Exact small ball asymptotics in L_2 -norm for some perturbations of the Brownian bridge

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Symposium on Probability Theory and Random Processes Saint-Petersburg, 9 June, 2017 We are interested in the exact L_2 small ball asymptotics $\mathbb{P}\left(\left\|\tilde{B}(t)\right\|_{L_2[0,1]}<\varepsilon\right)\sim?\quad\text{as }\varepsilon\to0.$

$$\mathbb{I}\left(\|B(t)\|_{L_2[0,1]} < \varepsilon\right) \sim: \quad \text{as } \varepsilon \to 0.$$

• $\tilde{B}(t)$ — one-dimentional perturbation of the Brownian bridge B(t):

$$\tilde{B}(t) = B(t) - \alpha \ h(t) \int_0^1 B(s)\varphi(s) \, ds,$$

(1)

(2)

- $\alpha \in \mathbb{R}$ parameter
- ullet $arphi\in L_{1,loc}[0,1]$ generates a linear measurable functional on B(t)
- $h(t) = \int G_B(s,t)\varphi(s) ds$:

• The covariance function of $\tilde{B}(t)$

$$\mathbf{q} := \mathbb{E}\langle \varphi, B \rangle^2 = \int_0^1 \int_0^1 G_B(s, t) \varphi(s) \varphi(t) \, ds \, dt < +\infty,$$

where $G_B(s,t) = \mathbb{E}B(s)B(t)$ is covariance.

$$G_{\tilde{B}}(s,t) = G_B(s,t) + Qh(s)h(t), \quad Q = q\alpha^2 - 2\alpha.$$

2007 — P. Deheuvels:
$$\varphi(t) \equiv 1$$
, $h(t) = t(1-t)/2$

2009 — A. Nazarov: general case X(t) — Gaussian function on $O \subset \mathbb{R}^n$

Two useful facts

1. Due to the Karhunen-Loève (KL) expansion we have

$$\mathbb{P}\left(\left\|X(t)\right\|_{L_{2}[0,1]}^{2}<\varepsilon^{2}\right)=\mathbb{P}\left(\sum_{k=1}^{\infty}\mu_{k}\xi_{k}^{2}<\varepsilon^{2}\right).$$

- \bullet ξ_k is a sequence of i.i.d. N(0,1) random variables
- ullet μ_k are eigenvalues of the integral operator with kernel $G_X(s,t)$.

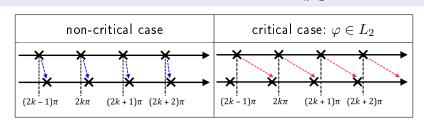
2. The Wenbo Li principle (W. Li 1992, F. Gao et al 2003)

- X(t) Gaussian process, $\mathbb{E}X(t) = 0$, μ_k positive eigenvalues of integral operator with kernel $G_X(s,t)$
- $\tilde{X}(t)$ Gaussian process, $\mathbb{E}\tilde{X}(t)=0$, $\tilde{\mu}_k$ positive eigenvalues of integral operator with kernel $G_{\tilde{X}}(s,t)$.
- If $\prod \tilde{\mu}_k/\mu_k < \infty$ then as $\varepsilon \to 0$ $\mathbb{P}\Big\{ \big\| X \big\|_{L_2[0,1]} < \varepsilon \Big\} \sim \mathbb{P}\Big\{ \big\| \tilde{X} \big\|_{L_2[0,1]} < \varepsilon \Big\} \cdot \left(\prod_{k=1}^\infty \frac{\tilde{\mu}_k}{\mu_k} \right)^{1/2}$

Theorem (A. Nazarov, 2009)

1. (non-critical case) If
$$\alpha \neq 1/\mathbf{q}$$
 then $\prod_{k=1}^{\infty} \frac{\mu_k}{\tilde{\mu}_k} < +\infty$.

 $2. \ \text{(critical case)} \qquad \text{If } \alpha = 1/\mathbf{q}, \ \varphi \in L_2 \ \text{then} \ \prod_{k=2}^{\infty} \frac{\mu_k}{\tilde{\mu}_{k-1}} < +\infty.$



3. (intermediate case) If $\alpha = 1/\mathbf{q}, \varphi \notin L_2$ then ???

Process $ilde{B}(t), \ \mathbb{E} ilde{B}(t)=0,$ with covariance function

Frocess
$$B(t)$$
, $\mathbb{E}B(t)=0$, with covariance function
$$G(s,t)=G_{B}(s,t)-h(s)h(t)=\min(s,t)-st-h(s)h(t)$$

- ullet Additional condition: h'(t) is a slowly-varying function at t=0 or t=1

- Such processes appear in statistics as limiting ones when building goodness-of-fit tests of ω^2 -type for testing if the sample comes from some distribution when parameters are estimated from the sample.
- 2015 A. Nazarov, Yu. Petrova:

Kac-Kiefer-Wolfowitz processes, testing normality

$$h_1(t) = \phi(\Phi^{-1}(t))$$
 $h_2(t) = \frac{1}{\sqrt{2}} \cdot \phi(\Phi^{-1}(t)) \cdot \Phi^{-1}(t)$

Here $\phi(t)$, $\Phi(t)$ are the probability density and the distribution function of standard normal distrubition, respectively.

 Main tool: asymptotics of oscillating integrals with slowly-varying amplitudes such as

$$\int_{0}^{\frac{1}{2}} F(t) \cos(\omega t) dt, \qquad \int_{0}^{\frac{1}{2}} \int_{0}^{\tau} F(t) F(\tau) \sin(\omega \tau) \cos(\omega t) dt d\tau,$$

 $\omega \to \infty$, in case F(t) and $F_i(t) = tF'_{i-1}(t)$, $i \in \mathbb{N}$, are SVF.

2017 — Yu. Petrova:

• the constructed method works for limiting processes when we test a sample to come from the following distributions:

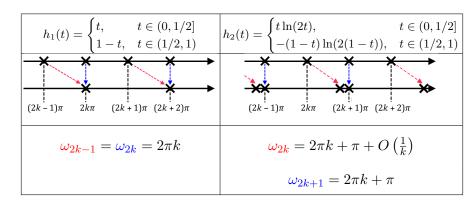
Distribution	$h_1(t)$	$h_2(t)$
Exponential	_	$t \ln(t)$
Laplace	$\begin{cases} s, & s \in (0, 1/2] \\ 1 - s, & s \in (1/2, 1) \end{cases}$	$\begin{cases} s \ln(2s), & s \in (0, 1/2] \\ -(1-s) \ln(2(1-s)), & s \in (1/2, 1) \end{cases}$
Logistic	$\sqrt{3}t(1-t)$	$\frac{3}{\sqrt{3+\pi^2}} t(t-1) \ln \left(\frac{1-t}{t}\right)$
EVD	$t \ln(t)$	$C \cdot t \ln(t) \cdot \ln(-\ln(t))$

EVD = Extreme Value Distribution C is a known constant

• and other distributions with exponential tails

Example 1 (simple): Laplace distribution

$$F_{lap}(x) = \begin{cases} \frac{1}{2} \exp(\beta(x - \alpha)), & x \leq \alpha \\ 1 - \frac{1}{2} \exp(-\beta(x - \alpha)), & x > \alpha \end{cases}$$



Example 2 (more complicated): Extreme Value Distribution

$$F_{evd}(x) = \exp\left(-\exp\left(-\frac{x-\alpha}{\beta}\right)\right)$$

$$h_{1}(s) = s \ln(s) \qquad h_{2}(s) = C \cdot s \ln(s) \cdot \ln(-\ln(s))$$

$$(2k-1)\pi \quad 2k\pi \quad (2k+1)\pi \quad (2k+2)\pi$$

$$\omega_{k} = \pi k + \frac{\pi}{2} + O\left(\frac{1}{k}\right) \qquad \omega_{k} = \pi k + \frac{\pi}{2} + F(k) + O\left(\frac{1}{\ln(k)(\ln(\ln(k)))^{2}}\right)$$

$$F(k) = (-1)^k \cdot 2 \arctan\left(\frac{1}{\ln(\ln(k)) + 1}\right) - \frac{1}{\ln(k)\ln(\ln(k))}$$

 $ilde{\omega}_k=\pi k+rac{\pi}{2}+F(k)$ is a «good» approximation because $\prod rac{\omega_k}{ ilde{\omega}_k}<+\infty$

Small ball probabilities: $\mathbb{P}\left(\|X\|_{L_2[0,1]}<\varepsilon\right)\sim$

B(t)	$\frac{2\sqrt{2}}{\sqrt{\pi}} \qquad \exp\left(-\frac{1}{8\varepsilon^2}\right)$
Laplace h_1	$\frac{\sqrt{2}}{\sqrt{\pi}} \varepsilon^{-1} \exp\left(-\frac{1}{8\varepsilon^2}\right)$
Laplace h_2	$\frac{2\sqrt{2}}{\pi^{3/2}} \varepsilon^{-1} \exp\left(-\frac{1}{8\varepsilon^2}\right)$
$EVD\ h_1$	$\frac{4}{\pi^{3/2}} \varepsilon^{-1} \exp\left(-\frac{1}{8\varepsilon^2}\right)$
$EVD\ h_2$	$\frac{1}{\ln(\ln(\varepsilon^{-1}))} C \cdot \varepsilon^{-1} \exp\left(-\frac{1}{8\varepsilon^2}\right)$
Normal h_1	$\sqrt{\ln(\varepsilon^{-1})}$ $C \cdot \varepsilon^{-1} \exp\left(-\frac{1}{8\varepsilon^2}\right)$

Thank you for your attention!