

Interval-Dividing Processes

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Summary. If $\forall n \sum_{\pi} P(X_{\pi_1} < \dots < X_{\pi_n}) = 1$ and $\forall \pi, n, P(X_{\pi_1} < \dots < X_{\pi_n}) = P(Y_{\pi_1} < \dots < Y_{\pi_n})$ then $P(n^{-1} \cdot [\delta(Y_1) + \dots + \delta(Y_n)])$ converges to cnts. law on $R^1) = P(n^{-1} \cdot [\delta(Y_1) + \dots + \delta(Y_n)])$ converges to a cnts. law on R^1). Thus if $P(X_{\pi_1} < \dots < X_{\pi_n}) = (n!)^{-1} \forall \pi, n$ then $n^{-1} [\delta(X_1) + \dots + \delta(X_n)]$ converges a.s. The main result here generalizes this: Let $X_{(1)}^n, X_{(2)}^n, \dots, X_{(n)}^n$ be the order statistics associated with X_1, X_2, \dots, X_n . Define random variables Z_1, Z_2, \dots by $\{Z_n = i\} = \{X_n = X_{(i)}^n\}$. Then if Z_1, Z_2, Z_3, \dots are independent and $P(Z_n \leq i) \leq i/n$, and $\{X_i\}$ is bounded, $n^{-1} \cdot [\delta(X_1) + \dots + \delta(X_n)]$ converges a.s.

§1. Introduction

Let X_1, X_2, \dots be a sequence of real valued random variables such that $P(X_i = X_j) = 0 \forall i, j$. Let $X_{(i)}^n$ be the i^{th} order statistic among X_1, \dots, X_n , i.e. $\{X_{(1)}^n, \dots, X_{(n)}^n\} = \{X_1, \dots, X_n\}$ and $X_{(1)}^n < \dots < X_{(n)}^n$ a.s. For convenience let $X_{(0)}^n = -\infty$ and $X_{(n+1)}^n = +\infty$. Define a sequence Z_1, Z_2, \dots such that Z_n takes on only the values $1, 2, 3, \dots, n$ by letting $\{Z_n = i\} = \{X_n = X_{(i)}^n\}$. In other words, Z_n indicates which of the n intervals $(-\infty, X_{(1)}^{n-1}), (X_{(1)}^{n-1}, X_{(2)}^{n-1}), \dots, (X_{(n-1)}^{n-1}, +\infty)$ X_n falls into. Let F_Z denote $\sigma(Z_1, Z_2, \dots)$; equivalently F_Z is the σ -algebra generated by the events $\{X_i < X_j\}, i, j = 1, 2, 3, \dots$. This definition of the Z -process from a sequence X_1, X_2, \dots will be used throughout.

The aim of this paper is to relate hypotheses on the distribution of Z_1, Z_2, \dots to convergence of the empirical distributions $n^{-1} \cdot [\delta(X_1) + \dots + \delta(X_n)]$ as $n \rightarrow \infty$. Throughout $\delta(x)$ will denote the point mass at x . The hypotheses on the distribution of Z_1, Z_2, \dots may be given directly or in terms of the events $\{X_i < X_j\}$.

Recent work on interval-dividing has centered on Kakutani's scheme, in which at each stage the longest remaining interval is divided according to a fixed [1] or random proportion [4, 5]. The results in the present paper seem quite distinct from these. In the Kakutani scheme, the interval the $(n+1)$ st

point falls into is determined by the first n points, i.e. $Z_{n+1} \subset \sigma(X_1, \dots, X_n)$. In Theorem 2 below, the Z_i will be assumed to form an independent sequence, so the $(n+1)$ st point falls into an interval picked independently of the ordering of the first n points. These situations

$$(Z_{n+1} \subset \sigma(X_1, \dots, X_n) \text{ and } Z_{n+1} \perp \sigma(Z_1, \dots, Z_n) \subset \sigma(X_1, \dots, X_n))$$

are of course not mutually exclusive but for the Kakutani scheme with the longest interval divided uniformly at each stage [5], the Z_i are not an independent sequence (Z_2 and Z_3 are not independent for example).

In §2 it will be shown (Theorem 1) that the probability of the event $\{n^{-1} \cdot [\delta(X_1) + \dots + \delta(X_n)]$ converges to a continuous law on $R^1\}$ depends only on the numbers $P(X_{\pi_1} < \dots < X_{\pi_n})$ for all n and permutations π of $\{1, 2, \dots, n\}$. A corollary is that $n^{-1} \cdot [\delta(X_1) + \dots + \delta(X_n)]$ converges a.s. if $P(X_{\pi_1} < \dots < X_{\pi_n}) = (n!)^{-1}$ for all π and n . The familiar example of sequences X_1, X_2, \dots satisfying this condition, in addition to iid continuous sequences, is the exchangeable case (for which the Glivenko-Cantelli theorem is an immediate consequence of deFinetti's theorem.) A very different example is as follows: there exists a sequence X_1, X_2, \dots satisfying $P(X_{\pi_1} < \dots < X_{\pi_n}) = (n!)^{-1}$ such that a.s. X_1, X_2, \dots is an enumeration of the rationals.

Of course Theorem 1 "generalizes" the Kakutani scheme (or any scheme for which $\lim n^{-1} [\delta(X_1) + \dots + \delta(X_n)]$ is known to be continuous). If X_1, X_2, \dots arise from the Kakutani scheme, and Y_1, Y_2, \dots satisfy $P(Y_{\pi_1} < \dots < Y_{\pi_n}) = P(X_{\pi_1} < \dots < X_{\pi_n})$ then $n^{-1} [\delta(Y_1) + \dots + \delta(Y_n)]$ converges almost surely. But the numbers $P(X_{\pi_1} < \dots < X_{\pi_n})$ seem hard to compute (at least exactly) for the Kakutani scheme.

Convergence to a possibly discontinuous law is discussed in §3. Though, as examples show, the event $\{n^{-1} \cdot [\delta(X_1) + \dots + \delta(X_n)]$ converges to a law on $R^1\}$ is not in F_Z , a sufficient condition for convergence based only on the events $\{X_i < X_j\}$ can be found. Theorem 2 applies this condition to show that if $\{X_i\}$ is bounded and Z_1, Z_2, \dots is an independent sequence with $P(Z_n \leq i) \leq i/n$ then $n^{-1} [\delta(X_1) + \dots + \delta(X_n)]$ converges a.s. This extends the $P(X_{\pi_1} \dots X_{\pi_n}) = (n!)^{-1}$ condition, for which $P(Z_n \leq i) = i/n$. Some discussion of the limits obtained in Theorem 2 follows the proof.

§2. The Continuous Limit Case

The lemma below refers to a sequence of distinct reals, not random variables. Let $x_{(i)}^n$ be defined analogously to $X_{(i)}^n$, that is $\{x_{(1)}^n, \dots, x_{(n)}^n\} = \{x_1, \dots, x_n\}$ and $x_{(1)}^n < \dots < x_{(n)}^n$; let $x_{(0)}^n = -\infty$ and $x_{(n+1)}^n = +\infty$. For any set A let $\mu_\infty(A)$ denote $\lim_{n \rightarrow \infty} n^{-1} \cdot \sum_{i=1}^n I(x_i \in A)$ whenever the limit exists; here "I" denotes "indicator function of".

Lemma 1. *Let x_1, x_2, \dots be a sequence of distinct reals. Then $n^{-1} \cdot [\delta(x_1) + \dots + \delta(x_n)]$ converges to a continuous law if and only if*

- (1) $\mu_\infty(-\infty, x_k)$ exists for each k , and
- (2) $\max_{i=0, 1, \dots, n} \mu_\infty(x_{(i)}^n, x_{(i+1)}^n) \rightarrow 0$ as $n \rightarrow \infty$.

Proof. only if: Since the limit of $n^{-1} \cdot [\delta(x_1) + \dots + \delta(x_n)]$ is a continuous law (call this limit law μ), $n^{-1} \cdot \sum_{i=1}^n I(x_i \in A)$ converges for every interval A , so (1) holds and each $\mu_\infty(x_{(i)}^n, x_{(i+1)}^n)$ is defined. Also $\mu_\infty(A) = \mu(A)$ for every interval A .

Assume that the max in (2) does not converge to 0. Then there must exist $\varepsilon > 0$ and a sequence of nested intervals A_n of the form $(x_{(i_n)}^n, x_{(i_n+1)}^n)$ such that for all n , $\mu(A_n) > \varepsilon$. (A compactness argument shows that the intervals may be chosen to be nested: Let B_n be the union of all intervals of the form $[x_{(i)}^n, x_{(i+1)}^n]$ such that $\mu(x_{(i)}^n, x_{(i+1)}^n) > \varepsilon$; adjoin $\pm\infty$ to compactify R . If the max in (2) is greater than ε for all n , then each B_n is nonempty. Of course $B_n \supset B_{n+1} \forall n$. Choose $x \in \bigcap_n B_n$. Then $x \in [x_{(i_n)}^n, x_{(i_n+1)}^n]$ for some i_n ; pick the leftmost interval if there is a choice of two. Then $A_n = (x_{(i_n)}^n, x_{(i_n+1)}^n)$ is a nested sequence with $\mu(A_n) > \varepsilon$.) Note that $A_n \cap \{x_1, x_2, \dots, x_n\} = \phi$. The only possibilities for $\bigcap_n A_n$ are ϕ , a singleton, or an interval. Since by countable additivity $\mu(\bigcap_n A_n) \geq \varepsilon$, $\bigcap_n A_n$ must be an interval. But $[\bigcap_n A_n] \cap \{x_1, x_2, \dots\} = \phi$ since $A_n \cap \{x_1, \dots, x_n\} = \phi$, so $m^{-1} \cdot \sum_{i=1}^m I(x_i \in \bigcap_n A_n) = 0$ for every m , contradicting $\mu(\bigcap_n A_n) \geq \varepsilon$ and establishing (2).

if: Since the max in (2) converges to 0, $\mu_\infty(x_{(1)}^n, x_{(n)}^n)$ converges to 1. Given ε choose n such that $\mu_\infty(x_{(1)}^n, x_{(n)}^n) > 1 - \varepsilon/2$. Since

$$m^{-1} \cdot \sum_{i=1}^m I(x_i \in (x_{(1)}^n, x_{(n)}^n)) \rightarrow \mu_\infty(x_{(1)}^n, x_{(n)}^n),$$

for m large enough $m^{-1} \cdot [\delta(x_1) + \dots + \delta(x_m)](x_{(1)}^n, x_{(n)}^n) > 1 - \varepsilon$. Thus $\{m^{-1} \cdot [\delta(x_1) + \dots + \delta(x_m)]\}$ is a tight sequence. It suffices to show that $\mu_\infty(-\infty, a)$ exists for every a . By (1), $\mu_\infty(-\infty, a)$ exists when $a \in \{x_1, x_2, \dots\}$, so assume $a \notin \{x_1, x_2, \dots\}$. For each n there exists i_n such that $x_{(i_n)}^n < a < x_{(i_n+1)}^n$. Since

$$\begin{aligned} (-\infty, x_{(i_n)}^n) &\subset (-\infty, a) \subset (-\infty, x_{(i_n+1)}^n), \mu_\infty(-\infty, x_{(i_n)}^n) \\ &\leq \liminf_{m \rightarrow \infty} m^{-1} \cdot [\delta(x_1) + \dots + \delta(x_m)](-\infty, a) \\ &\leq \limsup_{m \rightarrow \infty} m^{-1} \cdot [\delta(x_1) + \dots + \delta(x_m)](-\infty, a) \leq \mu_\infty(-\infty, x_{(i_n+1)}^n). \end{aligned}$$

Let $n \rightarrow \infty$. Then $\mu_\infty(-\infty, x_{(i_n+1)}^n) - \mu_\infty(-\infty, x_{(i_n)}^n) = \mu_\infty(x_{(i_n)}^n, x_{(i_n+1)}^n) \rightarrow 0$ by condition (2). So

$$\begin{aligned} \liminf_{m \rightarrow \infty} m^{-1} \cdot [\delta(x_1) + \dots + \delta(x_m)](-\infty, a) \\ = \limsup_{m \rightarrow \infty} m^{-1} \cdot [\delta(x_1) + \dots + \delta(x_m)](-\infty, a) \end{aligned}$$

and $\mu_\infty(-\infty, a)$ exists. This completes the proof of the lemma. \square

Now let X_1, X_2, \dots be a sequence of random variables with $P(X_i = X_j) = 0$. Using Lemma 1, the event $\{n^{-1} \cdot [\delta(X_1) + \dots + \delta(X_n)]$ converges to a continuous law} can be shown to be measurable with respect to the σ -algebra F_2 , i.e. the

σ -algebra generated by the events $\{X_i < X_j\}$, $i, j = 1, 2, 3, \dots$. This is done as follows: When condition (1) is written as $\{\lim_{n \rightarrow \infty} n^{-1} \cdot \sum_{i=1}^n I(X_i < X_K)\}$ exists then it is transparently F_Z -measurable.

To see that condition (2) is F_Z -measurable, note (as above) that $\mu_\infty(-\infty, X_k)$ is F_Z -measurable. Now $\mu_\infty(-\infty, X_{(i)}^n)$ is also F_Z -measurable, since

$$\mu_\infty(-\infty, X_{(i)}^n) = \sum_{k=1}^n \mu_\infty(-\infty, X_k) \cdot I(X_k = X_{(i)}^n)$$

and $I(X_k = X_{(i)}^n) = \bigcup_A I(X_j < X_k \text{ iff } j \in A)$ where the union is taken over all $A \subset \{1, 2, \dots, n\}$ with $i-1$ elements. Since $\mu_\infty(X_{(i)}^n, X_{(i+1)}^n) = \mu_\infty(-\infty, X_{(i+1)}^n) - \mu_\infty(-\infty, X_{(i)}^n)$ this shows that condition (2) is F_Z -measurable. A restatement of this fact is given in the theorem below.

Theorem 1. *Let X_1, X_2, \dots and Y_1, Y_2, \dots be two sequences of random variables, such that $P(X_i = X_j) = 0$, and $P(X_{\pi_1} < \dots < X_{\pi_n}) = P(Y_{\pi_1} < \dots < Y_{\pi_n})$ for every n and every permutation π of $\{1, 2, \dots, n\}$. Then $P(n^{-1} \cdot [\delta(X_1) + \dots + \delta(X_n)])$ converges to a continuous law) = $P(n^{-1} \cdot [\delta(Y_1) + \dots + \delta(Y_n)])$ converges to a continuous law.*

The conclusion is immediate since the joint law of the random variables $\{I(X_i < X_j)\}$ $i, j = 1, 2, \dots$ must equal that of $\{I(Y_i < Y_j)\}$ $i, j = 1, 2, \dots$

Corollary. *Let X_1, X_2, \dots be any sequence of random variables such that $P(X_{\pi_1} < \dots < X_{\pi_n}) = (n!)^{-1}$ for all n and permutations π . Then $n^{-1} \cdot [\delta(X_1) + \dots + \delta(X_n)]$ converges almost surely to a continuous law.*

Proof. Let Y_1, Y_2, \dots be any sequence of continuous iid random variables and apply the Glivenko-Cantelli theorem and Theorem 1 above. \square

Define the Komogorov-Smirnov statistic as $\sup_x |F_n(x) - F(x)|$ for any sequence X_1, X_2, \dots such that the empirical distribution function $n^{-1}[\delta(X_1) + \dots + \delta(X_n)](-\infty, x] =: F_n(x)$ converges to a (possibly random) distribution function $F(x)$. This statistic can be written as $\max_{\substack{j=1, \dots, n \\ i=1, \dots, j}} |j/n - \mu_\infty(-\infty, X_{(i)}^n)|$

and hence is also F_Z -measurable. So the distribution of the Kolmogorov-Smirnov statistic is the same for any sequence satisfying $P(X_{\pi_1} < \dots < X_{\pi_n}) = (n!)^{-1}$ as it is for an iid sequence of continuous random variables.

§3. Possibly Discontinuous Limits

The simple first example below shows that the event $\{n^{-1} \cdot [\delta(X_1) + \dots + \delta(X_n)]$ converges to a law on $R^1\}$ is not an F_Z -measurable event.

Example 1. Let $x_1 < x_2 < x_3 < \dots$ and $y_1 < y_2 < y_3 < \dots$ be two sequences of reals such that $x_n \rightarrow x < \infty$ and $y_n \rightarrow +\infty$. If X_1, X_2, X_3, \dots is a sequence of random variables such that $P(X_i = x_i \forall i) = 1/2 = P(X_i = y_i \forall i)$ then $P(Z_i = i \forall i) = 1$. [Recall the definition of the Z -process in §1.] So F_Z is trivial, but $\{n^{-1} \cdot [\delta(X_1) + \dots + \delta(X_n)]$ converges to a law on $R^1\} = \{X_i = x_i \forall i\}$ which has probability $1/2$.

As the next example shows, the difficulty is not only in the escape of mass to infinity.

Example 2. Let $n(\cdot)$ and $m(\cdot)$ be two increasing sequences of positive integers such that $\{n(k)\}_{k=1}^\infty$ and $\{m(k)\}_{k=1}^\infty$ are disjoint and have union $\{1, 2, 3, \dots\}$. Further assume that $\lim_{k \rightarrow \infty} n(k)/k$ does not exist. Now let x_1, x_2, \dots be a sequence of reals such that $x_{n(1)} < x_{n(2)} < x_{n(3)} < \dots$ and $x_{m(1)} > x_{m(2)} > x_{m(3)} > \dots$ and such that $\lim_{k \rightarrow \infty} x_{n(k)} = \lim_{k \rightarrow \infty} x_{m(k)}$. Let y_1, y_2, \dots be a sequence with $y_{n(1)} < y_{n(2)} < \dots$, $y_{m(1)} > y_{m(2)} > \dots$ and $\lim_{k \rightarrow \infty} y_{n(k)} < \lim_{k \rightarrow \infty} y_{m(k)}$. If X_1, X_2, \dots are random variables with $P(X_i = x_i \forall i) = 1/2 = P(X_i = y_i \forall i)$, then each event $\{X_i < X_j\}$ has probability 0 or 1. Each Z_i is a constant and F_Z is the trivial σ -algebra. But $n^{-1} \cdot [\delta(X_1) + \dots + \delta(X_n)]$ converges (to $\delta(\lim x_{n(k)})$) if and only if $X_i = x_i \forall i$.

There is another application for Example 2. Consider the sequence y_1, y_2, \dots given above. For each $j, m^{-1} \cdot \sum_{i=1}^m I(y_i < y_j)$ converges as $m \rightarrow \infty$, to 0 if $j = n(k) \exists k$, and to 1 if $j = m(k)$. But $n^{-1} \cdot [\delta(y_1) + \dots + \delta(y_n)]$ does not converge. Thus condition (1) of Lemma 1 is not sufficient for the convergence of $n^{-1} \cdot [\delta(y_1) + \dots + \delta(y_n)]$ even if $\{y_i\}$ is bounded. The purpose of the next lemma is to provide a sufficient condition for convergence to a possibly discontinuous law, based only on hypotheses on the ordering of the points.

Lemma 2. *Let x_1, x_2, x_3, \dots be distinct points in a bounded interval. Then I and II are equivalent.*

I. $n^{-1} \cdot [\delta(y_1) + \dots + \delta(y_n)]$ converges to a law on R^1 for every bdd set $\{y_i\}$ satisfying $y_i < y_j$ iff $x_i < x_j$.

II. (1) $\lim_{n \rightarrow \infty} n^{-1} \cdot \sum_{i=1}^n I(x_i < x_k) =: \mu_\infty(-\infty, x_k)$ exists for all k ,

and

(3) $\lim_{n \rightarrow \infty} n^{-1} \cdot \sum_{i=1}^n I(\mu_\infty(-\infty, x_i) < r)$ exists for every rational r .

The only part of this lemma that will be applied in the sequel is $II \Rightarrow I$, i.e. that II, based only on the ordering of x_1, x_2, \dots , is sufficient for the convergence of $n^{-1} \cdot [\delta(x_1) + \dots + \delta(x_n)]$. The equivalence of I and II shows that II is actually the best possible sufficient condition based only on ordering.

Pf. $II \Rightarrow I$. It is enough to show that (1) and (3) imply the convergence of $n^{-1} \cdot [\delta(x_1) + \dots + \delta(x_n)]$, since if (1) and (3) hold for x_1, x_2, \dots then they must hold for any sequence y_1, y_2, \dots satisfying $y_i < y_j$ iff $x_i < x_j$. The assumption of boundedness has eliminated tightness considerations, so it suffices to prove that

$$n^{-1} \cdot [\delta(x_1) + \dots + \delta(x_n)](-\infty, a) = n^{-1} \cdot \sum_{i=1}^n I(x_i < a)$$

converges for each a . Assume, to the contrary, that for some a and rational r

$$\liminf_{n \rightarrow \infty} n^{-1} \cdot \sum_{i=1}^n I(x_i < a) < r < \limsup_{n \rightarrow \infty} n^{-1} \cdot \sum_{i=1}^n I(x_i < a).$$

If $x_k < a$, then

$$n^{-1} \cdot \sum_{i=1}^n I(x_i < x_k) \leq n^{-1} \cdot \sum_{i=1}^n I(x_i < a),$$

so

$$\mu_\infty(-\infty, x_k) \leq \liminf_{n \rightarrow \infty} n^{-1} \cdot \sum_{i=1}^n I(x_i < a) < r.$$

If $x_k \geq a$, then

$$n^{-1} \cdot \sum_{i=1}^n I(x_i < x_k) \geq n^{-1} \cdot \sum_{i=1}^n I(x_i < a),$$

so

$$\mu_\infty(-\infty, x_k) \geq \limsup_{n \rightarrow \infty} n^{-1} \cdot \sum_{i=1}^n I(x_i < a) > r.$$

Hence $x_k < a$ iff $\mu_\infty(-\infty, x_k) < r$, and

$$n^{-1} \cdot \sum_{i=1}^n I(x_i < a) \equiv n^{-1} \cdot \sum_{i=1}^n I(\mu_\infty(-\infty, x_i) < r).$$

But the righthand side converges by (3) and the left-hand side was assumed *not* to converge. The contradiction proves that $\text{II} \Rightarrow \text{I}$.

$\text{I} \Rightarrow \text{II}$. First assume that (1) fails to hold, i.e. for some x_k , $n^{-1} \cdot \sum_{i=1}^n I(x_i < x_k)$ does not converge. Let $y_j = x_j$ if $x_j \geq x_k$, and $y_j = x_j - \varepsilon$ if $x_j < x_k$. Then for any y in the interval $(x_k - \varepsilon, x_k)$,

$$n^{-1} \cdot \sum_{i=1}^n I(y_i < y) \equiv n^{-1} \cdot \sum_{i=1}^n I(x_i < x_k).$$

Since the right-hand side doesn't converge, $\{y: n^{-1} \cdot [\delta(y_1) + \dots + \delta(y_n)](-\infty, y)$ converges} cannot be dense and thus $n^{-1} \cdot [\delta(y_1) + \dots + \delta(y_n)]$ cannot converge.

Next assume that (1) holds but that (3) fails, i.e. for some r , $n^{-1} \cdot \sum_{i=1}^n I(\mu_\infty(-\infty, x_i) < r)$ doesn't converge. Let $A = \{x_k: \mu_\infty(-\infty, x_k) < r\}$, and let x denote the least upper bound of A . If $x_k < x$, then $x_k \in A$ by the definition of x . If $x_k > x$ then $x_k \notin A$. Also, no x_k can equal x because for such an x_k , if $i \neq k$, $x_i < x_k$ would hold iff $x_i \in A$ iff $\mu_\infty(-\infty, x_i) < r$; but $n^{-1} \cdot \sum_{i=1}^n I(x_i < x_k)$ converges and $n^{-1} \cdot \sum_{i=1}^n I(\mu_\infty(-\infty, x_i) < r)$ doesn't. Hence $x_k < x$ iff $x_k \in A$ iff $\mu_\infty(-\infty, x_k) < r$. Now let $y_j = x_j$ if $x_j > x$ and let $y_j = x_j - \varepsilon$ if $x_j < x$. Then $n^{-1} \cdot \sum_{i=1}^n I(y_i < y)$ cannot converge for any $y \in (x - \varepsilon, x)$, and as before, $n^{-1} \cdot [\delta(y_1) + \dots + \delta(y_n)]$ cannot converge, contradicting I. \square

The corollary in §2 can be restated in terms of the Z-process as follows. Let X_1, X_2, \dots be any sequence of random variables such that the corresponding Z_n are independent and uniform, i.e. $P(Z_n = i) = 1/n$ for $i = 1, 2, \dots, n$. Then

$n^{-1} \cdot [\delta(X_1) + \dots + \delta(X_n)]$ converges a.s. The main result of this section generalizes this result by applying Lemma 2.

Theorem 2. *Let X_1, X_2, \dots be random variables taking values in a bounded interval, with $P(X_i = X_j) = 0 \forall i, j$. Assume that the corresponding Z_1, Z_2, \dots are independent and stochastically larger than uniform, i.e. $P(Z_n \leq i) \leq i/n, i = 1, 2, \dots, n$. Then $n^{-1} \cdot [\delta(X_1) + \dots + \delta(X_n)]$ converges a.s.*

Pf. The conclusion will follow by Lemma 2 if it can be shown that $n^{-1} \cdot \sum_{i=1}^n I(X_i < X_k)$ converges a.s. as $n \rightarrow \infty$ for each k , and $n^{-1} \cdot \sum_{i=1}^n I(\mu_\infty(-\infty, X_i) < r)$ converges a.s. as $n \rightarrow \infty$ for every rational r . The a.s. convergence of $n^{-1} \cdot \sum_{i=1}^n I(X_i < X_k)$ for each k is equivalent to the a.s. convergence, for each N and $K \leq N$ of $m^{-1} \cdot \sum_{i=1}^m I(X_i < X_{(K)}^N)$. Convergence will now be proved in this form.

Fix N and $K \leq N$. Let $\xi_i = I(X_{N+i} < X_{(K)}^N)$ and let $S_n = \xi_1 + \xi_2 + \dots + \xi_n$. Now consider the event $\{S_n = \ell\}$. On this set ℓ of the points X_{N+1}, \dots, X_{N+n} must be less than $X_{(K)}^N$, so $X_{(K)}^N = X_{(\ell+K)}^{N+n}$. Thus

$$\begin{aligned} P(\xi_{n+1} = 1 | S_n = \ell) &= P(X_{n+N+1} < X_{(K)}^N | S_n = \ell) = P(X_{n+N+1} < X_{(\ell+K)}^{N+n} | S_n = \ell) \\ &= P(Z_{n+N+1} \leq \ell + K | S_n = \ell) \end{aligned}$$

by the definition of the Z -process. But S_n depends only on the values of Z_{N+1}, Z_{N+2}, \dots and Z_{N+n} , all of which are independent of Z_{N+n+1} . So $P(Z_{n+N+1} \leq \ell + K | S_n = \ell) = P(Z_{n+N+1} \leq \ell + K)$. The same reasoning shows that

$$\begin{aligned} P(\xi_{n+1} = 1 | S_1 = s_1, S_2 = s_2, \dots, S_{n-1} = s_{n-1}, S_n = \ell) \\ = P(Z_{n+N+1} \leq \ell + K) \end{aligned}$$

and hence that $\{S_n\}$ is a Markov chain with

$$P(S_{n+1} = \ell + 1 | S_n = \ell) = P(Z_{n+N+1} \leq \ell + K).$$

Now

$$E(S_{n+1} | S_1, \dots, S_n) = E(S_{n+1} | S_n)$$

and

$$\begin{aligned} E(S_{n+1} | S_n = \ell) &= E(S_n + \xi_{n+1} | S_n = \ell) = \ell + P(\xi_{n+1} = 1 | S_n = \ell) \\ &= \ell + P(Z_{n+N+1} \leq \ell + K) \leq \ell + (\ell + K)(n + N + 1)^{-1}. \end{aligned}$$

So

$$\begin{aligned} E((S_{n+1} + K)(n + 1 + N + 1)^{-1} | S_n = \ell) \\ \leq [\ell + (\ell + K)(n + N + 1)^{-1} + K] [n + 1 + N + 1]^{-1} \\ = (\ell + K)(n + N + 1)^{-1}. \end{aligned}$$

This shows that $(S_n + K)(n + N + 1)^{-1}$ is a supermartingale. (If the Z_i were actually uniform it would be the martingale associated with a Polya urn.) Now

$$(n+N)^{-1} \cdot \sum_{i=1}^{n+N} I(X_i < X_{(K)}^N) = (n+N)^{-1} \cdot \left[\sum_{i=1}^N I(X_i < X_{(K)}^N) + \sum_{N+1}^{n+N} I(X_i < X_{(K)}^N) \right] = (n+N)^{-1} \cdot [K-1 + S_n]$$

which converges as $n \rightarrow \infty$ because the supermartingale $(n+N+1)^{-1} \cdot (S_n + K)$ does.

The other step is to show the convergence of $n^{-1} \cdot \sum_{i=1}^n I(\mu_\infty(-\infty, X_i) < r)$. Let F_n denote the σ -algebra generated by $Z_{n+1}, Z_{n+2}, Z_{n+3}, \dots$ and let $T_n = \sum_{i=1}^n I(\mu_\infty(-\infty, X_i) < r)$. Rewriting T_n as $\sum_{i=1}^n I(\mu_\infty(-\infty, X_{(i)}^n) < r)$ and noting that $\mu_\infty(-\infty, X_{(i)}^n)$ is F_n -measurable shows that T_n is F_n -measurable. Also, $T_n = T_{n+1} - \sum_{i=1}^{n+1} I(\mu_\infty(-\infty, X_{(i)}^{n+1}) < r) I(Z_{n+1} = i)$ since the term corresponding to the point X_{n+1} must be omitted in going from T_{n+1} to T_n . Now

$$\begin{aligned} E(T_n | F_{n+1}) &= E(T_{n+1} | F_{n+1}) \\ &= \sum_{i=1}^{n+1} E(I(\mu_\infty(-\infty, X_{(i)}^{n+1}) < r) I(Z_{n+1} = i) | F_{n+1}) \\ &= T_{n+1} - \sum_{i=1}^{n+1} P(Z_{n+1} = i) I(\mu_\infty(-\infty, X_{(i)}^{n+1}) < r), \end{aligned}$$

since T_{n+1} is F_{n+1} -measurable, $I(\mu_\infty(-\infty, X_{(i)}^{n+1}) < r)$ is F_{n+1} -measurable, but Z_{n+1} is independent of $F_{n+1} = \sigma(Z_{n+2}, Z_{n+3}, \dots)$.

The random variables $I(\mu_\infty(-\infty, X_{(i)}^{n+1}) < r)$ are decreasing with i , since $X_{(1)}^{n+1} < X_{(2)}^{n+1} < \dots < X_{(n+1)}^{n+1}$. Thus the weighted sum

$$\sum_{i=1}^{n+1} P(Z_{n+1} = i) I(\mu_\infty(-\infty, X_{(i)}^{n+1}) < r)$$

is less than

$$\sum_{i=1}^{n+1} (n+1)^{-1} \cdot I(\mu_\infty(-\infty, X_{(i)}^{n+1}) < r)$$

since Z_{n+1} is stochastically larger than uniform. Using this inequality in the above expression for $E(T_n | F_{n+1})$ produces

$$\begin{aligned} E(T_n | F_{n+1}) &\geq T_{n+1} - \sum_{i=1}^{n+1} (n+1)^{-1} \cdot I(\mu_\infty(-\infty, X_{(i)}^{n+1}) < r) \\ &= T_{n+1} - (n+1)^{-1} \cdot T_{n+1} = n(n+1)^{-1} \cdot T_{n+1}. \end{aligned}$$

Dividing by n , $E(n^{-1} \cdot T_n | F_{n+1}) \geq (n+1)^{-1} T_{n+1}$. Thus $n^{-1} \cdot T_n$ is a reversed submartingale and must converge as $n \rightarrow \infty$ [2, p. 333] which was to be shown. \square

Perhaps Theorem 2 as stated does not make clear enough the latitude available in choosing the X_i subject to holding the distribution of the Z_i fixed. For example, the X_i can be restricted to $[0, 1]$ and then chosen to be the midpoint of the interval dictated by the Z_i . If $Z_1=1, Z_2=1, Z_3=3, Z_4=2$, the corresponding X_i obtained by following this scheme would be $X_1=1/2, X_2=1/4, X_3=3/4, X_4=3/8$. Of course the midpoint can be replaced by any other proportion or a point chosen randomly in the interval. As long as Z_1, Z_2, Z_3, \dots are independent and $P(Z_n \leq j) \leq j/n, n^{-1} \cdot [\delta(X_1) + \dots + \delta(X_n)]$ converges almost surely. In fact the X_i need not even be measurable functions and $\{n^{-1} \cdot [\delta(X_1) + \dots + \delta(X_n)] \text{ converges}\}$ still contains a set of probability 1.

It suffices, in Theorem 2, to assume that $\{X_i\}$ be bounded above a.s. (the asymmetry arising because the Z_i are assumed stochastically larger than uniform). No mass can escape to $-\infty$ because $\mu_\infty(-\infty, X_{(1)}^n)$ must have a law stochastically smaller than Beta $(1, n)$, the law in the uniform case.

The hypothesis that $\{X_i\}$ be bounded above cannot be dropped, even if it is assumed that $P(Z_n = i) \leq A/n$ uniformly for some $A > 1$. This can be shown using a result of Dubins and Freedman [3]. In these examples, however, EZ_n/n converges to a limit greater than $\frac{1}{2}$. Perhaps $EZ_n/n \rightarrow \frac{1}{2}$ is sufficient to guarantee the tightness of $\{n^{-1}[\delta(X_1) + \dots + \delta(X_n)]\}$.

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Received December 19, 1978