp(-u(x)/2) \sum_{k=-\infty}^{\infty} \exp(-u(|k|)/2) \\ \leq c_{25} \exp(-u(x)/2)$$

which is the statement with  $u(x)/2$  in place of  $u(x)$ .  $\square$

**3. Consequences of the theorems and problems.** To prove the corollary we

use a lemma. This lemma has already been proved in [4] (Lemma 1) but for the sake of completeness we give the proof here again.

LEMMA. *We are given distribution functions  $F_1(x)$ ,  $F_2(x)$  and  $G_1(x)$ ,  $G_2(x)$  and sums of i.i.d. rv's  $r_1^{(i)}, r_2^{(i)}, \dots, s_1^{(i)}, s_2^{(i)} \dots i = 1, 2$  such that  $r_1^{(i)}$  has distribution  $F_i(x)$  and  $s_1^{(i)}$  has distribution  $G_i(x)$ , and moreover*

$$P(|s_k^{(1)} - r_k^{(1)}| < a \text{ for all } k) = 1, \\ P(|s_k^{(2)} - r_k^{(2)}| < b \text{ for all } k) = 1.$$

Let  $p$  be an arbitrary number  $0 \leq p \leq 1$  and

$$F(x) = pF_1(x) + (1 - p)F_2(x), \\ G(x) = pG_1(x) + (1 - p)G_2(x).$$

Then there exist two sequences of sums of i.i.d. rv's  $r_1, r_2, \dots, s_1, s_2, \dots$  such that  $r_1$  has distribution  $F(x)$ ,  $s_1$  has distribution  $G(x)$ , and  $P(|s_k - r_k| < a + b \text{ for all } k) = 1$ .

PROOF. We may suppose that the two sequences of pairs  $\{r_k^{(1)}, s_k^{(1)}\}_{k=1}^\infty$  and  $\{r_k^{(2)}, s_k^{(2)}\}_{k=1}^\infty$  are independent. Define a sequence of i.i.d. rv's  $\varepsilon_1, \varepsilon_2, \dots$  with distribution  $P(\varepsilon_1 = 1) = 1 - P(\varepsilon_1 = 0) = p$  such that the sequence is independent of all the variables  $r_k^{(1)}, s_k^{(1)}, r_k^{(2)}, s_k^{(2)}$ .

Set  $\tau(n) = \sum_{i=1}^n \varepsilon_i$ , and

$$r_n = r_{\tau(n)}^{(1)} + r_{n-\tau(n)}^{(2)} \\ s_n = s_{\tau(n)}^{(1)} + s_{n-\tau(n)}^{(2)}.$$

Then the sequence  $r_n$  has the prescribed joint distribution, and the same holds for  $s_n$ . Furthermore,

$$|s_n - r_n| \leq \sup_k |s_k^{(1)} - r_k^{(1)}| + \sup_k |s_k^{(2)} - r_k^{(2)}| < a + b.$$

PROOF OF THE COROLLARY. Applying Theorem 2 with  $u(2^i x)$  instead of  $u(x)$  we obtain two distributions  $F_i(x)$ ,  $G_i(x)$  and sums of i.i.d. rv's  $r_1^{(i)}, r_2^{(i)}, \dots, s_1^{(i)}, s_2^{(i)}, \dots$  with distribution  $F_i(x)$  resp.  $G_i(x)$  such that

$$P\left(|r_n^{(i)} - s_n^{(i)}| < \frac{1}{2^i} \text{ for all } n\right) = 1$$

and  $F_i(x)$ ,  $G_i(x)$  satisfy (1).

Let  $\sum_{i=1}^\infty p_i = 1$ ,  $p_i > 0$ , and let  $p_i$  tend to zero fast enough. Define  $F(x) = \sum_{j=1}^\infty p_j F_j(x)$ ,  $\bar{G}_i(x) = \sum_{j \neq i} p_j F_j(x) + p_i G_i(x)$ . Then  $F(x)$  and  $\bar{G}_i(x)$  satisfy (1) and they cannot be distinguished if the error may exceed  $1/2^{i+1}$ , because the lemma enables us to construct two sums of i.i.d. rv's  $r_1, r_2, \dots, \bar{s}_1^{(i)}, \bar{s}_2^{(i)}, \dots$  with distributions  $F(x)$  and  $\bar{G}_i(x)$  in such a way that

$$|r_n - \bar{s}_n^{(i)}| < \frac{1}{2^i}. \quad \square$$

Our lemma enables us to construct a much wider class of distributions satisfying Theorem 2. Namely we have

**THEOREM 3.** *Let  $\int_{-\infty}^{\infty} (u(x)/x^2) dx < \infty$ , and let the distribution function  $F(x)$  have a density  $f(x)$  satisfying the inequality  $f(|x|) \geq Ce^{-u(x)}$ ,  $x \geq 0$ . Then there exist a distribution function  $G(x)$  and two sums of i.i.d. rv's  $r_1, r_2, \dots, s_1, s_2, \dots$  with distribution  $F(x)$  and  $G(x)$  in such a way that*

$$P(|r_n - s_n| \leq 1 \text{ for all } n) = 1.$$

**PROOF.** Let  $F_1(x)$  and  $G_1(x)$  be two distributions constructed in Theorem 2. Consider the convolutions

$$F_2(x) = F_1(x) * I(x)$$

and

$$G_2(x) = G_1(x) * I(x)$$

( $I(x)$  denotes the uniform distribution on  $[0, 1]$ .) Then  $F_2(x)$  and  $G_2(x)$ , too, satisfy Theorem 2 and  $F_2(x)$  has a density function  $f_2(x)$ ,  $f_2(x) \leq C'e^{-u(|x|)}$ . We can write  $f(x)$  in the form

$$f(x) = \alpha f_2(x) + (1 - \alpha)h(x)$$

where  $0 < \alpha \leq 1$  and  $h(x)$  is the density of a distribution function  $H(x)$ . Because of the lemma the distributions

$$F(x) = \alpha F_2(x) + (1 - \alpha)H(x)$$

$$G(x) = \alpha G_2(x) + (1 - \alpha)H(x)$$

satisfy Theorem 3.

One would also like to characterise the pairs of distributions  $F(x)$ ,  $G(x)$  satisfying Theorem 2. In all our previous examples the characteristic functions of these distributions  $F(x)$  and  $G(x)$  coincided in a neighbourhood of the origin. Using a slight generalization of the lemma we can get rid of this restriction. Another question is whether the moments of these distributions may differ. We can prove that if  $F(x)$  and  $G(x)$  have  $4 + \epsilon$ th moment  $\epsilon > 0$ , then the third moments must be the same. If the tails of the distributions satisfy (1) with  $u(x) = x^{4+\epsilon}$ , then even the fourth moments must agree, etc. But we cannot answer the following question. Let  $F(x)$  and  $G(x)$  have all moments and assume that they satisfy Theorem 2. Are all the moments of  $F(x)$  and  $G(x)$  necessarily equal?

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MATHEMATICAL INSTITUTE OF  
THE HUNGARIAN ACAD. OF SCIENCES  
H-1053 BUDAPEST V.,  
REALTANODA U. 13-15  
HUNGARY