

Small deviations of smooth Gaussian processes

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joint work with Frank Aurzada (Berlin), Fuchang Gao (Moscow, Idaho),
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Main aim of the talk

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- determine the exact asymptotic behaviour of small deviations of certain smooth Gaussian processes
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Plan of the talk

- 1 The small deviation problem for stochastic processes
- 2 Metric entropy
- 3 Relations between small deviations and metric entropy
- 4 Small deviations under L_2 -norm
- 5 Small deviations under \sup -norm

1. The small deviation problem for stochastic processes

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- General Problem.

Let $X = X(t), 0 \leq t \leq 1$, be a random process attaining values in some Banach space E , in most cases $E = L_2[0, 1]$ or $C[0, 1]$.

For $\varepsilon > 0$ consider the **small deviation probabilities** on the log -level,

$$\phi(\varepsilon) = \phi_X(\varepsilon) := -\log \mathbb{P}(\|X\|_E \leq \varepsilon)$$

and determine the **asymptotic behaviour as $\varepsilon \rightarrow 0$** .

1. The small deviation problem for stochastic processes

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- **Applications in probability and analysis.**

- law of the iterated logarithm of Chung type
- strong limit laws in statistics
- quantization (approximation) of stochastic processes
- metric entropy of linear operators

- Consider the family of centered Gaussian processes $X_{\alpha,\beta}(t)$, $t \geq 0$, defined by the **covariance function**

$$K(t, s) := \mathbb{E}X_{\alpha,\beta}(t)X_{\alpha,\beta}(s) = \frac{2^{2\beta+1}(ts)^\alpha}{(s+t)^{2\beta+1}}.$$

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- **Special problem.**

(posed at the Workshop in Palo Alto, December 2008)

Find the small deviation rates of the processes $X_{\alpha,\beta}$ w.r.t. the

- L_2 norm, if $\alpha > 0$ and $-1/2 < \beta < \alpha$
- sup norm, if $\alpha > \beta + 1/2 > 0$.

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- The main tool for answering this question is the close relation to **metric entropy**.

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- For a subset K of a metric space (E, d) we define its **entropy numbers** and **covering numbers**

$$\varepsilon_n(K) = \inf\{\varepsilon > 0 : K \text{ can be covered by } n \text{ balls of radius } \varepsilon\}$$

$$N(K, \varepsilon) = \min\{n \in \mathbb{N} : K \text{ can be covered by } n \text{ balls of radius } \varepsilon\}$$

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- The (dyadic) **entropy numbers** of an **operator** $T : X \rightarrow Y$ between Banach spaces are defined as

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- **Remark.** A set K is relatively compact $\iff \lim_{n \rightarrow \infty} \varepsilon_n(K) = 0$
An operator T is compact $\iff \lim_{n \rightarrow \infty} e_n(T) = 0$.

\curvearrowright The asymptotic behaviour of these quantities is a measure for the "degree" of compactness of sets/operators.

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- μ is uniquely determined by each of the following quantities:
 - **characteristic function** $\widehat{\mu}(a) := \int_E e^{ia(x)} d\mu(x)$, $a \in E'$
 - **covariance operator** $R : E' \rightarrow E$, $Ra := \underbrace{\int_E xa(x) d\mu(x)}_{\text{Bochner integral}}$
 - **RKHS** H_μ , i.e. the completion of $R(E')$ w.r.t. the inner product

$$\langle Ra, Rb \rangle_\mu = \int_E a(x)b(x) d\mu(x), \quad a, b \in E'$$

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$$\langle Ra, Rb \rangle_\mu = \int_E a(x)b(x) d\mu(x), \quad a, b \in E'$$

- \curvearrowright $\widehat{\mu}(a) = \exp(-\frac{1}{2}\langle Ra, Ra \rangle_\mu) = \exp(-\frac{1}{2}\|S'a\|_H^2)$
for some operator $S : H \rightarrow E$, where H is a Hilbert space.
- \curvearrowright $R = SS'$, and $S(B_H)$ is dense in the unit ball K_μ of H_μ .
Consequently, both sets have the same ε -entropy

- **Kuelbs-Li 1993.** Let $\phi(\varepsilon) = \phi_\mu(\varepsilon) := -\log \mu(\{x \in E : \|x\| \leq \varepsilon\})$.
Then

$$(i) \quad H(2\varepsilon/\lambda, K_\mu) \leq \phi(\varepsilon) + \lambda^2/2$$

$$\text{and } (ii) \quad H(\varepsilon/\lambda, K_\mu) \geq \phi(2\varepsilon) + \log \Phi(\lambda + \alpha_\varepsilon) \quad \text{for all } \lambda, \varepsilon > 0,$$

$$\text{where } \Phi(\alpha) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\alpha} e^{-t^2/2} dt$$

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- Some consequences. (\sim means equivalence up to constants)
 1. **Goodman 1990.** $H(\varepsilon, K_\mu) = o(\varepsilon^{-2}) \iff K_\mu$ is compact in E .
 2. **Li-Linde 1999.** $\phi(\varepsilon) \sim \varepsilon^{-\alpha} \iff H(\varepsilon, K_\mu) \sim \varepsilon^{-2\alpha/(2+\alpha)}$
 3. **Aurzada-Ibragimov-Lifshits-van Zanten 2008.**

$$\phi(\varepsilon) \sim (\log 1/\varepsilon)^\alpha \iff H(\varepsilon, K_\mu) \sim (\log 1/\varepsilon)^\alpha$$

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- **Translation to processes.** Let X be a Gaussian process that attains values in E and is related to an operator $S : H \rightarrow E$ via

$$(*) \quad \mathbb{E}e^{ia(X)} = \exp(-\frac{1}{2}\|S'a\|^2), a \in E'.$$

↪ For the Gaussian measure μ on E generated by X we have

$$\underbrace{\phi_\mu(\varepsilon)}_{=\phi_X(\varepsilon)} \sim (\log 1/\varepsilon)^\alpha \iff \underbrace{H(\varepsilon, K_\mu)}_{=H(\varepsilon, S(B_H))} \sim (\log 1/\varepsilon)^\alpha$$
$$\iff -\log e_n(S : H \rightarrow E) \sim n^{-1/\alpha}$$

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- It is easy to check that the processes $X_{\alpha,\beta} = X_{\alpha,\beta}(t), 0 \leq t \leq 1$ is related – via formula (*) – to the operator

$$(**) \quad (Sf)(t) = t^\alpha \int_0^\infty x^\beta e^{-xt} f(x) dx, \quad f \in L_2[0, \infty), t \in [0, 1]$$

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4. Small deviations under L_2 -norm

- **Theorem 1.** Let $\alpha > 0$ and $-1/2 < \beta < \alpha$. Then

$$-\log \mathbb{P} \left(\int_0^1 X_{\alpha,\beta}(t)^2 dt \leq \varepsilon^2 \right) \sim (\log 1/\varepsilon)^3 \quad \text{as } \varepsilon \rightarrow 0.$$

From our previous considerations it is clear that Theorem 1 is a consequence of the following

Proposition 2. For $\alpha > \beta > -1/2$, the entropy numbers of the operator $S : L_2[0, \infty) \rightarrow L_2[0, 1]$ given by (**) satisfy

$$-\log e_n(S) \sim \sqrt[3]{n} \quad \text{as } n \rightarrow \infty.$$

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Sketch of proof. The operator $T := SS' : L_2[0, 1] \rightarrow L_2[0, 1]$ is given by

$$(Tf)(t) = \Gamma(2\beta + 1) \int_0^1 \frac{(tx)^\alpha}{(t+x)^{2\beta+1}} dt.$$

The singular numbers of T are known (Laptev 1974),

$$-\log s_n(T) \approx 2\pi \sqrt{(\alpha - \beta)n} \quad (\text{strong equivalence } \approx),$$

and from $s_n(T) = s_n(S)^2$ we get, with $c = \pi\sqrt{\alpha - \beta}$,

$$-\log s_n(S) \approx c\sqrt{n}.$$

If D_σ is a **diagonal operator** in ℓ_2 with diagonal entries $\sigma_n \searrow 0$, then (a special case of results in Gordon-König Schütt 1987),

$$\sup_{n \geq 1} \left(2^{-k/n} (\sigma_1 \cdots \sigma_n)^{1/n} \right) \leq e_{k+1}(D_\sigma) \leq 6 \sup_{n \geq 1} \left(2^{-k/n} (\sigma_1 \cdots \sigma_n)^{1/n} \right) .$$

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In our case:

$$\begin{aligned} -\log e_k(S) &\approx \sup_{n \geq 1} \left(\frac{k \log 2}{n} + \frac{c}{n} \sum_{j=1}^n \sqrt{j} \right) \\ &\approx \sup_{n \geq 1} \left(\frac{k \log 2}{n} + \frac{c}{n} \cdot \frac{2}{3} n^{3/2} \right). \end{aligned}$$

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Finally we **optimize over n** . Taking $n \sim k^{2/3}$ we get

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Remark. The proof gives even the exact small deviation constant ,

$$\lim_{\varepsilon \rightarrow 0} \frac{-\log \mathbb{P}(\|X_{\alpha, \beta}\|_2 \leq \varepsilon)}{(\log 1/\varepsilon)^3} = \frac{1}{3(\alpha - \beta)\pi^2}.$$

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- Using again the "entropy connection", it is enough to show

Proposition 4. Let $\alpha > \beta + 1/2 > 0$, and let the operator $S : L_2[0, \infty) \rightarrow C[0, 1]$ be given by

$$(Sf)(t) = t^\alpha \int_0^\infty x^\beta e^{-xt} f(x) dx.$$

Then

$$-\log e_n(S : L_2[0, \infty) \rightarrow C[0, 1]) \sim n^{1/3}.$$

The proof of the **upper bound** is simple. Obviously

$$e_n(S : L_2[0, \infty) \rightarrow C[0, 1]) \geq e_n(S : L_2[0, \infty) \rightarrow L_2[0, 1]),$$

and Proposition 2 gives immediately

$$-\log e_n(S : L_2 \rightarrow C[0, 1]) \leq -\log e_n(S : L \rightarrow L_2[0, 1]) \sim n^{1/3}.$$

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The proof of the **lower bound** is less trivial. Starting point is the observation that S maps $L_2[0, \infty)$ even into a **smaller** space than $C[0, 1]$, namely the **Hölder space** $C^\lambda[0, 1]$ where $\lambda = \min(\alpha - \beta - 1/2, 1/2)$. It consists of all functions $f \in C[0, 1]$ with finite norm

$$\|f\|_{C^\lambda[0,1]} := \sup_{0 \leq s < t \leq 1} \frac{|f(t) - f(s)|}{|t - s|^\lambda} + \sup_{0 \leq t \leq 1} |f(t)|.$$

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But how can we take advantage of this fact? The answer is given by the following result, which might be of independent interest.

Lemma . Let $T : E \rightarrow C^\lambda[0, 1]$ be a bounded linear operator, where E is a Banach space and $0 < \lambda \leq 1$. Then, for some $c > 0$ and all $n \in \mathbb{N}$,

$$e_n(T : E \rightarrow C[0, 1]) \leq ce_n(T : E \rightarrow L_2[0, 1])^{\lambda/(\lambda+1/2)}$$

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Ingredients of the proof. We use the **smoothing/averaging operators**
 $P_\delta : L_2[0, 1] \rightarrow C[0, 1]$,

$$P_\delta f(t) = \frac{1}{|I_\delta(t)|} \int_{I_\delta(t)} f(x) dx,$$

over "moving" intervals $I_\delta(t) = [t - \delta, t + \delta] \cap [0, 1]$,

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for which we have the **simple norm estimates**

$$\begin{aligned} \|P_\delta : L_2[0, 1] \rightarrow C[0, 1]\| &\leq \delta^{-1/2} \\ \|id - P_\delta : C^\lambda[0, 1] \rightarrow C[0, 1]\| &\leq \delta^\lambda \end{aligned}$$

By elementary properties of entropy numbers we obtain

$$\begin{aligned} e_n(T : E \rightarrow C) &\leq e_n(P_\delta T : E \rightarrow C) + \|T - P_\delta T : E \rightarrow C\| \\ &\leq e_n(T : E \rightarrow L_2) \|P_\delta : L_2 \rightarrow C\| \\ &\quad + \|T : E \rightarrow C^\lambda\| \|id - P_\delta : C^\lambda \rightarrow C\| \\ &\leq e_n(T : E \rightarrow L_2) \cdot \delta^{-1/2} + \|T : E \rightarrow C^\lambda\| \cdot \delta^\lambda \end{aligned}$$

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$$\begin{aligned} e_n(T : E \rightarrow C) &\leq e_n(P_\delta T : E \rightarrow C) + \|T - P_\delta T : E \rightarrow C\| \\ &\leq e_n(T : E \rightarrow L_2) \|P_\delta : L_2 \rightarrow C\| \\ &\quad + \|T : E \rightarrow C^\lambda\| \|id - P_\delta : C^\lambda \rightarrow C\| \\ &\leq e_n(T : E \rightarrow L_2) \cdot \delta^{-1/2} + \|T : E \rightarrow C^\lambda\| \cdot \delta^\lambda \end{aligned}$$

Finally, for large enough n we can optimize δ and obtain the result. \square

By elementary properties of entropy numbers we obtain

$$\begin{aligned} e_n(T : E \rightarrow C) &\leq e_n(P_\delta T : E \rightarrow C) + \|T - P_\delta T : E \rightarrow C\| \\ &\leq e_n(T : E \rightarrow L_2) \|P_\delta : L_2 \rightarrow C\| \\ &\quad + \|T : E \rightarrow C^\lambda\| \|id - P_\delta : C^\lambda \rightarrow C\| \\ &\leq e_n(T : E \rightarrow L_2) \cdot \delta^{-1/2} + \|T : E \rightarrow C^\lambda\| \cdot \delta^\lambda \end{aligned}$$

Finally, for large enough n we can optimize δ and obtain the result. \square

Open question.

$$\lim_{\varepsilon \rightarrow 0} \frac{-\log \mathbb{P}(\sup_{0 \leq t \leq 1} |X_{\alpha, \beta}(t)| \leq \varepsilon)}{(\log 1/\varepsilon)^3} = ??$$

THANK YOU FOR YOUR ATTENTION!