Large deviations of Gaussian vectors

Let X be a centered Gaussian random vector, on some probability space $(\Omega, \mathcal{A}, \mathbb{P})$, with values in a real separable Banach space E equipped with its Borel σ -algebra \mathcal{B} , and with norm $\|\cdot\|$.

It is a consequence of the sharp integrability of the norms of Gaussian random vectors (cf. [1]) that

$$\lim_{t \to \infty} t^2 \log \mathbb{P}(\|X\| \ge t) = -\frac{1}{2\sigma^2} \tag{1}$$

where

$$\sigma^2 = \sup_{\xi \in E^*, \|\xi\| \le 1} E(\langle \xi, X \rangle^2). \tag{2}$$

This result is actually a particular case of a more general large deviation principle for the family of laws of εX as $\varepsilon \to 0$, providing further knowledge on tail behaviors.

The post briefly presents this large deviation theorem. General references on (Gaussian) large deviations include [14, 8, 7, 11, 6, 13] etc.

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1 Rate function

Given a centered Gaussian random vector X on $(\Omega, \mathcal{A}, \mathbb{P})$ with values in E, its law μ on the Borel sets of E gives rise to an abstract Wiener space structure (E, \mathcal{H}, μ) , in which the Hilbert space $\mathcal{H} \subset E$, with scalar product $\langle \cdot, \cdot \rangle_{\mathcal{H}}$, is the reproducing kernel Hilbert space associated to the covariance structure of μ (cf. [2]).

For the example of the Wiener measure μ on the Banach space E = C([0,1]) of real continuous functions on [0,1], law of a standard Brownian motion or Wiener process $W = (W(t))_{t \in [0,1]}$, the reproducing kernel Hilbert space \mathcal{H} is identified as the subspace of E = C([0,1]) consisting of the absolutely continuous functions $h:[0,1] \to \mathbb{R}$, with almost everywhere derivative h' in $L^2([0,1])$ (for the Lebesgue measure), and with

$$|h|_{\mathcal{H}} = \left(\int_0^1 h'(t)^2 dt\right)^{1/2}.$$

The rate function $\mathcal{I}: E \to [0, +\infty]$ which will govern the large deviation properties of εX as $\varepsilon \to 0$ is defined as

$$\mathcal{I}(x) = \begin{cases} \frac{1}{2}|x|_{\mathcal{H}}^2 & \text{if } x \in \mathcal{H}, \\ +\infty & \text{if } x \notin \mathcal{H}. \end{cases}$$
(3)

In the large deviation language, this rate function is a good rate function in the sense that its level sets $\{\mathcal{I} \leq a\}$, $a \geq 0$, are compact in E (due to the compactness of the \mathcal{H} -balls in E).

2 The large deviation principle

Large deviations for Gaussian measures go back to M. Schilder [12] for the Wiener measure, and to M. Donsker and S. Varadhan [9] in general. The study of [9] actually addresses the large deviation principle for sums of independent Banach space valued random variables, the Gaussian case being a particular case.

In the context exposed in the first section, the following theorem presents the large deviation behavior of the law of εX as $\varepsilon \to 0$. For a subset A of E, let

$$\mathcal{I}(A) = \inf_{x \in A} \mathcal{I}(x).$$

Theorem 1 (The Gaussian large deviation principle). For any closed set F in E,

$$\limsup_{\varepsilon \to 0} \varepsilon^2 \log \mathbb{P}(\varepsilon X \in F) \le -\mathcal{I}(F). \tag{4}$$

For any open set O in E,

$$\liminf_{\varepsilon \to 0} \varepsilon^2 \log \mathbb{P}(\varepsilon X \in O) \ge -\mathcal{I}(O). \tag{5}$$

Applied to complements of balls, this theorem easily produces the limit (1), together with the observation that $\sigma = \sup_{|h|_{\mathcal{H}} < 1} ||h||$.

The proof of the upper-bound (4) in Theorem 1 presented here relies on isoperimetric and concentration inequalities (cf. [3, 4]) which provide a very convenient tool to this task. The lower-bound (5) classically relies on the Cameron-Martin translation formula. The combined arguments actually produce a measurable version of the large deviation principle, without referring to any topology associated to the underlying abstract Wiener space (cf. [5, 10]).

Proof. A simple proof of the upper-bound (4) may therefore be provided by the Gaussian isoperimetric inequality (actually only the suitable concentration properties). Namely, let F be closed in E, and take r such that $0 < r < \mathcal{I}(F)$. By the very definition of $\mathcal{I}(F)$,

$$F \cap \sqrt{2r} \, \mathcal{K} \, = \, \emptyset,$$

where K is the (closed) unit ball in \mathcal{H} . Since F is closed and K is compact in E, there exists $\eta > 0$ such that it still holds true that

$$F \cap \left[\sqrt{2r} \,\mathcal{K} + B_E(0,\eta)\right] = \emptyset$$

where $B_E(0,\eta)$ is the ball with center the origin and with radius η for the norm $\|\cdot\|$ in E. Clearly

$$\lim_{\varepsilon \to 0} \mathbb{P} \big(\varepsilon X \in B_E(0, \eta) \big) = \lim_{\varepsilon \to 0} \mathbb{P} \big(X \in B_E(0, \frac{\eta}{\varepsilon}) \big) = 1.$$

Recall now the Gaussian isoperimetric inequality for the law of X (cf. [3]), expressing that, whenever $\mathbb{P}(X \in A) \geq \Phi(a) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{a} e^{-\frac{1}{2}x^2} dx$ for some $a \in \mathbb{R}$,

$$\mathbb{P}(X \in A + s \, \mathcal{K}) \, \ge \, \Phi(a + s)$$

for every $s \geq 0$. For $\varepsilon > 0$ small enough, $\mathbb{P}(X \in B_E(0, \frac{\eta}{\varepsilon})) \geq \frac{1}{2} = \Phi(0)$. Hence,

$$\mathbb{P}(\varepsilon X \in F) \leq \mathbb{P}\left(\varepsilon X \notin \sqrt{2r} \,\mathcal{K} + B_E(0,\eta)\right) \leq 1 - \Phi\left(\frac{\sqrt{2r}}{\varepsilon}\right) \leq e^{-r/\varepsilon^2}.$$

Therefore

$$\limsup_{\varepsilon \to 0} \varepsilon^2 \log \mathbb{P}(\varepsilon X \in F) \le -r,$$

which is the result since $r < \mathcal{I}(F)$ is arbitrary.

As mentioned above, the full strength of the Gaussian isoperimetric inequality is not really needed, and weaker concentration inequalities are enough to achieve the conclusion. For example, as emphasized in [4],

$$\mathbb{P}(X \in A + s \mathcal{K}) \ge 1 - e^{-\frac{1}{2}s^2 + \delta(\mu(A))s}$$

for every $s \geq 0$, where $\delta(\mu(A)) \to 0$ as $\mu(A) \to 1$, so that the proof may be developed similarly.

The proof of the lower-bound (5) is an application of the Cameron-Martin translation formula. Let $h \in O \cap \mathcal{H}$. Since O is open, there exists $\eta > 0$ such that $h + B_E(0, \eta) \subset O$, and thus

$$\mathbb{P}(\varepsilon X \in O) \geq \mathbb{P}(\varepsilon X \in h + B_E(0, \eta)).$$

In the notation of [2], the Cameron-Martin translation formula yields that

$$\mathbb{P}(\varepsilon X \in h + B_E(0, \eta)) = \mu(\frac{h}{\varepsilon} + B_E(0, \frac{\eta}{\varepsilon}))$$

$$= \exp\left(-\frac{|h|_{\mathcal{H}}^2}{2\varepsilon^2}\right) \int_{B_E(0, \frac{\eta}{\varepsilon})} \exp\left(-\frac{\widetilde{h}}{\varepsilon}\right) d\mu,$$

where it is recalled that \widetilde{h} is Gaussian under μ with variance $|h|_{\mathcal{H}}^2$ ($\widetilde{h} = \int_0^1 h'(t)dW(t)$ on the Wiener space). By Jensen's inequality,

$$\int_{B_E(0,\frac{\eta}{\varepsilon})} \exp\left(-\frac{\widetilde{h}}{\varepsilon}\right) d\mu \ge \mu\left(B_E(0,\frac{\eta}{\varepsilon})\right) \exp\left(-\int_{B_E(0,\frac{\eta}{\varepsilon})} \frac{\widetilde{h}}{\varepsilon} \cdot \frac{d\mu}{\mu(B_E(0,\frac{\eta}{\varepsilon}))}\right).$$

Now

$$\int_{B_E(0,\frac{\eta}{2})} \widetilde{h} \, d\mu \, \leq \, \int_E |\widetilde{h}| d\mu \, \leq \, \left(\int_E \widetilde{h}^2 d\mu \right)^{1/2} \, = \, |h|_{\mathcal{H}}.$$

For every $\varepsilon > 0$ small enough, $\mu(B_E(0, \frac{\eta}{\varepsilon})) \geq \frac{1}{2}$ (for example). As a consequence of the various preceding lower-bounds,

$$\mathbb{P}(\varepsilon X \in O) \ge \frac{1}{2} \exp\left(-\frac{|h|_{\mathcal{H}}^2}{2\varepsilon^2} - \frac{2|h|_{\mathcal{H}}}{\varepsilon}\right)$$

from which it follows that

$$\liminf_{\varepsilon \to 0} \varepsilon^2 \log \mathbb{P}(\varepsilon X \in O) \ge -\frac{1}{2} |h|_{\mathcal{H}}^2 = -\mathcal{I}(h).$$

This result for any $h \in O \cap \mathcal{H}$ yields the announced lower-bound (5), and completing therefore the proof of Theorem 1.

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