

On the convergence of Gaussian convex hulls

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St. Petersburg
January 2020

Problem.

The talk is devoted to the review of a number of recent results about asymptotic behavior of convex hulls

$$V_n = \frac{1}{b_n} \text{conv}\{X_1, \dots, X_n\},$$

where (X_k) is a sequence of Gaussian random elements of some linear space \mathbb{B} , and b_k are normalizing constants. The main attention is paid to results about the existence of a limit shape.

Motivation.

Let

$$W_n = \text{conv}\{X_1, \dots, X_n\}. \quad (1)$$

The first point of motivation: if $\mathbb{B} = \mathbb{R}^1$, then W_n is the segment

$$[\min\{X_1, \dots, X_n\}, \max\{X_1, \dots, X_n\}].$$

It means that in some sense our problem is closely connected with the classical theory of extrema.

It is well known that for orthonormal Gaussian r.v. with probability 1

$$V_n = \frac{1}{\sqrt{2 \ln n}} \max\{X_1, \dots, X_n\} \rightarrow 1,$$

which implies that in dimension 1 a.s.

$$V_n \rightarrow [-1, 1]$$

Motivation.

The second point is related to the study of convex hulls of paths of random processes.

Let $X_i = \{X_i(t), t \in T\}$ be \mathbb{R}^d -valued processes on a parametric set T . The random process X_j can be considered as a random element of some functional space \mathbb{B} . Consider the convex hulls

$$U_n = \text{conv}\{X_1(t), \dots, X_n(t), t \in T\}. \quad (2)$$

Then in many cases from the convergence of V_n (in \mathbb{B}) we can deduce important information on asymptotic behavior of $\frac{1}{b_n} U_n$.

Motivation.

My personal interest to the question was motivated by the paper by J. Randon-Furling, Satya N. Majumdar and A. Comtet (2009) inspired by an interesting implication in ecological context in estimating the home range of a herd of animals with population size n . Mathematical results of these articles consist in exact computation of a mean perimeter L_n and area A_n of W_n in the case when $d = 2$ and X is a standard Brownian motion on $T = [0, 1]$. It was shown that

$$L_n \sim 2\pi \sqrt{2 \ln n}, \quad A_n \sim 2\pi \ln n, \quad n \rightarrow \infty. \quad (3)$$

The relation between L_n and A_n being the same as the relation between the perimeter and area of a circle of the radius $\sqrt{2 \ln n}$, it seems credible to suppose that W_n rounds up with the growth of n .

Notation.

$\mathcal{K}(\mathbb{B})$ is the space of compact convex subsets of a Banach space \mathbb{B} provided with Hausdorff distance $\rho_{\mathbb{B}}$:

$$\rho_{\mathbb{B}}(A, B) = \max\{\inf\{\epsilon \mid A \subset B^{\epsilon}\}, \inf\{\epsilon \mid B \subset A^{\epsilon}\}\},$$

A^{ϵ} is the open ϵ -neighbourhood of A .

We set $\mathcal{K}^d = \mathcal{K}(\mathbb{R}^d)$ and $\rho = \rho_{\mathbb{R}^d}$.

X is a **centered** Gaussian random element of \mathbb{B} .

\mathcal{E} is the ellipsoid of concentration of X , that is the closed unit ball in the reproducing kernel Hilbert space of the distribution of X .

[In the finite dimensional case $\mathcal{E} = \{x \in \mathbb{R}^d \mid \langle R^{-1}x, x \rangle \leq 1\}$.]

Goodman's theorem.

Goodman, 1988

Suppose that X_k are i.i.d. \mathbb{B} -valued centered Gaussian random variables, the space \mathbb{B} is supposed to be separable. Then with probability 1,

$$\max_{i \leq n} d(X_i, \sqrt{2 \ln n} \mathcal{E}) \rightarrow 0,$$
$$\max_{y \in \sqrt{2 \ln n} \mathcal{E}} d(y, \{X_1, \dots, X_n\}) \rightarrow 0$$

as $n \rightarrow \infty$. Here $d(,)$ denotes the Banach norm distance from a point to a set.

Theorem 1

Let X be a **centered** Gaussian random element of a separable Banach space \mathbb{B} . Let (X_i) be a sequence of i.i.d. copies of X and W_n be the convex hull defined by (1). Then with probability 1

$$\rho\left(\frac{1}{\sqrt{2 \ln n}} W_n, \mathcal{E}\right) = o\left(\frac{1}{\sqrt{\ln n}}\right), \quad (4)$$

where \mathcal{E} is the ellipsoid of concentration of X .

Proof of Theorem 1 follows directly from Goodman's result.

Convex hulls of Gaussian processes.

T is a separable metric space.

$X = \{X(t), t \in T\}$ is a bounded centered Gaussian process with values in \mathbb{R}^d .

(X_i) is a sequence of i.i.d. copies of X .

$U_n = \text{conv}\{X_1(t), \dots, X_n(t), t \in T\}$ (in \mathbb{R}^d).

R_t is the covariance matrix of $X(t)$.

\mathcal{E}_t is the ellipsoid of concentration of $X(t)$:

$$\mathcal{E}_t = \{x \in \mathbb{R}^d \mid \langle R_t^{-1} x, x \rangle \leq 1\}.$$

Theorem 2 (D'2011)

1) Let $X = \{X(t), t \in T\}$ be a **bounded centered** Gaussian process with values in \mathbb{R}^d . Let (X_i) be a sequence of i.i.d. copies of X and U_n be defined by (1).

Then with probability 1

$$\frac{1}{\sqrt{2 \ln n}} U_n \xrightarrow{\mathcal{K}^d} U, \quad (5)$$

where $U = \text{conv}\{\mathcal{E}_t, t \in T\}$.

2) If T is **compact** and X is **continuous**, then a.s.

$$\rho\left(\frac{1}{\sqrt{2 \ln n}} U_n, U\right) = o\left(\frac{1}{\sqrt{\ln n}}\right). \quad (6)$$

Examples.

Brownian motion. Let X be a standard d -dimensional Brownian motion on $T = [0, 1]$. Then $\mathcal{E}_t = \sqrt{t}B_d(0, 1)$ and the limit shape is

$$U = \mathcal{E}_1 = B_d(0, 1).$$

Self-similar processes. $U = \mathcal{E}_1$.

Fractional Brownian motion (FBM). $U = \mathcal{E}_1$.

Fractional Brownian Bridge. It is a fractional Brownian motion Y under the condition $Y(1) = 0$. It coincides in distribution with the process

$$X(t) = \{X_1(t), \dots, X_d(t)\}, \quad X_i(t) = Y_i(t) - r(t, 1)Y_i(1), \quad t \in [0, 1].$$

It is clear that $\mathcal{E}_t = \sigma(t)B_d(0, 1)$, where

$\sigma^2(t) = t^{2H} - \frac{1}{4}(t^{2H} + 1 - |1 - t|^{2H})^2$. The function σ^2 reaches its maximum at $t = \frac{1}{2}$ and $\sigma_{\max}^2 = \frac{1}{2^{2H}} - \frac{1}{4}$. Finally we see that $U = \sigma_{\max}B_d(0, 1)$.

Weak dependent sequences.

Let (X_n) be a sequence of Gaussian \mathbb{B} -valued random elements satisfying the following condition:

They have the **same distribution** \mathcal{P} and for all $x^* \in \mathbb{B}^*$

$$\mathbf{E}\langle X_k, x^* \rangle \langle X_l, x^* \rangle \rightarrow 0 \text{ as } |k - l| \rightarrow \infty. \quad (7)$$

Theorem 3 (D& Paulauskas'2014)

Under condition (7) with probability 1

$$\frac{1}{\sqrt{2 \ln n}} W_n \rightarrow \mathcal{E},$$

where \mathcal{E} is the concentration ellipsoid of \mathcal{P} .

Stationary fields.

Let now $X = \{X_t, t \in \mathbb{R}^m\}$ be a Gaussian stationary continuous m -parametric random field and (X_j) are i.i.d. copies of X .

Let (T_n) be an increasing sequence of subsets of \mathbb{R}^m such that $\nu_n = \lambda^m(T_n) \rightarrow \infty$ and for all $\varepsilon > 0$

$$\lim_{n \rightarrow \infty} \frac{\lambda^m\{(\partial T_n)^\varepsilon\}}{\lambda^m(T_n)} = 0. \quad (8)$$

Theorem 4 (D& Paulauskas'2014)

Suppose that conditions of weak dependence (7) and (8) are fulfilled. Then a.s.

$$\frac{1}{\sqrt{2 \ln(\nu_n)}} U_n \rightarrow \mathcal{E}.$$

Weak convergent sequences.

In condition (7):

R.v. X_n have the **same distribution** \mathcal{P} and for all $x^* \in \mathbb{B}^*$

$$\mathbf{E}\langle X_k, x^* \rangle \langle X_l, x^* \rangle \rightarrow 0 \text{ as } |k - l| \rightarrow \infty$$

the equality of marginal distributions can be essentially relaxed substituting it by the weak convergence of the sequence $\{X_n\}$.

Theorem 5 (D&Paulauskas'2020)

Suppose that a centered Gaussian sequence of \mathbb{B} -valued random elements $\{X_k, k \in \mathbb{N}\}$ satisfies (7) and the following condition:

$$X_n \Rightarrow X. \quad (9)$$

Then a.s.

$$\frac{1}{\sqrt{2 \ln n}} W_n \xrightarrow{\mathcal{K}_{\mathbb{B}}} \mathcal{E}, \text{ as } n \rightarrow \infty. \quad (10)$$

Examples

It is clear, that if the dependence between elements X_k of the sequence is stronger, the sequence of their convex hulls is more concentrated.

1st example

Consider the extreme case, when $X_k \equiv X_0$ for all $k \geq 1$.

Then $W_n = \{X_0\}$ is one point and

$$\lim_{n \rightarrow \infty} \frac{1}{g(n)} W_n = \{0\}$$

for any sequence $g(n) \rightarrow \infty$.

2nd example

Consider the case $\mathbb{B} = \mathbb{R}$. Let

$X_n = p\xi_n + q\xi_0$, $p, q > 0$, $p^2 + q^2 = 1$, $n = 1, 2, \dots$,

where $\{\xi_k, k \geq 0\}$, are orthogaussian r.v.

Then for $m \neq n$ $EX_n X_m = q^2 \rightarrow 0$ when $|m - n| \rightarrow \infty$.

Now

$$\begin{aligned} W_n &= \text{conv}\{X_k, k = 1, \dots, n\} = \text{conv}\{p\xi_k + q\xi_0, k = 1, \dots, n\} \\ &= p \text{conv}\{\xi_1, \dots, \xi_n\} + q\xi_0. \end{aligned}$$

Hence, a.s.,

$$\frac{1}{\sqrt{2 \ln n}} W_n \rightarrow p[-1, 1].$$

Example 3

Let $\{\xi_j\}$, $j \geq 1$, be orthogaussian variables and let $X_k = k^{-1/2} \sum_{j=1}^k \xi_j$. We are in the setting of Theorem 5, but the condition (7) is not satisfied, since, if $n = m + k$, $k > 0$, then

$$EX_m X_n = \frac{ES_m S_{m+k}}{(m(m+k))^{1/2}} = \frac{m}{(m(m+k))^{1/2}} = \left(1 + \frac{k}{m}\right)^{-1/2}. \quad (11)$$

On the other hand, we have:

Example 3

Proposition 1 (D&Paulauskas'2020)

With probability one

$$\frac{1}{c(n)} W_n \xrightarrow{\mathcal{K}_R} [-1, 1], \quad \text{as } n \rightarrow \infty, \quad (12)$$

where $W_n = \text{conv}\{X_1, \dots, X_n\}$ and $c(n) = \sqrt{2 \ln \ln n}$.

In previous results for Gaussian sequences the limit set of convex hulls was the concentration ellipsoid of limit Gaussian measure. If we dismiss the condition of weak convergence of Gaussian sequence $\{X_k\}$, the limit set may exist, but will not necessarily be an ellipsoid.

Theorem 6 (D'2020)

Let \mathbb{B} be a separable Banach space. Let $V \subset \mathbb{B}$ be a central symmetric compact convex set. Then there exists a sequence of independent Gaussian vectors $\{X_k\}$ such that a.s.

$$\frac{1}{b(n)} W_n \rightarrow V.$$

Open questions

1. Suppose that a sequence $\{X_n\}$ has standard normal marginal distributions and covariance function $\rho(m, n)$.

For which functions $g(n)$ and under what conditions for covariance function ρ we can get the relation

$$\frac{1}{c(n)} W_n \xrightarrow{\mathcal{K}_{\mathbb{R}}} [-1, 1], \quad \text{as } n \rightarrow \infty, \quad (13)$$

with function g instead of c ?

Proposition 1 and Theorem 5 give us two examples of such functions g . What other normalizing functions are possible in relation (13)?

2. Let $\{X_n\}$ be a stationary Gaussian sequence with covariance function $r(k)$. We know that the condition $r(k) \rightarrow 0$ implies the convergence

$$\frac{1}{\sqrt{2 \ln n}} W_n \xrightarrow{\mathcal{K}_B} \mathcal{E}, \quad \text{as } n \rightarrow \infty. \quad (14)$$

It is interesting to understand whether this condition is also necessary? If not, can it be replaced by the ergodicity condition of the sequence?

References

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