

## ON A NEW LAW OF LARGE NUMBERS

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### §1. Introduction

We shall prove first (in §2) the new law of large numbers for the simplest special case, that is for independent repetitions of a fair game. For this special case the theorem can be stated as follows: if the game is played  $N$  times, the maximal average gain of a player over  $[C \log_2 N]$  consecutive games\* ( $C \geq 1$ ), tends with probability one to the limit  $\alpha$ , where  $\alpha$  is the only solution in the interval  $0 < \alpha \leq 1$  of the equation

$$\frac{1}{C} = 1 - \left(\frac{1+\alpha}{2}\right) \log_2 \left(\frac{2}{1+\alpha}\right) - \left(\frac{1-\alpha}{2}\right) \log_2 \left(\frac{2}{1-\alpha}\right).$$

In §3 we generalize this result to an arbitrary sequence  $\eta_n$  ( $n = 1, 2, \dots$ ) of independent, identically distributed random variables with expectation 0, the common distribution of which satisfies the condition, that its moment-generating function  $\phi(t) = E(e^{\eta_n t})$  exists in an open interval around the origin. We prove that for every  $\alpha$  in a certain interval  $0 < \alpha < \alpha_0$  one has

$$(1.1) \quad P\left(\lim_{N \rightarrow +\infty} \max_{0 \leq n \leq N - [C \log N]} \frac{\eta_{n+1} + \eta_{n+2} + \dots + \eta_{n+[C \log N]}}{[C \log N]} = \alpha\right) = 1,$$

where  $C = C(\alpha)$  is defined by the equation

$$(1.2) \quad e^{-(1/C)} = \min_t \phi(t) e^{-\alpha t}.$$

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\* Here and in what follows  $[x]$  denotes the integral part of  $x$ .

In §4 we discuss the special case of Gaussian random variables, in which case our result is essentially equivalent to a previous result of *Paul Lévy* about the Brownian movement process.

In §5 we give as an application of the result of §3, a new proof of the theorem of *P. Bártfai* on the "stochastic geyser problem", using the fact that the functional dependence between  $C$  and  $\alpha$  in (1.1) determines the distribution of the variables uniquely (Theorem 3). The result of §2 can also be applied in probabilistic number theory; as a matter of fact it was such an application which led the first named author to raise the problem which is solved in the present paper.

## §2. The maximal average gain of a player over a short period.

Let  $\xi_1, \xi_2, \dots, \xi_n, \dots$  be a sequence of independent random variables, each taking on the values  $\pm 1$  with probability  $1/2$ . We may interpret  $\xi_n$  as the gain of one of the players in the  $n^{\text{th}}$  repetition of a fair game. Let us put  $S_0 = 0$ ,

$$(2.1) \quad S_n = \xi_1 + \xi_2 + \dots + \xi_n \quad (n = 1, 2, \dots)$$

and

$$(2.2) \quad \vartheta(N, K) = \max_{0 \leq n \leq N-K} \frac{S_{n+K} - S_n}{K}.$$

Let us introduce the notation

$$(2.3) \quad h(x) = x \log_2 \frac{1}{x} + (1-x) \log_2 \frac{1}{1-x} \quad \text{for } 0 < x < 1;$$

i.e.  $h(x)$  is the entropy of the probability distribution  $(x, 1-x)$ . We shall prove the following

**Theorem 1.** *For every fixed  $c \geq 1$  we have\**

$$(2.4) \quad P(\lim_{N \rightarrow +\infty} \vartheta(N, [c \log_2 N]) = \alpha) = 1,$$

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\* Here and what follows  $P(\dots)$  denotes the probability of the event in the brackets.

where  $\alpha = \alpha(c)$  is the only solution with  $0 < \alpha \leq 1$  of the equation

$$(2.5) \quad \frac{1}{c} = 1 - h\left(\frac{1 + \alpha}{2}\right).$$

**Remark.** It is easy to see that  $\alpha(c)$  is a decreasing function of  $c$ , further  $\alpha(1) = 1$  and  $\lim_{c \rightarrow +\infty} \alpha(c) = 0$ .

**Proof of Theorem 1.** We shall use the following estimates, which follow immediately from Stirling's formula: If  $\frac{1}{2} \leq \gamma < 1$

$$(2.6) \quad A_1 \cdot n^{-1/2} \cdot 2^{n(h(\gamma)-1)} \leq 2^{-n} \sum_{n\gamma \leq K \leq n} \binom{n}{K} \leq B_1 \cdot n^{-1/2} \cdot 2^{n(h(\gamma)-1)}$$

where  $A_1$  and  $B_1$  are positive constants, depending only on  $\gamma$ . Let  $c \geq 1$  be fixed, and let  $\alpha$  be the unique solution of the equation (2.5) with  $0 < \alpha \leq 1$ . Let  $\varepsilon$  be an arbitrary small positive number and put  $\alpha' = \alpha + \varepsilon$ . It follows from (2.6) that

$$(2.7) \quad P(\vartheta(N, [c \log_2 N]) \geq \alpha') \leq B_1 N^{-\delta_1}$$

where  $\delta_1$  is a positive number, depending only on  $\alpha$  and  $\varepsilon$ . Thus the series

$$(2.8) \quad \sum_{j=1}^{+\infty} P(\vartheta(2^{(j+1)/c} - 1, j) \geq \alpha')$$

is convergent, and therefore by the Borel-Cantelli lemma one has

$$(2.9) \quad \vartheta(2^{(j+1)/c} - 1, j) < \alpha'$$

with probability 1 for all but a finite number of values of  $j$ . As however

$$(2.10) \quad \vartheta(N, [c \log_2 N]) \leq \vartheta(2^{(j+1)/c} - 1, j) \text{ for } 2^{j/c} \leq N \leq 2^{(j+1)/c} - 1,$$

it follows that with probability one, for all but a finite number of values of  $N$  one has

$$(2.11) \quad \vartheta(N, [c \log_2 N]) < \alpha'.$$

As  $\varepsilon > 0$  is arbitrary, we obtain

$$(2.12) \quad P(\limsup_{N \rightarrow +\infty} \vartheta(N, [c \log_2 N]) \leq \alpha) = 1.$$

Now let again  $\varepsilon$  be an arbitrary small positive number,  $0 < \varepsilon < \alpha$  and put  $\alpha'' = \alpha - \varepsilon$ . As

$$(2.13) \quad P(\vartheta(N, K) \leq \alpha'') \leq P\left(\frac{S_{(r+1)K} - S_{rK}}{K} \leq \alpha'', 0 \leq r \leq \frac{N}{K} - 1\right)$$

and because of the independence of the random variables  $S_{(r+1)K} - S_{rK}$  ( $r = 0, 1, \dots$ ) it follows that

$$(2.14) \quad P(\vartheta(N, [c \log_2 N]) \leq \alpha'') \leq \left(1 - \frac{A_1 N^{\delta_2}}{N}\right)^{N/([c \log_2 N]) - 1} \leq e^{-(A_2 N^{\delta_2})/\log N}$$

where  $A_2$  and  $\delta_2$  are positive constants. Thus the series

$$(2.15) \quad \sum_{N=1}^{\infty} P(\vartheta(N, [c \log_2 N]) \leq \alpha'')$$

is convergent and using again the Borel-Cantelli lemma we get

$$(2.16) \quad P \liminf_{N \rightarrow +\infty} \vartheta(N, [c \log_2 N]) \geq \alpha) = 1.$$

As (2.12) and (2.16) imply (2.4), Theorem 1 is proved.

It should be remarked, that the same argument as that used to prove (2.12) can be used to show that if  $K(N)$  is an integer-valued function of  $N$  such that  $\frac{K(N)}{\log N} \rightarrow +\infty$  we have

$$(2.17) \quad P\left(\lim_{N \rightarrow +\infty} \vartheta(N, K(N)) = 0\right) = 1.$$

This result can be interpreted as follows: if  $K(N)$  grows faster than  $\log N$ , then the ordinary law of large numbers applies. On the other hand if  $K(N) \leq c \log_2 N$  with  $0 < c < 1$  then with probability 1 for all except for a

finite number of values of  $N$  there exists at least one  $n \leq N - K(N)$  such that  $\xi_{n+1} = \xi_{n+2} = \dots = \xi_{n+K(N)} = 1$ , which of course implies  $\vartheta(N, K(N)) = 1$ . Thus the case of real interest is just when  $K(N) \sim c \log_2 N$  with  $c \geq 1$ , and Theorem 1 gives an answer to the question what happens in this case.

### §3. The general case.

We shall prove now the following

**Theorem 2.** *Let  $\eta_1, \eta_2, \dots, \eta_n, \dots$ , be a sequence of independent, identically distributed nondegenerate random variables. We suppose that the moment generating function*

$$(3.1) \quad \phi(t) = E(e^{t\eta_n})$$

*of the common distribution of the  $\eta_n$  exists\* for  $t \in I$  where  $I$  is an open interval\*\* containing  $t = 0$ . Let us suppose that*

$$(3.2) \quad E(\eta_n) = 0.$$

*Let  $\alpha$  be any positive number such that the function  $\phi(t)e^{-\alpha t}$  takes on its minimum in some point in the open interval  $I$  and let us put*

$$(3.3) \quad \min_{t \in I} \phi(t)e^{-\alpha t} = \phi(\tau)e^{-\alpha\tau} = e^{-(1/C)}.$$

*Then  $C > 0$  and putting  $S_0 = 0$ ,*

$$(3.4) \quad S_n = \eta_1 + \eta_2 + \dots + \eta_n \quad \text{for } n \geq 1$$

*and*

$$(3.5) \quad \vartheta(N, K) = \max_{0 \leq n \leq N-K} \frac{S_{n+K} - S_n}{K} \quad (1 \leq K \leq N),$$

*we have\*\*\**

$$(3.6) \quad P \lim_{N \rightarrow +\infty} \vartheta(N, [C \log N]) = \alpha = 1.$$

\*  $E(\dots)$  denotes the expectation of the random variable in the brackets.

\*\* We suppose that  $I$  is the largest open interval in which  $\phi(t)$  exists.

\*\*\* In this and the following §§  $\log N$  denotes the natural logarithm of  $N$ .

**Proof of Theorem 2.** Let us notice first that  $\psi(t) = \phi(t)e^{-\alpha t}$  is a strictly convex function: thus  $\tau$  in (3.3) is determined uniquely. As clearly  $\psi(0) = 1$  and in view of (3.2)  $\psi'(0) = -\alpha < 0$  it follows that  $\tau > 0$  and  $\psi(\tau) < 1$  and thus  $C > 0$ . Let us mention that the condition that  $\psi(t)$  takes on its minimum in the interval  $I$  is satisfied if for instance  $P(\eta_n > \alpha) > 0$  because in this case  $\psi(t)$  tends to  $+\infty$  if  $t$  tends to the upper endpoint of  $I$  (which may be the point  $+\infty$ ). We have evidently

$$\frac{\phi'(\tau)}{\phi(\tau)} = \alpha.$$

The proof of Theorem 2 follows exactly that of Theorem 1, only instead of (2.6) we have to use the following result, which under some restrictions is due to *H. Cramér* (see [1]), and in the form needed for our purpose is due to *R. R. Bahadur* and *R. Ranga Rao* (see [2], Theorem 1):

$$(3.7) \quad P(S_n > \alpha n) = \frac{e^{-(n/C)}}{\sqrt{2\pi n}} b_n \cdot (1 + o(1))$$

where  $b_n$  is a sequence of positive numbers such that  $0 < b \leq b_n \leq B$ ; if the  $\eta_n$  are not lattice variables,  $b_n$  does not depend on  $n$ .

**Remark.** In the special case when  $P(\eta_n = \pm 1) = 1/2$ , we have  $\phi(t) = \frac{1}{2}(e^t + e^{-t})$  therefore if  $0 < \alpha < 1$   $\tau = \frac{1}{2} \log \frac{1+\alpha}{1-\alpha}$  and  $\frac{1}{C} = \frac{1+\alpha}{2} \log(1+\alpha) + \frac{1-\alpha}{2} \log(1-\alpha)$ . Passing to logarithms with base 2 it is easily seen that  $e^{-(1/C)} = 2^{h((1+\alpha)/2)-1} = 2^{-(1/c)}$  i.e.  $c = C \log 2$ . Thus the statement of Theorem 1 for  $c > 1$  is contained as a special case in Theorem 2.

#### §4. The Gaussian case.

Let us consider the special case in which the random variables have a normal distribution with mean 0 and variance 1. (In this case of course  $S_n$  is also normally distributed and we do not even need the result (3.7).) As regards the connection between  $C$  and  $\alpha$  this can be explicitly determined in this special

case: we have evidently for every  $\alpha > 0$   $C = \frac{2}{\alpha^2}$ , and thus we get from (3.6)

$$(4.1) \quad P(\lim_{N \rightarrow +\infty} \vartheta(N, [C \log N]) = \sqrt{\frac{2}{C}} = 1 \text{ for every } C > 0.$$

From (4.1) one can deduce the following remarkable theorem, due to *P. Lévy* (see [3]): Let  $x(t)$  be a Brownian movement process, then

$$(4.2) \quad \lim_{h \rightarrow 0} P\left(|x(t+h) - x(t)| < \lambda \sqrt{2h \log \frac{1}{h}} \text{ for } 0 \leq t \leq 1 - h\right) = \begin{cases} 1 & \text{if } \lambda > 1 \\ 0 & \text{if } \lambda < 1. \end{cases}$$

Notice that if the variance of the random variables  $\eta_n$  is equal to 1 then we have in general for  $\alpha \rightarrow 0$   $C \sim 2/\alpha^2$ ; as a matter of fact we have for  $t \rightarrow 0$   $\phi'(t) \sim t$  and thus for  $\alpha \rightarrow 0$  we get  $\tau \sim \alpha$  and therefore  $C \sim 2/\alpha^2$ . Thus for very small values of  $\alpha$  the relation between  $\alpha$  and  $C$  in Theorem 2 becomes in the limit independent from the distribution of the variables  $\eta_n$ ; however for a fixed not too small value of  $\alpha$  the functional relation between  $\alpha$  and  $C$  depends essentially on the distribution of the random variables  $\eta_n$ . Clearly the reason why the relation between  $\alpha$  and  $C$  in Theorem 2 depends on the distribution of the variables  $\eta_n$ , is that Theorem 2 is a theorem about big deviations, while the reason for the disappearance of this dependence in the limit if  $\alpha \rightarrow 0$  is that if  $\alpha$  is decreasing we approach the domain of validity of the central limit theorem.

**§5. An application.**

Let  $\eta_n$  ( $n = 1, 2, \dots$ ) be a sequence of independent and identically distributed random variables and let  $F(x)$  denote their common distribution function. Let us put

$$(5.1) \quad \xi_n = S_n + r_n$$

where  $S_n$  is defined by (3.4) and  $r_n$  ( $n = 1, 2, \dots$ ) is an arbitrary sequence of bounded random variables such that

$$(5.2) \quad |r_n| \leq R_n \text{ where } R_n = o(\log n)$$

(Nothing is supposed concerning the dependence between the variables  $S_n$  and  $r_n$ ). *P. Bártfai* has proved (see [4]) that if the moment generating function

$$(5.3) \quad \phi(t) = \int_{-\infty}^{+\infty} e^{tx} dF(x)$$

of the variables  $\eta_n$  exists in a neighbourhood of  $t = 0$ , then given the values  $\xi_n$  ( $n = 1, 2, \dots$ ) the distribution function  $F(x)$  is thereby uniquely determined with probability one. A new proof of this result of *Bártfai* can be obtained from Theorem 2 as follows: We may suppose without restricting the generality that  $E(\eta_n) = 0$ ; in this case all conditions of Theorem 2 are satisfied and thus it follows that for  $0 < \alpha < a$  where  $a$  is a sufficiently small positive number we have (in view of (5.2)) with probability one

$$(5.4) \quad \lim_{N \rightarrow +\infty} \left( \max_{0 \leq n \leq N - [c \log N]} \frac{\xi_{n+[c \log N]} - \xi_n}{[c \log N]} \right) = \alpha.$$

Thus knowing the sequence  $\xi_n$  we can determine the functional dependence between  $\alpha$  and  $c$ .

To prove *Bártfai's* theorem we shall need the following

**Theorem 3.** *The functional dependence between  $\alpha$  and  $c = c(\alpha)$  in Theorem 2 determines the distribution of the random variables  $\eta_n$  uniquely.*

**Proof.** If the function  $c = c(\alpha)$  is given for  $0 < \alpha < a$ , we can determine the function

$$(5.5) \quad \lambda(\alpha) = e^{-(1/c(\alpha))}$$

and thus also the function

$$(5.6) \quad \frac{\lambda'(\alpha)}{\lambda(\alpha)} = -\tau.$$

As clearly  $\tau = \tau(\alpha)$  is an increasing function of  $\alpha$ , its inverse function  $\alpha = \alpha(\tau)$  can also be determined. This means however that we can determine the function

$$(5.7) \quad \phi(\tau) = \alpha(\alpha(\tau))e^{\tau\alpha(\tau)}$$

in some interval  $0 \leq \tau \leq \tau_0$ . As it is well known that the moment-generating function  $\phi(t)$  determines the distribution function  $F(x)$  uniquely, (even if  $\phi(t)$  is given only in some interval, it being an analytic function if it exists), the statement of Theorem 3 follows.

It follows from Theorem 3 that in the stochastic geyser problem if we know a single realization of the sequence  $\zeta_n$  ( $n = 1, 2, \dots$ ) we can determine the distribution function  $F(x)$  with probability one; this proves *Bárfai's* theorem.

#### REFERENCES

1. H. Cramér, *Sur un nouveau théorème-limite de la théorie des probabilités*. Actualités Scientifiques et Industrielles, No 736, Hermann et Cie, Paris, 1938.
2. R. R. Bahadur and R. Ranga Rao, On deviations of the sample mean, *Annals of Mathematical Statistics*, **31** (1960), 1015–1027.
3. P. Lévy, *Théorie de l'addition des variables aléatoires indépendantes*, Paris, Gauthier-Villars.
4. P. Bárfai, Die Bestimmung der zu einem wiederkehrenden Prozess gehörenden Verteilungsfunktion aus den mit Fehlern behafteten Daten einer einzigen Realisation. *Studia Scientiarum Mathematicarum Hungarica*, **1** (1966), 161–168.

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