

Empirical and Poisson Processes on Classes of Sets or Functions Too Large for Central Limit Theorems*

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Summary. Let P be the uniform probability law on the unit cube I^d in d dimensions, and P_n the corresponding empirical measure. For various classes \mathcal{C} of sets $A \subset I^d$, upper and lower bounds are found for the probable size of $\sup\{|P_n - P|(A)|: A \in \mathcal{C}\}$. If \mathcal{C} is the collection of lower layers in I^2 , or of convex sets in I^3 , an asymptotic lower bound is

$$((\log n)/n)^{1/2} (\log \log n)^{-\delta-1/2} \quad \text{for any } \delta > 0.$$

Thus the law of the iterated logarithm fails for these classes.

If $\alpha > 0$, β is the greatest integer $< \alpha$, and $0 < K < \infty$, let \mathcal{C} be the class of all sets $\{x_d \leq f(x_1, \dots, x_{d-1})\}$ where f has all its partial derivatives of orders $\leq \beta$ bounded by K and those of order β satisfy a uniform Hölder condition $|D^\beta(f(x) - f(y))| \leq K|x - y|^{\alpha - \beta}$. For $0 < \alpha < d - 1$ one gets a universal lower bound $\delta n^{-\alpha/(d-1+\alpha)}$, for a constant $\delta = \delta(d, \alpha) > 0$. When $\alpha = d - 1$ the same lower bound is obtained as for the lower layers in I^2 or convex sets in I^3 . For $0 < \alpha \leq d - 1$ there is also an upper bound equal to a power of $\log n$ times the lower bound, so the powers of n are sharp.

1. Introduction

First let us define a collection of sets in d -dimensional Euclidean space \mathbb{R}^d whose boundaries are given by functions with derivatives up through some order β bounded and satisfying a Hölder condition of order $0 < \alpha - \beta \leq 1$. Specifically, let $\alpha > 0$ and $K > 0$. Let β be the greatest integer $< \alpha$. Let

$$D^p = \partial^{[p]} / \partial x_1^{p_1} \dots \partial x_d^{p_d}, \quad [p] = p_1 + \dots + p_d,$$

for p_i integers ≥ 0 , $p = (p_1, \dots, p_d)$. For a function f on \mathbb{R}^d such that $D^p f$ is continuous whenever $[p] \leq \beta$, let

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$$\begin{aligned} \|f\|_\alpha &= \max_{|p| \leq \beta} \sup \{|D^p f(x)|: x \in \mathbb{R}^d\} \\ &\quad + \max_{|p| = \beta} \sup_{x \neq y} \{|D^p f(x) - D^p f(y)|/|x - y|^{\alpha - \beta}\} \end{aligned}$$

where $|u| = (u_1^2 + \dots + u_k^2)^{1/2}$, $u \in \mathbb{R}^k$.

Let I^d be the unit cube $\{x \in \mathbb{R}^d: 0 \leq x_j \leq 1, j = 1, \dots, d\}$. Let $x_{(d)} = (x_1, \dots, x_{d-1})$, $x \in \mathbb{R}^d$. Then let $\mathcal{C}(\alpha, d, K)$ be the collection of all sets of the form

$$\{x \in I^d: 0 \leq x_d \leq f(x_{(d)})\}$$

for all f on \mathbb{R}^{d-1} with $\|f\|_\alpha \leq K$.

As the most difficult result in this paper (Theorem 3) gives an asymptotic lower bound for empirical and Poisson processes over classes $\mathcal{C}(d-1, d, K)$, the relatively small class $\mathcal{C}(\alpha, d, K)$ just defined will suffice here. Larger classes with the same degree of boundary smoothness, but allowing unions and intersections of a fixed (for each class) number of such sets have been defined and studied previously ([5, 6, 14], Révész (1976a-b)). Corresponding asymptotic results will also hold for them.

Throughout, let P be the uniform Lebesgue measure on I^d . Let $X(1), X(2), \dots$, be independent and identically distributed with law P , $P_n = n^{-1} \sum_{j=1}^n \delta_{X(j)}$, and $\nu_n = n^{1/2}(P_n - P)$. Let \mathcal{A} be the σ -algebra of measurable sets completed for P .

The main results of the paper will be stated in this section and proved in later sections.

For any collection \mathcal{C} of measurable sets and finite signed measure μ let $\|\mu\|_{\mathcal{C}} = \sup_{A \in \mathcal{C}} |\mu(A)|$. If $\mathcal{C} = \mathcal{C}(\alpha, d, K)$ let

$$\|\mu\|_{\alpha, d, K} = \|\mu\|_{\mathcal{C}(\alpha, d, K)}.$$

Theorem 1. *If $0 < \alpha < d - 1$ then for any $K > 0$ there is a $\delta > 0$ such that for all possible values of P_n , we have*

$$\|P_n - P\|_{\alpha, d, K} \geq \delta n^{-\alpha/(d-1+\alpha)}.$$

Remarks. Theorem 1 is related to a result of N.S. Bakhvalov (1959) and will be proved, by a technique similar to his, in Sect. 2.

Specifically, Bakhvalov (1959, Teorema 1, p. 6) implies that for each $d = 1, 2, \dots$, and $\alpha > 0$, there is a $\gamma = \gamma(d, \alpha) > 0$ such that for all possible values of P_n , we have

$$(1.1) \quad \sup \{\int f d(P_n - P): \|f\|_\alpha \leq 1\} \geq \gamma n^{-\alpha/d}.$$

This gives information for empirical measures mainly when $\alpha \leq d/2$, since for $\alpha > d/2$ the supremum even over $\pm f$ for a single $f \neq 0$ tends to be of order $n^{-1/2}$.

In (1.1) one can, replacing γ by $\gamma/2$ if necessary, restrict the supremum to those f with $\int f dP = 0$, implying the results of Kaufman and Philipp (1978, Sect.

4) with some improvements: $\delta=1$, $\varepsilon=0$, and no independence, lacunarity or other probabilistic assumption is needed.

The next result applies to a general probability space (X, \mathcal{A}, Q) . Here $v_n = n^{1/2}(Q_n - Q)$. For a collection $\mathcal{C} \subset \mathcal{A}$ and $\varepsilon > 0$ let [6]

$$N_T(\varepsilon, \mathcal{C}, Q) = \inf \{m: \exists A_1, \dots, A_m \in \mathcal{A}: \forall A \in \mathcal{C} \exists i, j: A_i \subset A \subset A_j \text{ and } Q(A_j \setminus A_i) < \varepsilon\}.$$

Let $\Pr^*(A) = \inf \{\Pr(U): U \supset A\}$.

Theorem 2. *If $\mathcal{C} \subset \mathcal{A}$ and for some constants ζ , $1 \leq \zeta < \infty$, and $K < \infty$, $N_T(\varepsilon, \mathcal{C}, Q) \leq \exp(K\varepsilon^{-\zeta})$ for $0 < \varepsilon \leq 1$, then*

$$\Pr^* \{ \|v_n\|_{\mathcal{C}} > n^\theta (\log n)^\eta \} \rightarrow 0$$

as $n \rightarrow \infty$, where $\theta = (\zeta - 1)/(2\zeta + 2)$ and for any $\eta > 2/(\zeta + 1)$.

Remarks. The classes $\mathcal{C}(\alpha, d, K)$ will satisfy the hypothesis of Theorem 2 for $\zeta = (d - 1)/\alpha$ (Kolmogorov and Tikhomirov, 1959, Sect. 5, Theorems XIII-XV; [5, (3.2), as corrected, 1979, with its proof]). Then in Theorem 2, we get $\theta = \frac{1}{2} - \frac{\alpha}{d - 1 + \alpha}$. This θ cannot be reduced, by Theorem 1. Conversely, the exponent $\alpha/(d - 1 + \alpha)$ in Theorem 1 cannot be improved. It remains to find the best exponent η for $\log n$ in Theorem 2, a problem left open here.

The condition $\zeta \geq 1$ in Theorem 2 is necessary, as we clearly cannot have $\theta < 0$ even for \mathcal{C} consisting of a single set A with $0 < Q(A) < 1$.

Theorem 2 will also be proved in Sect. 2.

On I^d , for each $\lambda > 0$ let X_λ be the Poisson point process with intensity measure λP . That is, for each measurable set $A \subset I^d$, $X_\lambda(A)$ has a Poisson distribution with parameter $\lambda P(A)$, and for disjoint measurable sets A_i , the $X_\lambda(A_i)$ are independent. Let Y_λ be the centered process

$$Y_\lambda(A, \omega) = X_\lambda(A, \omega) - \lambda P(A),$$

which has mean 0 and still has independent values on disjoint sets. In Theorems 3 and 4 P is again uniform on I^d ; $\ln = \log$.

Theorem 3. *If $0 < \alpha = d - 1$ then for any $K > 0$ and $\delta > 0$ there is a $c > 0$ such that as $\lambda \rightarrow +\infty$*

$$\Pr \{ \|Y_\lambda\|_{\alpha, d, K} > c(\lambda \ln \lambda)^{1/2} (\ln \ln \lambda)^{-0.5 - \delta} \} \rightarrow 1$$

and as $n \rightarrow \infty$,

$$\Pr \{ n \|P_n - P\|_{\alpha, d, K} > c(n \ln n)^{1/2} (\ln \ln n)^{-0.5 - \delta} \} \rightarrow 1.$$

Theorem 3 will be proved in Sects. 3-4. Kaufman (1980) proved that $\|v_n\|_{d-1, d, K}$ is unbounded in probability.

If $\alpha > d - 1$, then $\|v_n\|_{\alpha, d, K}$ is bounded in probability (and further, central limit theorems and laws of the iterated logarithm hold: Révész, 1976b; Sun and Pyke, 1982; [6, 14]).

If $\alpha < d - 1$, then it was known (without Theorem 1 above) that the central limit theorem must fail since the limiting Gaussian process is almost surely unbounded over $\mathcal{C}(\alpha, d, K)$ [4, Theorem 4.2]. For $\alpha = d - 1$, the power η of $\log n$, between $1/2$ (Theorem 3) and 1 (Theorem 2) remains to be settled.

A lower layer in \mathbb{R}^2 is a set B such that if $(x, y) \in B$, $u \leq x$ and $v \leq y$, then $(u, v) \in B$.

Steele (1978, Sect. 7), Wright (1981), and others they cite, prove laws of large numbers (Glivenko-Cantelli theorems) uniformly over the lower layers, for suitable P , as had R. Ranga Rao (1962) for convex sets, in all dimensions.

For the central limit theorem or law of the iterated logarithm the critical dimension is 2 for the lower layers and 3 for the convex sets. For these classes the central limit theorem fails since $\|v_n\|_{\mathcal{C}}$ is unbounded in probability [7]. The next result, apparently for the first time, allows us to conclude that $\|v_n\|_{\mathcal{C}}/(\log \log n)^{1/2}$ is also almost surely unbounded for \mathcal{C} =lower layers in \mathbb{R}^2 or convex sets in \mathbb{R}^3 (for previous results see e.g. Stute, 1977).

Theorem 4. *The conclusion of Theorem 3 also holds if $d=2$ and $\mathcal{C}(1, 2, K)$ is replaced by the collection of all lower layers, or by the set of all lower layers in $\mathcal{C}(1, 2, K)$. For $d=3$, the conclusion of Theorem 3 holds if $\mathcal{C}(2, 3, K)$ is replaced by the collection of all convex sets in \mathbb{R}^3 .*

Theorem 4 will be proved in Sect. 5.

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2. Proof of Theorems 1 and 2

First, to prove Theorem 1, let f be a C^∞ function on \mathbb{R}^{d-1} , 0 outside I^{d-1} , with $f > 0$ in the interior of I^{d-1} . For any ε with $0 < \varepsilon \leq 1$, set $f_\varepsilon(x) = \varepsilon^\alpha f(x/\varepsilon)$. Then

$$(2.1) \quad \|f_\varepsilon\|_\alpha \leq \|f\|_\alpha.$$

Given n , let $j = j_n = [(2nc)^{1/(\alpha+d-1)}]$ where $[x]$ is the greatest integer $\leq x$ and $c = K \int f dx / (2 \|f\|_\alpha)$. Then $1/(2n) \leq c j^{1-d-\alpha}$. We have

$$\sup_{n \geq 1} 2nc j_n^{1-d-\alpha} = M < \infty.$$

Let $\theta_n = j_n^{\alpha+d-1} / (2nc)$. Then $1/M \leq \theta_n \leq 1$.

Let $h = K \theta_n f / (2 \|f\|_\alpha)$. We decompose I^{d-1} into j^{d-1} disjoint cubes C_i , $i = 1, \dots, j^{d-1}$, of side $1/j$. Let $c_i \in I^{d-1}$ be the vertex of C_i closest to 0. Let

$$A_i = \{x \in I^d: 0 < x_d \leq j^{-\alpha} h(j(x_{(d)} - c_i))\}.$$

Then the sets A_i are disjoint. Since by (2.1)

$$K \theta_n \|f_{1/j}\|_\alpha / (2 \|f\|_\alpha) \leq K/2,$$

the union of any set of the A_i , together with $\{x \in I^d: x_d = 0\}$ forms a set in $\mathcal{C}(\alpha, d, K)$. We have for each i

$$P(A_i) = j^{1-d-\alpha} \int h dx = j^{1-d-\alpha} \theta_n c = 1/(2n),$$

and $P_n(A_i) = 0$ or $P_n(A_i) \geq 1/n$. Either at least half the A_i have $P_n(A_i) = 0$, or at least half have $P_n(A_i) \geq 1/n$. In either case,

$$\|P_n - P\|_{\alpha, d, K} \geq j^{d-1}/(4n) \geq c j^{-\alpha}/(2M) \geq \delta n^{-\alpha/(\alpha+d-1)}$$

for some $\delta = \delta(\alpha, d, K) > 0$, proving Theorem 1.

Proof of Theorem 2. The proof is similar to that of [6, Theorem 5.1]. Given n , let

$$k(n) = [(\frac{1}{2} - \theta) \cdot \log_2 n - \eta \log_2 \log n] \sim (\frac{1}{2} - \theta) \cdot \log_2 n$$

as $n \rightarrow \infty$ ($\log_2 = \log$ to base 2).

For $k = 1, 2, \dots$, let $N(k) = N_I(2^{-k}, \mathcal{C}, Q)$. By its definition choose sets $A_{ki} \in \mathcal{A}$, $i = 1, \dots, N(k)$, such that for all $A \in \mathcal{C}$ there are i and j with $A_{ki} \subset A \subset A_{kj}$ and $Q(A_{kj} \setminus A_{ki}) \leq 2^{-k}$. Let $A_{01} = \emptyset$ (empty set) and $A_{02} = X$. For each $A \in \mathcal{C}$ and $k = 0, 1, \dots$, choose such an $i = i(k, A)$ and $j = j(k, A)$. Then for $k \geq 1$,

$$Q(A_{k, i(k, A)} \Delta A_{k-1, i(k-1, A)}) \leq 2^{2-k},$$

where Δ denotes symmetric difference.

Let $\mathcal{B}(k)$ be the collection of all sets $B = A_{ki} \setminus A_{k-1, j}$ or $A_{k-1, j} \setminus A_{ki}$ or $A_{kj} \setminus A_{ki}$ such that $Q(B) \leq 2^{2-k}$ ($k \geq 1$). Then $\text{card}(\mathcal{B}(k)) \leq 2N(k-1)N(k) + N(k)^2 \leq 3 \exp(2K 2^{k\zeta})$.

For each $B \in \mathcal{B}(k)$ we have by Bernstein's inequality (Bennett, 1962) for any $t > 0$

$$(2.2) \quad \Pr \{|v_n(B)| > t\} \leq \exp(-t^2/(2^{3-k} + t n^{-1/2})).$$

Set $t = t_{n,k} = n^\theta (\log n)^\zeta c k^{-1-\delta}$ for a δ such that $0 < \delta < 1$ and $\eta > (2 + 2\delta)/(1 + \zeta)$, as is possible since $\eta > 2/(1 + \zeta)$, and where $c = \delta/(1 + \delta)$. Then for $1 \leq k \leq k(n)$,

$$2^{3-k} \geq 8 n^{\theta-1/2} (\log n)^\zeta \geq t_{n,k} n^{-1/2}.$$

Then (2.2) gives

$$\Pr \{|v_n(B)| > t_{n,k}\} \leq \exp(-t_{n,k}^2/2^{4-k}).$$

Hence

$$\begin{aligned} p_{nk} &= \Pr \{ \sup_{B \in \mathcal{B}(k)} |v_n(B)| > t_{n,k} \} \\ &\leq 3 \exp(2K 2^{k\zeta} - 2^{k-4} t_{n,k}^2) \\ &= 3 \exp(2K 2^{k\zeta} - 2^{k-4} c^2 n^{2\theta} (\log n)^{2\zeta} k^{-2-2\delta}). \end{aligned}$$

We have $2\theta/(\frac{1}{2} - \theta) = \zeta - 1 \geq 0$. For $k \leq k(n)$ we have $n^{0.5-\theta} \geq 2^k (\log n)^\zeta$, so $n^{2\theta} \geq 2^{k(\zeta-1)} (\log n)^{\zeta-1}$, and

$$p_{nk} \leq 3 \exp(2K 2^{k\zeta} - 2^{k\zeta-4} c^2 (\log n)^{\zeta+1} k^{-2-2\delta}).$$

Now $k \leq \log n$ since $\frac{1}{2} - \theta < \log 2$, so

$$p_{nk} \leq 3 \exp(2^{k\zeta} (2K - c^2 2^{-4} (\log n)^\gamma))$$

where $\gamma = \eta(\zeta + 1) - 2 - 2\delta > 0$ by choice of δ . Thus for n large enough so that $(\log n)^\gamma > 32K/c^2$,

$$\sum_{k=1}^{k(n)} p_{nk} \leq 3(\log n) \exp(4K - c^2 2^{-3} (\log n)^\gamma) \rightarrow 0$$

as $n \rightarrow \infty$.

Let \mathcal{E}_n be the event that $|v_n(B)| \leq t_{n,k}$ for all $B \in \mathcal{B}(k)$, $k=1, \dots, k(n)$. Then $\Pr(\mathcal{E}_n) \rightarrow 1$ as $n \rightarrow \infty$. On \mathcal{E}_n , for each $A \in \mathcal{C}$ and $i = i(k(n), A)$, $j = j(k(n), A)$,

$$\begin{aligned} |v_n(A_{k(n),i})| &\leq 2 \sum_{k=1}^{k(n)} t_{n,k} = 2cn^\theta (\log n)^\eta \sum_{k \geq 1} k^{-1-\delta} \\ &\leq 2n^\theta (\log n)^\eta, \end{aligned}$$

and $|v_n(A_{k(n),j} \setminus A_{k(n),i})| \leq n^\theta (\log n)^\eta$. Now

$$n^{1/2} Q(A_{k(n),j} \setminus A_{k(n),i}) \leq n^{1/2} / 2^{k(n)} < 2n^\theta (\log n)^\eta.$$

Thus $n^{1/2} Q_n(A_{k(n),j} \setminus A_{k(n),i}) \leq 3n^\theta (\log n)^\eta$, so $|v_n(A \setminus A_{k(n),i})| \leq 3n^\theta (\log n)^\eta$. Thus on \mathcal{E}_n , $|v_n(A)| \leq 5n^\theta (\log n)^\eta$ for our arbitrary $A \in \mathcal{C}$. Using a smaller η we can drop the 5, proving Theorem 2.

If $\alpha = d - 1$, the method of proof of Theorem 1 shows that for larger n there are smaller and smaller sets on which v_n is not small. But Theorem 3 gives better information.

The proof of (1.1) above by Bakhvalov (1959) is like the proof of Theorem 1 here, replacing $d - 1$ by d , and letting $j = [(2n)^{1/d}] + 1$. On the $j^d \geq 2n$ little cubes C_i let $g = 0$ on those with $P_n(C_i) > 0$. On all other C_i let $g(x) = -f_{1,j}(x - c_i)$. Then $\|g\|_\alpha \leq \|f\|_\alpha$ and using g gives (1.1). Bakhvalov notes, in turn, that Kolmogorov had used a similar method to prove a lower bound for the metric entropy of classes $\{f: \|f\|_\alpha \leq K\}$ in the supremum norm [13]. Later, W. Schmidt (1975) applied such a method to classes of convex sets.

3. Lemmas: Poissonization and Random Sets

First, let us relate empirical and Poisson processes ("Poissonization"). Consider the following property of a function f defined for large enough $x > 0$:

(*) for any $\varepsilon > 0$ there is a $\delta > 0$ such that whenever

$$x > 1/\delta \quad \text{and} \quad \left| 1 - \frac{y}{x} \right| < \delta \quad \text{then} \quad \left| 1 - \frac{f(y)}{f(x)} \right| < \varepsilon.$$

If f is continuous, and slowly varying (Karamata), i.e. for all $k > 0$, $f(kx)/f(x) \rightarrow 1$ as $x \rightarrow +\infty$; or if f is regularly varying, i.e. for some real r , $f(x) \equiv x^r L(x)$ where L is slowly varying, then (*) holds (see e.g. Feller, Vol. II,

VIII.8, Lemma 2). The following Lemma will treat more general situations than are needed in this paper. For any probability space (S, \mathcal{A}, P) we can define the Poisson processes X_λ and Y_λ , as in Sect. 1 for the uniform P , and the empirical processes P_n and v_n .

(3.1) **Lemma.** *Let (S, \mathcal{A}, P) be a probability space and $\mathcal{C} \subset \mathcal{A}$, where we assume that for each n and constant t , $\sup_{A \in \mathcal{C}} (P_n - tP)(A)$ is measurable. Let f be a function satisfying (*) such that $f(\lambda) \rightarrow +\infty$ and $f(\lambda)/\lambda \rightarrow 0$ as $\lambda \rightarrow +\infty$. Suppose that for some constant $c > 0$ and some κ with $0 \leq \kappa \leq 1$, we have*

$$\liminf_{\lambda \rightarrow \infty} \Pr \left\{ \sup_{A \in \mathcal{C}} Y_\lambda(A) \geq cf(\lambda) \lambda^{1/2} \right\} = \kappa.$$

Then for $0 < K < c$ we have

$$\liminf_{n \rightarrow \infty} \Pr \left\{ \sup_{A \in \mathcal{C}} v_n(A)/f(n) \geq K \right\} \geq \kappa.$$

Proof. Let $n(\lambda)$ be a Poisson variable with parameter λ , independent of the $X(i)$. Then $n(\lambda)P_{n(\lambda)}$ has the properties of X_λ , as is well known (Kac, 1949; Csörgő and Révész, 1981, pp. 250–251). Also, $n(\lambda)$ can be defined from X_λ or Y_λ by $n(\lambda) = X_\lambda(S) = (Y_\lambda + \lambda P)(S)$. We can then write

$$(3.2) \quad \begin{aligned} Y_\lambda &= n(\lambda)P_{n(\lambda)} - \lambda P = n(\lambda)(P_{n(\lambda)} - P) + (n(\lambda) - \lambda)P, \\ Y_\lambda/\lambda^{1/2} &= (n(\lambda)/\lambda)^{1/2} v_{n(\lambda)} + (n(\lambda) - \lambda)\lambda^{-1/2}P, \end{aligned}$$

where if $n(\lambda) = 0$, we replace $P_{n(\lambda)}$ and $v_{n(\lambda)}$ by 0. As $\lambda \rightarrow \infty$, $\Pr(n(\lambda) > 0) \rightarrow 1$, $n(\lambda)/\lambda^{1/2} \rightarrow 1$ in probability, and $(n(\lambda) - \lambda)\lambda^{-1/2}$ is bounded in probability.

From this construction we see that $\sup_{A \in \mathcal{C}} Y_\lambda(A)$ is also measurable.

If the Lemma fails, then there is a $\theta < \kappa$ and an infinite sequence of values $m = m_k \rightarrow +\infty$ such that

$$\Pr(\sup_{A \in \mathcal{C}} v_m(A) \geq Kf(m)) \leq \theta.$$

Take $0 < \varepsilon < 1/3$ such that $K(1 + 7\varepsilon) < c$. Then take a $\delta > 0$ such that (*) holds for f . We may assume $\delta < 1/2$ and $(1 + \delta)(1 + 5\varepsilon) < 1 + 6\varepsilon$. We may also assume that for all k , $m = m_k \geq 2/\delta$ and $1 + 2\varepsilon < K\varepsilon f(m)^{1/2}$.

Let $\delta_m = (f(m)/m)^{1/2}$. Then since $f(m)/m \rightarrow 0$ we may assume that $\delta_m < \delta/2$ for all $m = m_k$. For any $m = m_k$, if $(1 - \delta_m)m \leq n \leq m$ and $A \in \mathcal{A}$, then $mP_m(A) \geq nP_n(A)$, so $m(P_m - P)(A) \geq n(P_n - P)(A) - m\delta_m$, and

$$v_m(A) \geq (n/m)^{1/2} v_n(A) - f(m)^{1/2} \geq (1 + \delta)^{-1} v_n(A) - f(m)^{1/2},$$

or $v_n(A) \leq (1 + \delta)(v_m(A) + f(m)^{1/2})$. Now

$$\left| 1 - \frac{m}{n} \right| = \frac{m}{n} - 1 < 2\delta_m < \delta \quad \text{implies} \quad \left| \frac{f(m)}{f(n)} - 1 \right| < \varepsilon$$

and $1/f(n) < (1 + \varepsilon)/f(m)$, so if $v_n(A) \geq 0$ then

$$v_n(A)/f(n) \leq (1 + 2\varepsilon)(v_m(A)/f(m))^{-1} + f(m)^{-1/2}.$$

So since $(1 + 2\varepsilon)f(m)^{-1/2} < K\varepsilon$,

$$\Pr \left\{ \sup_{A \in \mathcal{G}} v_n(A) \geq Kf(n)(1 + 3\varepsilon) \right\} \leq \theta.$$

For each $m = m_k$, set $\lambda = (1 - \delta_m/2)m$. Then as $k \rightarrow \infty$, since $f(m_k) \rightarrow \infty$ we will have

$$\Pr((1 - \delta_m)m \leq n(\lambda) \leq m) \rightarrow 1.$$

Then for any γ with $\theta < \gamma < \kappa$ and k large enough, since the $X(i)$ are independent of $n(\lambda)$,

$$\Pr \left\{ \sup_{A \in \mathcal{G}} v_{n(\lambda)}(A) \geq Kf(n(\lambda))(1 + 3\varepsilon) \right\} < \gamma.$$

By (*), for $(1 - \delta_m)m \leq n \leq m$ we have $\left| 1 - \frac{f(n)}{f(\lambda)} \right| < \varepsilon$, so that for k large enough we may assume

$$\Pr \left\{ \sup_{A \in \mathcal{G}} v_{n(\lambda)}(A) \geq Kf(\lambda)(1 + 5\varepsilon) \right\} < \gamma.$$

By (3.2), we then have for k large enough

$$\Pr \left\{ \sup_{A \in \mathcal{G}} Y_\lambda(A) \geq K\lambda^{1/2}f(\lambda)(1 + 7\varepsilon) \right\} < (\gamma + \kappa)/2 < \kappa,$$

a contradiction, proving Lemma 3.1.

Note. Pyke (1968) has related estimates with and without Poissonization.

For any real x let $x^+ = \max(x, 0)$.

(3.3) **Lemma.** *There is a constant $c > 0$ such that whenever z has a Poisson law with parameter $m \geq 1$ then*

$$E(z - m)^+ \geq cm^{1/2}.$$

Proof. Let j be the greatest integer $\leq m$. Then by a telescoping sum and Stirling's formula with an error bound (e.g. Feller, Vol. I, Sect. II.9, p. 54),

$$\begin{aligned} E(z - m)^+ &= \sum_{k > m} e^{-m} m^k (k - m) / k! \\ &\geq m e^{-m} m^j / ((j/e)^j (2\pi j)^{1/2} e^{1/(12j)}) \\ &\geq (m^{j+1} / j^{j+1/2}) e^{-13/12} (2\pi)^{-1/2} \geq cm^{1/2} \quad (\text{with } c = 0.135). \quad \text{Q.E.D.} \end{aligned}$$

Now the Poisson process X_λ has the property that for any two disjoint measurable sets $A, B \in \mathcal{A}$, given the σ -algebra generated by X_λ on B and its measurable subsets, or any sub- σ -algebra \mathcal{G} of that σ -algebra, the conditional distribution of $X_\lambda(A)$ given \mathcal{G} is Poisson with parameter $\lambda P(A)$. This property will be extended to suitable random sets $A = C_\omega$ and $B = L_\omega$ where $P(A)$ is \mathcal{G} -measurable.

More generally, let (X, \mathcal{A}) be a measurable space. Let $\mathcal{A}_f \subset \mathcal{A}$ be such that for any $A, B \in \mathcal{A}_f$ and $C \in \mathcal{A}$, $A \cup B \in \mathcal{A}_f$ and $A \cap C \in \mathcal{A}_f$. (For example if (X, \mathcal{A}, μ) is a σ -finite measure space, we can take $\mathcal{A}_f = \{A \in \mathcal{A} : \mu(A) < \infty\}$.) Let

$Y: \langle A, \omega \rangle \rightarrow Y(A)(\omega)$ be a real-valued stochastic process indexed by $A \in \mathcal{A}_f$, with $\omega \in \Omega$ for a probability space $(\Omega, \mathcal{B}, \Pr)$, such that for any disjoint $A_1, \dots, A_n \in \mathcal{A}_f$, $Y(A_j)$ are independent, $1 \leq j \leq m$, and $Y(A_1 \cup A_2) = Y(A_1) + Y(A_2)$. Then we say Y has *independent pieces*. Clearly each Y_λ is such a process.

For each $C \in \mathcal{A}$ let \mathcal{B}_C be the smallest σ -algebra for which all $Y(A)(\cdot)$ are measurable for $A \subset C$, $A \in \mathcal{A}_f$.

Let G be a function from Ω into \mathcal{A} . Then (by analogy with stopping times) we call $G(\cdot)$ a *stopping set* iff for all $C \in \mathcal{A}$, $\{\omega: G(\omega) \subset C\} \in \mathcal{B}_C$.

Given a stopping set $G(\cdot)$, let \mathcal{B}_G denote the σ -algebra of all sets $B \in \mathcal{B}$ such that for all $C \in \mathcal{A}$, $B \cap \{G \subset C\} \in \mathcal{B}_C$.

(3.4) **Lemma.** *Suppose Y has independent pieces and we have random sets $G_j(\omega) = G(j)(\omega)$, $j=0, \dots, m$, and $A(\omega)$ in \mathcal{A}_f such that:*

- i) $G_0(\omega)$ is a fixed set $G_0 \in \mathcal{A}_f$;
- ii) for all ω , $G_0 \subset G_1(\omega) \subset \dots \subset G_m(\omega)$, and $G_m(\omega) \cap A(\omega) = \emptyset$;
- iii) each $G_j(\omega)$, and $A(\omega)$, has only countably many possible values $G(j, i) = G_{ji}$ and $C_i = C(i)$ respectively;
- (iv) for all i and for $1 \leq j \leq m$, $\{G_j(\cdot) = G_{ji}\} \in \mathcal{B}_{G(j-1)}$ and $\{A(\cdot) = C_i\} \in \mathcal{B}_{G(m)}$. Then the $G_j(\cdot)$ are all stopping sets, and the conditional probability

$$\Pr \{Y(A)(\cdot) \leq t \mid \mathcal{B}_{G(m)}\} = \sum_i 1_{\{A(\omega) = C(i)\}} \Pr \{Y(C_i) \leq t\}$$

almost surely, for each $t \in \mathbb{R}$.

Proof. First it will be shown by induction on j that $G_j(\cdot)$ are stopping sets. Clearly G_0 is. For the induction step, given $C \in \mathcal{A}$ and $j \geq 1$,

$$\{G_j \subset C\} = \bigcup_i \{\{G_j = G_{ji}\}: G_{ji} \subset C\}.$$

For each i , $\{G_j = G_{ji}\} \in \mathcal{B}_{G(j-1)}$. If $G_{ji} \subset C$, then by ii),

$$\{G_j = G_{ji}\} = \{G_j = G_{ji}\} \cap \{G_{j-1} \subset C\} \in \mathcal{B}_C$$

by definition of $\mathcal{B}_{G(j-1)}$ and the induction hypothesis. Thus $\{G_j \subset C\}$, as a countable union of sets in \mathcal{B}_C , is in \mathcal{B}_C , so G_j is a stopping set.

If $A(\omega) = C_i$ and $G_m(\omega) = G_{mj}$ for some ω , then $C_i \cap G_{mj} = \emptyset$ by ii), so $Y(C_i)$ is independent of $\mathcal{B}_{G_{mj}}$. Let $B_i = \{A(\cdot) = C_i\} \in \mathcal{B}_{G(m)}$ by iv). For each j , $\{G_m = G_{mj}\} \in \mathcal{B}_{G(m-1)}$, by iv), so by ii),

$$\{G_m = G_{mj}\} = \{G_m = G_{mj}\} \cap \{G_{m-1} \subset G_{mj}\} \in \mathcal{B}_{G_{mj}}$$

For any $B \in \mathcal{B}_{G(m)}$, $B \cap \{G_m = G_{mj}\} = B \cap \{G_m \subset G_{mj}\} \cap \{G_m = G_{mj}\} \in \mathcal{B}_{G_{mj}}$. So a.s.

$$\begin{aligned} \Pr(Y(A) \leq t \mid \mathcal{B}_{G(m)}) &= \sum_{i,j} \Pr(Y(A) \leq t \mid \mathcal{B}_{G(m)}) 1_{B_i} 1_{\{G_m = G_{mj}\}} \\ &= \sum_{i,j} \Pr(Y(C_i) \leq t \mid \mathcal{B}_{G_{mj}}) 1_{B_i} 1_{\{G_m = G_{mj}\}} \\ &= \sum_i \Pr(Y(C_i) \leq t) 1_{B_i}. \quad \text{Q.E.D.} \end{aligned}$$

Note. Evstigneev (1977, Theorem 1) proves a strong Markov property for suitable random fields, indexed by closed subsets of a Euclidean space, which might also be used, with some work, in place of Lemma 3.4 above.

4. Proof of Theorem 3

$\|P_n - P\|_{\alpha, d, K}$ is a measurable random variable [6, proof of (5.12)]. Writing $X_\lambda = n(\lambda)P_{n(\lambda)}$ as in the proof of Lemma (3.1) we see that $\|Y_\lambda\|_{\alpha, d, K}$ is also measurable.

Theorem 3 for Y_λ implies it for $P_n - P$, taking a smaller value of c and using (3.1). Let us prove it for Y_λ .

By assumption $d \geq 2$. Let $J = [0, 1[$, so

$$J^{d-1} = \{x \in \mathbb{R}^{d-1} : 0 \leq x_j < 1, j = 1, \dots, d-1\}.$$

Let $x_{(d)} = \langle x_1, \dots, x_{d-1} \rangle, x \in \mathbb{R}^d$.

Let f be a C^∞ function on \mathbb{R}^{d-1} with $f(x) = 0$ outside the unit cube J^{d-1} and $f(x) > 0$ for x in the interior of J^{d-1} . We choose f so that

$$\sup_x \sup_{|p| \leq d-1} |D^p f(x)| \leq 1$$

and such that at all points x of the sub-cube

$$\{x : 1/3 \leq x_j \leq 2/3, j = 1, \dots, d-1\}, \quad f(x) = \sup \{f(t) : t \in I^{d-1}\} = \gamma,$$

say, $\gamma < 1$.

A sequence of sets and functions, some of them random, will be defined recursively as follows. As the j th stage, $j = 1, 2, \dots, J^{d-1}$ is decomposed into $3^{j(d-1)}$ disjoint sub-cubes A_{ji} of side 3^{-j} for $i = 1, \dots, 3^{j(d-1)}$, where each A_{ji} is also a Cartesian product of left closed, right open intervals.

Let B_{ji} be a cube of side 3^{-j-1} , concentric with and parallel to A_{ji} . Let x_{ji} be the point of A_{ji} closest to 0 and y_{ji} the point of B_{ji} closest to 0. For $\delta > 0$ and $j = 1, 2, \dots$, let

$$c_j = Cj^{-1} (\log(j+1))^{-1-2\delta}$$

where the constant $C > 0$ is chosen so that $\sum_{j \geq 1} c_j \leq 1$.

For $x \in \mathbb{R}^{d-1}$ let

$$f_{ji}(x) = c_j 3^{-j(d-1)} f(3^j(x - x_{ji})),$$

$$g_{ji}(x) = c_j 3^{-(j+1)(d-1)} f(3^{j+1}(x - y_{ji})).$$

Then the supports of f_{ji} and g_{ji} are the closures of A_{ji} and B_{ji} respectively. Note that on B_{ji} , $f_{ji}/g_{ji} \geq 3^{d-1} > 1$.

Let $S_0 = 1/2$. We will define recursively a sequence of random variables $s_{ji}(\omega) = \pm 1$ and let

$$(4.0) \quad S_k = S_0 + \sum_{j=1}^k \sum_{i=1}^{3^{j(d-1)}} s_{ji}(\omega) f_{ji}.$$

Then since $\sum_{j \geq 1} c_j 3^{-j(d-1)} \leq 1/3, d \geq 2$, we have $0 < S_k < 1$ for all k .

Given $S_{j-1}, j \geq 1$, let $C_{ji} = C_{ji}(\omega) = \{x \in J^d: |x_d - S_{j-1}(x_{(d)})(\omega)| < g_{ji}(x_{(d)})\}$. Let $s_{ji}(\omega) = +1$ if $Y_\lambda(C_{ji}(\omega)) > 0$, otherwise $s_{ji}(\omega) = -1$. This completes the recursive definition of the s_{ji} and so of the S_k .

Recursively, one sees that each C_{ji} has only finitely many possible values, each on a measurable event, so the s_{ji} and S_k are all measurable.

Since the interiors of the A_{ji} are disjoint, we have for any $k \geq 1$

$$\sup_{\{p\} \leq d-1} \sup_x |D^p S_k(x)| \leq \sum_{j=1}^k \sup_{\{p\} \leq d-1} |D^p f_{j1}(x)| \leq \sum_{j=1}^k c_j < 1.$$

The volume of $C_{ji}(\omega)$ is always

$$(4.1) \quad P(C_{ji}(\omega)) = 2 \int g_{ji} dx = 2\mu c_j / 9^{(j+1)(d-1)}$$

where $0 < \mu = \int f dx < 1$.

Now let us show that $C_{ji}(\omega)$ for different i, j are always disjoint. For $1 \leq j \leq k$ and any ω, i and $x \in B_{ji}$ we have

$$\begin{aligned} |S_k(x) - S_{j-1}(x)|(\omega) &\geq \gamma c_j 3^{-j(d-1)} - \sum_{r>j} \gamma c_r 3^{-r(d-1)} \\ &\geq \gamma c_j 3^{-j(d-1)} (1 - \frac{1}{2}) \\ &\geq \gamma c_j 3^{-j(d-1)} / 2 \geq \sup_y (g_{ji} + \sup_r g_{k+1,r})(y). \end{aligned}$$

Thus if $s_{ji}(\omega) = +1$, then for any r and any $x \in B_{ji}$,

$$S_k(x)(\omega) - g_{k+1,r}(x) \geq S_{j-1}(x)(\omega) + g_{ji}(x),$$

so $C_{ji}(\omega)$ is disjoint from $C_{k+1,r}(\omega)$. They are likewise disjoint if $s_{ji}(\omega) = -1$, interchanging $+$ and $-$, \geq and \leq .

For the same j and different i , the $C_{ji}(\omega)$ are disjoint since they project into disjoint B_{ji} .

Given $\lambda > 0$ let $r = r(\lambda)$ be the largest j , if one exists, such that $2\lambda\mu c_j \geq 9^{(j+1)(d-1)}$. Then as $\lambda \rightarrow +\infty, r(\lambda) \sim (\log \lambda) / ((d-1) \log 9)$.

Let $G_0(\omega) = \emptyset$. For $m = 1, 2, \dots$, let

$$G(m)(\omega) = G_m(\omega) = \bigcup \{C_{ji}(\omega): j \leq m\}.$$

Let $H_m(\omega) = \{x: 0 \leq x_d \leq S_m(x_{(d)})(\omega)\}$, so that for all $\omega, H_m \in \mathcal{C}(d-1, d, 2d)$. Let $A_m(\omega) = H_m(\omega) \setminus G_m(\omega)$. Then from the disjointness proof,

$$H_m(\omega) \cap G_m(\omega) = \bigcup \{C_{ji}(\omega): j \leq m, s_{ji} = +1\}.$$

For each m , each of these sets has finitely many possible values, each on a measurable event. For each m , we apply Lemma 3.4 to these G_j , with $A = A_m$. Then each G_j is $\mathcal{B}_{G(j-1)}$ measurable, $A_m(\cdot)$ is $\mathcal{B}_{G(m)}$ measurable, and the other hypotheses of Lemma (3.4) clearly hold. Thus, conditional on $\mathcal{B}_{G(m)}, X_\lambda(A)$ is Poisson with parameter $\lambda P(A_m(\omega))$. Also,

$$(4.2) \quad Y_\lambda((H_m \cap G_m)(\omega)) = \sum_{j=1}^m \sum_{i=1}^{3^{j(d-1)}} Y_\lambda(C_{ji})^+.$$

Now $P(C_{ji})$ does not depend on ω nor i , and $C_{ji}(\cdot)$ is $\mathcal{B}_{G(j-1)}$ measurable. Thus by Lemma (3.4), applied to $A = C_{mi}$, replacing G_m by $G_m \setminus C_{mi}$, the $Y_\lambda(C_{ji})$ for different i or j are jointly independent, and each has the law of $Y_\lambda(C)$ for a fixed set C with $P(C) = 2 \int g_{j1} dx$.

Taking $m = r(\lambda)$, (4.2) is a sum of independent nonnegative parts of centered Poisson variables with parameters $\lambda P(C_{ji}) \geq 1$, by (4.1). Thus by Lemma (3.3), for a constant $c > 0$,

$$\begin{aligned} \lambda^{-1/2} EY_\lambda((H_m \cap G_m)(\omega)) &\geq c \sum_{j=1}^{r(\lambda)} \sum_{i=1}^{3^{j(d-1)}} P(C_{ji})^{1/2} \\ &= c \sum_{j=1}^{r(\lambda)} 3^{j(d-1)} (2\mu c_j / 9^{(j+1)(d-1)})^{1/2} \quad \text{by (4.1)} \\ &= c 3^{1-d} (2\mu)^{1/2} \sum_{j=1}^{r(\lambda)} (Cj^{-1} (\log(j+1))^{-1-2\delta})^{1/2} \quad \text{(def. of } c_j) \\ &= c (2\mu C)^{1/2} 3^{1-d} \sum_{j=1}^{r(\lambda)} j^{-1/2} (\log(j+1))^{-0.5-\delta} \\ &\geq a_d (\log(r(\lambda)+1))^{-0.5-\delta} \sum_{j=1}^{r(\lambda)} j^{-1/2} \\ &\geq 2a_d (r(\lambda)^{1/2} - 1) (\log(r(\lambda)+1))^{-0.5-\delta} \end{aligned}$$

for some constant $a_d > 0$. For λ large the above is

$$\geq 3b_d (\log \lambda)^{1/2} (\log \log \lambda)^{-0.5-\delta}$$

for some $b_d > 0$.

By independence of the $Y_\lambda(C_{ji})$, the variance of $Y_\lambda((H_{r(\lambda)} \cap G_{r(\lambda)})(\omega))$ is less than

$$\sum_{j=1}^{r(\lambda)} \sum_{i=1}^{3^{j(d-1)}} \lambda P(C_{ji}) = \lambda \sum_{j=1}^{r(\lambda)} 3^{j(d-1)} 2\mu Cj^{-1} (\log(j+1))^{-1-2\delta} q^{-(j+1)(d-1)} < \lambda.$$

Thus by Chebyshev's inequality,

$$\Pr \{ \lambda^{-1/2} Y_\lambda(H_{r(\lambda)} \cap G_{r(\lambda)})(\omega) \geq 2b_d (\log \lambda)^{1/2} (\log \log \lambda)^{-0.5-\delta} \} \rightarrow 1$$

as $\lambda \rightarrow +\infty$.

By Lemma (3.4), the conditional distribution of $Y_\lambda(A_{r(\lambda)}(\omega))(\omega)$ given $\mathcal{B}_{G(r(\lambda))}$ is that of $Y_\lambda(D)$ for $P(D) = P(A_{r(\lambda)}(\omega))$, where $EY_\lambda(D)^2 \leq \lambda$ for all D . Thus $EY_\lambda(D_{r(\lambda)})^2 \leq \lambda$, $Y_\lambda(A_{r(\lambda)})/\lambda^{1/2}$ is bounded in probability, and

$$\Pr \{ Y_\lambda(H_{r(\lambda)}) \geq b_d (\lambda \log \lambda)^{1/2} (\log \log \lambda)^{-0.5-\delta} \} \rightarrow 1$$

as $\lambda \rightarrow +\infty$. This proves Theorem 3 (for Y_λ) if $K \geq 2d$. For smaller values of $K > 0$ we can just multiply the constant C (in c_j , f_{ji} and g_{ji}) by $K/(2d)$, completing the proof of Theorem 3.

5. Convex Sets and Lower Layers

We have measurability of the relevant norms as in [6, (4.3), (4.4), (5.13)]. Theorem 4 will be proved first for the convex sets in case $d=3$. In the proof of Theorem 3 in the last section, let us take $d=3$ and define $S_k, k \geq 1$, by (4.0) with a new definition of S_0 :

$$S_0 = \frac{3}{4} - (x_1 - \frac{1}{2})^2 - (x_2 - \frac{1}{2})^2.$$

Then since $\sum_{j \geq 1} c_j/9^j < 1/4, 0 < S_k < 1$ for all k . The rest of the proof remains the same, to prove Theorem 4 for the convex sets, except for the consideration of second derivatives, as follows. We now get

$$\sup_{|p| \leq 2} \sup_x |D^p(S_k - S_0)(x)| \leq 1.$$

Let $H(f)$ denote the Hessian matrix $H_{ij} = \partial^2 f / \partial x_i \partial x_j$ for the function f . Then $H(S_0) \equiv \begin{pmatrix} -2 & 0 \\ 0 & -2 \end{pmatrix}$ and $H(S_k - S_0)$ is symmetric with all its entries in $[-1, 1]$. Hence $-H(S_k)$ is everywhere nonnegative definite. Since S_k is C^∞ , it is concave (Roberts and Varberg, 1973, pp. 100, 103) so that the set

$$H_{r(d)}(\omega) = \{x: 0 \leq x_d \leq S_{r(d)}(x_{(d)})(\omega)\}$$

is now convex. Thus Theorem 4 is proved for the convex sets in \mathbb{R}^3 .

To prove Theorem 4 for lower layers, we take $d=2$ in the proof in Sect. 4 and make the following changes. Choose C now so that $\sum_j c_j < 1/2$. Let $S_0 = \frac{3}{4} - \frac{x}{2}$. Then $0 < S_k < 1$ for all k , since $\sum_{j \geq 1} c_j 3^{-j} < 1/6$. Also

$$S'_k(x) \leq -\frac{1}{2} + \sum_{j \geq 1} c_j < 0$$

for all k and x . Thus each H_k is a lower layer. The rest of the proof works as before, proving Theorem 4.

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