

On the Law of Iterated Logarithm for Occupation Measures of Empirical Processes

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Summary. Let $\{K(s, t): 0 \leq s \leq 1, t \geq 0\}$ be a Kiefer process. Let

$$L_t(E) = \int_0^1 I_E((t/\log \log t)^{-1/2} K(s, t)) ds$$

denote the occupation distribution. Using the ideas of Mogul'skii, Donsker and Varadhan, the limit behavior of L_t is studied. These and strong approximation results are then used to derive LIL in Chung's form for various functions of empirical processes.

Introduction

Let $\{X_n\}$ be i.i.d. random variables with common distribution $F(x)=x$ for $0 < x < 1$. Let F_n denote the empirical distribution of X_1, \dots, X_n . Recently Mogul'skii [4] proved that

$$\liminf_{n \rightarrow \infty} \sup_{0 \leq s \leq 1} |F_n(s) - s| \sqrt{n \log \log n} = \frac{\pi}{\sqrt{8}} \quad \text{a.e.} \quad (1)$$

This result follows from strong approximations and a similar result for Kiefer process K , namely,

$$\liminf_{t \rightarrow \infty} \sup_{0 \leq s \leq 1} |K(s, t) a(t)| = \frac{\pi}{\sqrt{8}} \quad \text{a.e.,} \quad (2)$$

where $a(t) = (t/\log \log t)^{-1/2}$. A Kiefer process $\{K(s, t): 0 \leq s \leq 1, t \geq 0\}$ is a mean zero Gaussian process with continuous paths and satisfying

$$E(K(s, t) K(s', t')) = \{\min(s, s') - ss'\} \min(t, t').$$

The strong approximation result mentioned here is stated below for easy reference.

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Theorem A. (See Theorem 4.4.3 of [5]) $F_n, n \geq 1$ and K can be defined on the same probability space such that a.e.

$$\sup_{0 \leq s \leq 1} |[n(F_n(s) - s) - K(s, n)]| \ll (\log n)^2. \tag{3}$$

In the case of Wiener process $\{W(s), s \geq 0\}$, we have the following result due to Jain and Pruitt [3],

$$\liminf_{t \rightarrow \infty} \sup_{0 \leq s \leq t} |a(t) W(s)| = \frac{\pi}{\sqrt{8}} \text{ a.e.} \tag{4}$$

Using their powerful theory on Markov processes, Donsker and Varadhan [2] obtained results about the occupation distribution of $\{a(t) W(s): 0 \leq s \leq t\}$. One of the consequences of these results is (4). In the same way we shall generalize (2) by studying the occupation measures of $\{K(s, t) a(t): 0 \leq s \leq 1\}$.

As $\{K(s, 1), 0 \leq s \leq 1\}$ is not a Markov process one cannot use Donskar-Varadhan theory directly. We use combination of several methods developed by Mogul'skii, Donsker and Vardhan, to study L_t defined by

$$L_t(E) = \int_0^1 I_E(a(t) K(s, t)) ds.$$

L_t can be viewed as an element in the space M of sub-probability measures λ on $R(\lambda(R) \leq 1)$, with the topology of vague convergence. Let \mathcal{U} denote the class of infinitely differentiable functions u on R , which are constant outside a compact set and $0 < a \leq u \leq b < \infty$, where a, b depend on u . For $\lambda \in M$, let

$$I(\lambda) = - \inf_{u \in \mathcal{U}} \int \frac{u''}{2u}(x) \lambda(dx).$$

We shall show that the set of limit points of L_t is the set $C = \{\lambda \in M: I(\lambda) \leq 1\}$. The I appearing here is the same I -function for the Brownian motion introduced by Donskar and Varadhan. It then follows for suitable functions Φ on M .

$$\limsup_{t \rightarrow \infty} \Phi(L_t) = \sup_{\lambda \in C} \Phi(\lambda) \text{ a.e.}$$

By taking $\Phi(\lambda) = \inf\{a: \lambda(x: |x| \leq a) = 1\}$, we deduce (1) and (2). Several other consequences are given in the last section.

The Results

Theorem 1. For almost all ω , the set of limit points, as $t \rightarrow \infty$, of L_t is $C = \{\lambda \in M: I(\lambda) \leq 1\}$.

Proof of this theorem will be given later.

This has the following Corollary.

Corollary 2. If Φ is a functional on M which is lower semi-continuous on M , then $\limsup_{t \rightarrow \infty} \Phi(L_t) \geq \sup_{\lambda \in C} \Phi(\lambda)$ a.s. The inequality gets reversed, if instead, Φ is upper semi-continuous. In particular, equality holds if Φ is continuous on M .

From Theorems A and 1 and Corollary 2, we have the following

Corollary 3. *The limit results of Theorem 1 and Corollary 2 hold, as $n \rightarrow \infty$, if L_t is replaced by \bar{L}_n , where*

$$\bar{L}_n(E) = \int_0^1 I_E(\sqrt{n \log \log n}(F_n(s) - s)) ds.$$

Theorem 4 (Upper bound). *Let D be a closed set in M . Then*

$$\limsup_{t \rightarrow \infty} \frac{1}{t} \log P(A_t \in D) \leq - \inf_{\lambda \in D} I(\lambda),$$

where $A_t(E) = \int_0^1 I_E(K(s, t)) ds$.

To prove Theorem 4, we require the following two lemmas. First some notation. Put $\lambda(f) = \int f(x) \lambda(dx)$, for $\lambda \in M$.

Lemma 5. *Let $J(\lambda, x) = \inf_{u \in \mathcal{U}} \lambda \left(\frac{u''}{2u} - x \frac{u'}{u} \right)$. Then*

$$J(\lambda, x) \leq -I(\lambda) - \frac{1}{2}x^2 \lambda(R), \tag{5}$$

for all $x \in R$ and $\lambda \in M$.

Proof. If $\lambda(R) = 0$, then the result is obvious. Suppose $\lambda(R) > 0$ and λ has a density f , which is continuously differentiable and $f(y) > 0$ for all $y \in R$. Now following the lines of proof of Lemma 2.2 of [1] (see Eqs. 2.33-2.35) we obtain

$$\int g(y) (f'(y) - 2xf(y)) dy \leq \sqrt{-8J(\lambda, x)} \sqrt{g^2(y) f(y)} dy, \tag{6}$$

for all continuous functions g with compact support. Suppose ϕ has all derivatives, has compact support and $0 \leq \phi(y) \leq 1$ for all $y \in R$. By putting $g = (f' - 2xf) \phi / f$, we conclude

$$J(\lambda, x) \leq -\frac{1}{8} \int \left(\frac{f' - 2xf}{f} \right)^2 (y) \phi(y) f(y) dy.$$

This holds for all such ϕ , so

$$J(\lambda, x) \leq -\frac{1}{8} \int \frac{(f')^2}{f} (y) dy - \frac{1}{2}x^2 \lambda(R) = -I(\lambda) - \frac{1}{2}x^2 \lambda(R).$$

The last equality follows from Lemma 2.2 of [1]. Now suppose $\lambda \in M$ and $\lambda(R) > 0$. For any $\varepsilon > 0$, let Ψ_ε be the Gaussian distribution with mean 0 and variance ε . For our given λ , define $\lambda_\varepsilon = \lambda * \Psi_\varepsilon$. By concavity and the argument given above we have

$$\begin{aligned} J(\lambda, x) &\leq J(\lambda_\varepsilon, x) \leq -I(\lambda_\varepsilon) - \frac{1}{2}x^2 \lambda_\varepsilon(R) \\ &= -I(\lambda_\varepsilon) - \frac{1}{2}x^2 \lambda(R). \end{aligned} \tag{7}$$

Since I is lower semicontinuous on M and since λ_ε converges vaguely, we have $\liminf_{\varepsilon \rightarrow 0} I(\lambda_\varepsilon) \geq I(\lambda)$. The lemma now follows from (7).

Before stating the next lemma, we note that for any $t > 0$, $\{K(s, t): 0 \leq s \leq 1\}$ and $\{W(s, t) - sW(t): 0 \leq s \leq 1\}$ have the same distribution. Define

$$B_t(E) = \int_0^1 I_E(W(s \cdot t) - sW(t)) ds,$$

and

$$\mathcal{C} = \{f: f \text{ is continuous on } R \text{ and } f(x) \rightarrow 0 \text{ as } |x| \rightarrow \infty\}.$$

Lemma 6. *Let $(a, b) \subset R$, $\lambda \in M$ and V a neighborhood of λ in M . Then there exists a open set N containing λ such that $N \subset V$ and*

$$\begin{aligned} & \limsup_{t \rightarrow \infty} (1/t) \log P(B_t \in N, at < W(t) < bt) \\ & \leq \inf_{u \in \mathcal{U}} [\sup_{a \leq y \leq b} (\sup_{\beta \in V} G(\beta, y, u))], \end{aligned}$$

where $G(\beta, y, u) = \beta \left(\frac{u''}{2u} - y \frac{u'}{u} \right)$.

Proof. Let $D(t, y)(E) = \frac{1}{t} \int_0^t I_E(W(s) - sy) ds$. First note that there exist $\varepsilon > 0$, $f_1, \dots, f_k \in \mathcal{C}$ such that

$$\{\beta \in M: |\beta(f_i) - \lambda(f_i)| < 2\varepsilon, 1 \leq i \leq k\} \subset V.$$

Put $N = \{\beta \in M: |\beta(f_i) - \lambda(f_i)| < \varepsilon, 1 \leq i \leq k\}$. Since f_i are uniformly continuous, there exists a $\delta \in (0, 1)$ such that

$$\max_{1 \leq i \leq k} |f_i(x) - f_i(y)| < \varepsilon,$$

whenever $|x - y| < \delta$. So

$$\begin{aligned} & (B_t \in N, at < W(t) < bt) \\ & \subset \bigcup_{at \leq r\delta \leq bt} (D(t, r\delta/t) \in V) \cap (|W(t) - r\delta| < \delta). \end{aligned}$$

Hence

$$\begin{aligned} & \limsup_{t \rightarrow \infty} \frac{1}{t} \log P(B_t \in N, at < W(t) < bt) \\ & \leq \limsup_{t \rightarrow \infty} \left(\sup_{a \leq y \leq b} \left(\frac{1}{t} \log [(2 + |a| + |b|)(t/\delta) P(D(t, y) \in V)] \right) \right) \\ & = \limsup_{t \rightarrow \infty} \left[\sup_{a \leq y \leq b} \left(\frac{1}{t} \log P(D(t, y) \in V) \right) \right] \end{aligned} \tag{8}$$

Because $\{W(s) - sy: s \geq 0\}$ is a Markov process with generator $\frac{1}{2} \frac{\partial^2}{\partial x^2} - y \frac{\partial}{\partial x}$, we have using Feynman-Kac formula that for any $u \in \mathcal{U}$,

$$E \left\{ u(W(t) - ty) \exp \left[- \int_0^t \left(\frac{u''}{2u} - y \frac{u'}{u} \right) (W(s) - sy) ds \right] \right\} = u(o).$$

So

$$P(D(t, y) \in V) \leq [\sup_x u(x) / \inf_x u(x)] \exp \left(t \sup_{\beta \in V} \beta \left(\frac{u''}{2u} - y \frac{u'}{u} \right) \right).$$

Thus

$$\begin{aligned} & \limsup_{t \rightarrow \infty} \left[\sup_{a \leq y \leq b} \left(\frac{1}{t} \log P(D(t, y) \in V) \right) \right] \\ & \leq \inf_{u \in \mathcal{U}} \left(\sup_{a \leq y \leq b} \left(\sup_{\beta \in V} G(\beta, y, u) \right) \right). \end{aligned} \tag{9}$$

The lemma follows now from (8) and (9)

Proof of Theorem 4. Let $d > 0$, $\varepsilon > 0$ and

$$\sup_{|y| \leq d} \sup_{\lambda \in D} \inf_{u \in \mathcal{U}} G(\lambda, y, u) = h < \infty$$

(if $h = \infty$ there is nothing to prove.) Note that for each $u \in \mathcal{U}$, $G(\lambda, y, u)$ is continuous in (λ, y) . So for each $y \in [-d, d]$ and $\lambda \in D$, there exist an open interval I_y containing y , a neighborhood V_λ of λ and $u_{\lambda, y} \in \mathcal{U}$ such that $G(\beta, x, u_{\lambda, y}) < h + \varepsilon$ for all $x \in I_y$ and $\beta \in V_\lambda$. Now by Lemma 6, there exists a open set $N_\lambda \subset V_\lambda$ and $\lambda \in N_\lambda$ such that

$$\limsup_{t \rightarrow \infty} \frac{1}{t} \log P(B_t \in N_\lambda, (W(t)/t) \in I_y) \leq h + \varepsilon. \tag{10}$$

Since D is closed and M is compact, D is compact. As $D \times [-d, d]$ is compact for any $d > 0$, we can choose $\lambda_1, \dots, \lambda_k \in D$ and $y_1, \dots, y_k \in [-d, d]$ such that

$$D \times [-d, d] \subset \bigcup_{i=1}^k (N_{\lambda_i} \times I_{y_i}). \tag{11}$$

From (10) and (11) we obtain, for any $d > 2$, that

$$\begin{aligned} & \limsup_{t \rightarrow \infty} \frac{1}{t} \log P(B_t \in D, |W(t)| \leq td) < h + \varepsilon \\ & = \sup_{|y| \leq d} [\sup_{\beta \in D} J(\beta, y)] + \varepsilon \\ & \leq - \inf_{\beta \in D} I(\beta) + \varepsilon \end{aligned}$$

the last inequality follows from Lemma 5. Since $\varepsilon > 0$ is arbitrary and for $d > 2$,

$$\limsup_{t \rightarrow \infty} \frac{1}{t} \log P(|W(t)| \geq td) \leq -\frac{1}{2}d^2 < -d,$$

we have

$$\limsup_{t \rightarrow \infty} \frac{1}{t} \log P(B_t \in D) \leq \max(-d, - \inf_{\beta \in D} I(\beta)).$$

The theorem now follows as $d > 2$ is arbitrary and as A_t and B_t have the same distribution.

Theorem 7. (Lower bound) Let \mathcal{M} denote the space of probability measures on R with the topology of weak convergence. Let $\lambda \in \mathcal{M}$ with $\lambda(x: |x| \leq a) = 1$ and N be a weak neighborhood of λ in \mathcal{M} , then for any $d > a > 0$

$$\liminf_{t \rightarrow \infty} \frac{1}{t} \log P(A_t \in N, |K(s, t)| \leq d; 0 \leq s \leq 1) \geq -I(\lambda). \quad (12)$$

Proof. Without loss of generality we may take $I(\lambda) < \infty$ and

$$N = \{\beta \in \mathcal{M}: |\lambda(f_i) - \beta(f_i)| < \varepsilon, 1 \leq i \leq k\},$$

where $\varepsilon > 0$ and f_i are uniformly continuous and bounded functions on R . Let $|f_i(x)| \leq H$ for all $x \in R, 1 \leq i \leq k$. By uniform continuity of f_i there exists $\delta > 0$ such that $|f_i(x) - f_i(y)| < (\varepsilon/4)$, whenever $|x - y| < \delta, 1 \leq i \leq k$. Since $\{K(s, t): 0 \leq s \leq 1\}$ has the same distribution as $\{W(s \cdot t) - sW(t): 0 \leq s \leq 1\}$, the probability in (12) dominates

$$P \left(\left| \frac{1}{t} \int_0^t f_i(W(s)) ds - \lambda(f_i) \right| < (3\varepsilon/4), \right. \\ \left. 1 \leq i \leq k, |W(s)| \leq d - \delta, 0 \leq s < t, |W(t)| < \delta \right). \quad (13)$$

Let t_0 be such that $8H < \varepsilon(t_0 - 1)$, $a < b < d$ and $0 < \theta < \min(\delta, d - b)/2$. Since W has independent increments and since for $t \geq t_0$,

$$\left| \frac{1}{t} \int_0^t f_i(W(s)) ds - \frac{1}{t-1} \int_0^{t-1} f_i(W(s)) ds \right| \leq \frac{2H}{t-1} < \frac{\varepsilon}{4},$$

the probability in (13) dominates

$$P \left(\left| \frac{1}{t-1} \int_0^{t-1} f_i(W(s)) ds - \lambda(f_i) \right| < \frac{\varepsilon}{2}; 1 \leq i \leq k, |W(s)| < b + \theta, \right. \\ \left. 0 \leq s < t, |W(t)| \leq \theta \right) \\ \geq P \left(\left| \frac{1}{t-1} \int_0^{t-1} f_i(W(s)) ds - \lambda(f_i) \right| < \frac{\varepsilon}{2}; 1 \leq i \leq k, |W(s)| < b, 0 \leq s \leq t-1 \right) \\ \times \inf_{|z| \leq b} P(|W(s) + z| < b + \theta, 0 \leq s < 1, |W(1) + z| \leq \theta) \\ = M_t \cdot J \quad (\text{say}). \quad (14)$$

Clearly

$$J \geq \inf_{|z| \leq b} P(|W(s) + sz| < \theta, 0 \leq s \leq 1) > 0$$

and by Lemma 2.12 of [2],

$$\liminf_{t \rightarrow \infty} \frac{1}{t} \log M_t \geq -I(\lambda).$$

The theorem now follows from (14).

Theorem 8. Let $\lambda \in \mathcal{M}$ be such that $\lambda\{x: |x| \leq a\} = 1$ and $I(\lambda) < 1$. Let N be a weak neighborhood of λ in \mathcal{M} . For $d > a$, let $E_t = (L_t \in N, |a(t)K(s, t)| \leq d; 0 \leq s \leq 1)$. Then, for almost all ω , $\omega \in E_t$ for a sequence of times t increasing to infinity.

Proof. Let $p > 1$ be such that $pI(\lambda) < 1$ and let t_n denote the integral part of $\exp(n^p)$. We shall show that $P(E_{t_n} \text{ i.o.}) = 1$. Since $K(\cdot, t)$ has the same distribution as that of $\sqrt{t}K(\cdot, 1)$, we have for any $\eta > 0$

$$\begin{aligned} P(\sup_{0 \leq s \leq 1} |K(s, t_n)| > 2\eta \sqrt{t_n \log t_n}) \\ = P(\sup_{0 \leq s \leq 1} |K(s, 1)| > 2\eta \sqrt{\log t_n}) \\ \leq 2P(\sup_{0 \leq s \leq 1} |W(s)| > \eta \sqrt{\log t_n}) \ll n^{-2}. \end{aligned}$$

So by Borel-Cantelli lemma,

$$\sup_{0 \leq s \leq 1} |K(s, t_n)(t_n \log t_n)^{-1/2}| \rightarrow 0 \quad \text{a.e.} \tag{15}$$

Since $(\log t_n)^2 t_{n-1}/t_n \rightarrow 0$ as $n \rightarrow \infty$, (15) implies that

$$\sup_{0 \leq s \leq 1} |K(s, t_{n-1})|s_n \rightarrow 0 \quad \text{a.e.}, \tag{16}$$

where $s_n = ((\log \log t_n)/t_n)^{1/2}$.

Let N be as in the proof of Theorem 7 and $a < b < d$. Define

$$\begin{aligned} H_n = \left\{ \int_0^1 f_i [s_n(K(s, t_n) - K(s, t_{n-1}))] ds - \lambda(f_i) < \frac{\varepsilon}{2}, 1 \leq i \leq k, \right. \\ \left. s_n |K(s, t_n) - K(s, t_{n-1})| < b \text{ for } 0 \leq s \leq 1 \right\}. \end{aligned}$$

By (16) for almost all ω , n sufficiently large, if H_n occurs, E_{t_n} occurs. As $\{K(\cdot, t_n) - K(\cdot, t_{n-1}); n \geq 1\}$ are independent ($K(\cdot, m)$ has the same distribution as the sum of m independent brownian bridges), the events H_n are independent. So by Borel-Cantelli it is enough to show that $\Sigma P(H_n) = \infty$. Now by Theorem 7

$$\begin{aligned} P(H_n) = P \left(\int_0^1 f_i [K(s, s_n^2(t_n - t_{n-1}))] ds - \lambda(f_i) < \frac{\varepsilon}{2}; 1 \leq i \leq k, \right. \\ \left. |K(s, s_n^2(t_n - t_{n-1}))| < b \text{ for } 0 \leq s \leq 1 \right) \\ \geq \exp[-I(\lambda)s_n^2(t_n - t_{n-1}) + o(s_n^2(t_n - t_{n-1}))]. \end{aligned}$$

Since $s_n^2(t_n - t_{n-1}) \sim \log \log t_n \sim p \log n$, we have

$$P(H_n) \geq n^{-pI(\lambda) + o(1)}.$$

As $pI(\lambda) < 1$, it follows that $\Sigma P(H_n) = \infty$. This completes the proof.

We are now ready to prove Theorem 1.

Proof of Theorem 1. Let N be an open set containing C . As N^c is compact $\theta = \inf_{\beta \in N^c} I(\beta) > 1$. Let $0 < p < 1$ be such that $\theta p > 1$. Put $t_n = [e^{n^p}]$. Clearly for any $k \geq 1$, $(t_n - t_{n-1}) (\log \log t_n)^k t_{n-1}^{-1} \rightarrow 0$ as $n \rightarrow \infty$. By a representation of Kiefer process (see Sect. 1.15 of [5]) and by the Corollaries 1.12.4 and 1.15.1 of [5], we have

$$\begin{aligned} & \sup_{t_{n-1} \leq t \leq t_n} \left(\sup_{0 \leq s \leq 1} |a(t) K(s, t) - a(t_n) K(s, t_n)| \right) \\ & \leq \sup_{t_{n-1} \leq t \leq t_n} |a(t) - a(t_n)| \sup_{0 \leq s \leq 1} |K(s, t_n)| \\ & \quad + a(t_{n-1}) \sup_{t_{n-1} \leq t \leq t_n} \left(\sup_{0 \leq s \leq 1} |K(s, t) - K(s, t_n)| \right) \\ & \rightarrow 0 \quad \text{a.e.} \end{aligned} \tag{17}$$

Now as in the proof of Theorem 2.8 of [2], it follows from (17) and Theorem 4, that

$$\bigcap_T \bigcup_{t \leq T} L_t \subset C \quad \text{a.e.}$$

The converse follows from Lemma 2.16 of [2] and Theorem 8.

Applications

The following statements are immediate consequences of results in Sect. 4 of [2], Theorem 1 and Corollaries 2 and 3.

A.1. Let g be a continuous function on R such that $g(x) \rightarrow 0$ as $|x| \rightarrow \infty$. Then

$$\limsup_{t \rightarrow \infty} \int_0^1 g(a(t) K(s, t)) ds = \sup_{\lambda \in C} \lambda(g) \quad \text{a.e.}$$

and

$$\limsup_{n \rightarrow \infty} \int_0^1 g(\sqrt{n \log \log n} (F_n(s) - s)) ds = \sup_{\lambda \in C} \lambda(g) \quad \text{a.e.}$$

A.2. Let g be a continuous function on R with $g(x) \rightarrow \infty$ as $|x| \rightarrow \infty$. Define Φ on M as

$$\begin{aligned} \Phi(\lambda) &= \lambda(g) \quad \text{if } \lambda \in \mathcal{M} \quad \text{and if } \int |g(x)| \lambda(dx) < \infty \\ &= \infty \quad \text{otherwise.} \end{aligned}$$

Then

$$\liminf_{t \rightarrow \infty} \int_0^1 g(a(t) K(s, t)) ds = \inf_{\lambda \in C \cap \mathcal{M}} \lambda(g) \quad \text{a.e.}$$

and

$$\liminf_{n \rightarrow \infty} \int_0^1 g(\sqrt{n \log \log n} (F_n(s) - s)) ds = \inf_{\lambda \in C \cap \mathcal{M}} \lambda(g) \quad \text{a.e.}$$

In particular these results hold if $g(x) = |x|^\theta$, $\theta > 0$. As in [2] if we take $g(x) = x^2$ we get

$$\liminf_{t \rightarrow \infty} \int_0^1 \left(\frac{\log \log t}{t} \right) K^2(s, t) ds = \frac{1}{8} \quad \text{a.e.}$$

and

$$\liminf_{n \rightarrow \infty} (n \log \log n) \int_0^1 (F_n(s) - s)^2 ds = \frac{1}{8} \quad \text{a.e.}$$

A.3. For each $a > 0$, there exists $k(a)$ such that

$$\limsup_{t \rightarrow \infty} \text{Leb meas} \{s: 0 \leq s \leq 1, |K(s, t)| a(t) \leq a\} = k(a) \quad \text{a.e.}$$

and

$$\limsup_{n \rightarrow \infty} \text{Leb meas} \{s: 0 \leq s \leq 1, \sqrt{n \log \log n} (F_n(s) - s) \leq a\} = k(a) \quad \text{a.e.}$$

A.4. Using Theorem 8, we obtain

$$\liminf_{t \rightarrow \infty} a(t) \sup_{0 \leq s \leq 1} |K(s, t)| = \frac{\pi}{\sqrt{8}} \quad \text{a.e.}$$

and

$$\liminf_{n \rightarrow \infty} (\sqrt{n \log \log n}) \sup_{0 \leq s \leq 1} |F_n(s) - s| = \frac{\pi}{\sqrt{8}} \quad \text{a.e.}$$

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Received January 26, 1983; in revised form June 3, 1983