

22

A GEOMETRIC APPROACH TO MAXIMUM LIKELIHOOD ESTIMATION FOR INFINITE-DIMENSIONAL LOCATION. III*

B. S. TSIREL'SON

(Translated by Laila Ellis)

In the second part [2] of our series of articles we formulated four theorems without proofs. Their proofs are given here, in this third part, along with the necessary lemmas; the theorems are not stated here, nor are the definitions. We continue to use the objects and notation introduced in the first part [1]: $E, \gamma, E_0, \langle \theta, x \rangle, \|\theta\|, \gamma_\theta, \gamma_{\theta, \sigma}, \mathcal{L}_\sigma(\theta, x), V, C_1(V), C_2(V, \theta)$, as well as $B(\theta, r)$, and those introduced in [2]: $\mathcal{M}_k(V)$ and γ_V , and those appearing in the statements of Theorems 1-4: $F_k, K(\theta)$ and the ρ -correlated random elements. As in [2], the set V is assumed to be convex and such that $C_1(V) < +\infty$, and consequently $C_1(V) = 0$. Recall that

$$(1) \quad \mathcal{M}_k(V) \subseteq \mathcal{M}_1^k(V),$$

as well as

$$(2) \quad \mathcal{M}_1(V \cap B(\theta, r)) \subseteq r \mathcal{M}_1(V \cap B(\theta, 1)) \quad \text{for } r \geq 1, \quad \theta \in V;$$

see [2, formulas (4) and (1)]. A significant role will be played by the following function on E :

$$\varphi(x) = \sup_{\theta \in V} \log \mathcal{L}(\theta, x) = \sup_{\theta \in V} (\langle \theta, x \rangle - \frac{1}{2} \|\theta\|^2);$$

as Theorem 1 in [1] shows, the function φ is well defined and finite γ_σ -a.e. for any σ . According to formula (5) in [2],

$$(3) \quad \frac{\gamma_V(dx)}{\gamma(dx)} = \exp \varphi(x).$$

Finally, by definition, $a_+ = \max(a, 0)$; accordingly, $(a-b)_+^2$ is equal to $(a-b)^2$ for $a \geq b$ and to 0 for $a \leq b$.

Let us begin with the finite-dimensional case. We assume that $E = \mathbb{R}^n$, $\gamma = \gamma^n$, the metric is Euclidean, and $\hat{\theta}(x)$ is the closest point in V to x . Let us point out some useful inequalities:

$$(4) \quad \langle \hat{\theta}(x) - \theta, x - \hat{\theta}(x) \rangle \geq 0$$

for any $x \in \mathbb{R}^n, \theta \in V$;

$$(5) \quad \langle \hat{\theta}(x) - \hat{\theta}(y), x - y \rangle \geq \|\hat{\theta}(x) - \hat{\theta}(y)\|^2$$

for any $x, y \in \mathbb{R}^n$; and if $0 \in V$, then

$$(6) \quad \langle \hat{\theta}(x), x \rangle \geq \|\hat{\theta}(x)\|^2$$

for any $x \in \mathbb{R}^n$. Inequality (4) is geometrically obvious: the hyperplane passing through $\hat{\theta}(x)$ perpendicular to the segment joining $\hat{\theta}(x)$ with x separates V from x .

* Received by the editors June 18, 1984.

Inequality (6) is obtained from (4) for $\theta = 0$. Inequality (5) is derived as follows: for $\theta = \hat{\theta}(y)$ we find from (4) that $\langle \hat{\theta}(x) - \hat{\theta}(y), x - \hat{\theta}(x) \rangle \geq 0$; we switch the places of x and y , add the resulting inequality to the original one

$$\begin{aligned} \langle \hat{\theta}(y) - \hat{\theta}(x), y - \hat{\theta}(y) \rangle + \langle \hat{\theta}(x) - \hat{\theta}(y), x - \hat{\theta}(x) \rangle &\geq 0; \\ \langle \hat{\theta}(x) - \hat{\theta}(y), x - \hat{\theta}(x) - y + \hat{\theta}(y) \rangle &\geq 0; \end{aligned}$$

and obtain (5).

Remark 1. Inequalities (4), (5) and (6) remain valid in the infinite-dimensional case (for almost all x and y) if $V \in GC$.

We shall study the function φ in the finite-dimensional case. We have

$$\begin{aligned} \varphi(x) &= \frac{1}{2} \sup_{\theta \in V} (\|x\|^2 - \|x - \theta\|^2) \\ (7) \quad &= \frac{1}{2} \|x\|^2 - \frac{1}{2} \|x - \hat{\theta}(x)\|^2. \end{aligned}$$

This function is convex on \mathbb{R}^n and continuously differentiable; it is not hard to calculate its differential:

$$(8) \quad D\varphi(x, h) = \langle \hat{\theta}(x), h \rangle.$$

Now let us suppose that V is a convex solid with a C^2 -smooth boundary ∂V . Then the principal curvatures $\kappa_1(\theta), \dots, \kappa_{n-1}(\theta)$ of the surface ∂V are defined at each point $\theta \in \partial V$; their order of enumeration is of no consequence for us. In this case also φ will be C^2 -smooth: $\varphi(x+h) = \varphi(x) + D\varphi(x, h) + \frac{1}{2} D^2\varphi(x, h) + o(\|h\|^2)$; $D^2\varphi(x, h)$ is a quadratic form (in h); let us consider its characteristic values $\lambda_1(x), \dots, \lambda_n(x)$. For $x \in \mathbb{R}^n \setminus V$ one of them is equal to zero since the form is singular in the direction of the vector $x - \hat{\theta}(x)$; we shall assume that $\lambda_n(x) = 0$. The other characteristic values are associated with the principal curvatures:

$$(9) \quad \lambda_i(x) (1 + \|x - \hat{\theta}(x)\| \kappa_i(\hat{\theta}(x))) = 1.$$

Clearly, $0 < \lambda_i(x) \leq 1$. Of course for $x \in V \setminus \partial V$ the expression $\kappa_i(\hat{\theta}(x))$ becomes meaningless; in this case, $\lambda_i(x) = 1$ for $i = 1, \dots, n$. It is clear from (8) that the $\lambda_i(x)$ are also the eigenvalues of the differential of the mapping $\hat{\theta}$ at x . The following lemma links these numbers to the thicknesses.

LEMMA 1. For any $z \in (-\infty, +\infty)$,

$$\int_{\mathbb{R}^n} \prod_{i=1}^n (1 + z\lambda_i(x)) \gamma_V(dx) = \sum_{k=0}^n \frac{1}{k!} \mathcal{M}_k(V) (1+z)^k.$$

Proof. The one-to-one mapping $x \rightarrow (\hat{\theta}(x), \|x - \hat{\theta}(x)\|)$ of the set $\mathbb{R}^n \setminus V$ onto $\partial V \times (0, +\infty)$ has Jacobian $\lambda_1(x) \dots \lambda_{n-1}(x)$. Hence taking (3) and (9) into account we obtain the following change-of-variables formula (Ψ is any function on $\partial V \times (0, +\infty)$, for which the indicated integrals exist):

$$\begin{aligned} &\int_{\mathbb{R}^n \setminus V} \Psi(\hat{\theta}(x), \|x - \hat{\theta}(x)\|) \gamma_V(dx) \\ &= (2\pi)^{-n/2} \int_{\partial V} \int_0^\infty \Psi(\theta, t) \exp(-t^2/2) \prod_{i=1}^{n-1} (1 + t\kappa_i(\theta)) dt S(d\theta); \end{aligned}$$

and $S(d\theta)$ is the area element on ∂V . Let us apply this formula to the integral given in the hypotheses of the lemma, after first reducing it to the necessary form with the

aid of formula (9):

$$\begin{aligned} & \int_{\mathbb{R}^n} \prod_{i=1}^n (1 + z\lambda_i(x)) \gamma_V(dx) = \int_V (1+z)^n \gamma_V(dx) \\ & + \int_{\mathbb{R}^n \setminus V} \prod_{i=1}^{n-1} \left(1 + \frac{z}{1 + \|x - \hat{\theta}(x)\| \kappa_i(\hat{\theta}(x))} \right) \gamma_V(dx) \\ & = (1+z)^n (2\pi)^{-n/2} \text{meas}_n V + (2\pi)^{-n/2} \int_{\partial V} \int_0^\infty \prod_{i=1}^{n-1} \left(1 + \frac{z}{1 + t\kappa_i(\theta)} \right) \\ & \cdot \exp\left(-\frac{t^2}{2}\right) \prod_{i=1}^{n-1} (1 + t\kappa_i(\theta)) dt S(d\theta). \end{aligned}$$

The first term is equal to $(n!)^{-1} \mathcal{M}_n(V)(1+z)^n$ (see [3, 3.5.2]). Using the elementary symmetric functions of the principal curvatures

$$\sigma_\nu(\theta) = \sum_{1 \leq i_1 < \dots < i_\nu \leq n-1} \kappa_{i_1}(\theta) \cdots \kappa_{i_\nu}(\theta),$$

we transform the second term as follows:

$$\begin{aligned} & (2\pi)^{-n/2} \int_{\partial V} \int_0^\infty \prod_{i=1}^{n-1} (1 + t\kappa_i(\theta) + z) \exp(-t^2/2) dt S(d\theta) \\ & = (2\pi)^{-n/2} \int_{\partial V} \int_0^\infty \sum_{k=0}^{n-1} (1+z)^k t^{n-1-k} \sigma_{n-1-k}(\theta) \exp(-t^2/2) dt S(d\theta) \\ & = (2\pi)^{-n/2} \sum_{k=0}^{n-1} (1+z)^k \left(\int_{\partial V} \sigma_{n-k-1}(\theta) S(d\theta) \right) \\ & \cdot \left(\int_0^\infty t^{n-1-k} \exp(-t^2/2) dt \right) \\ & = (2\pi)^{-n/2} \sum_{k=0}^{n-1} (1+z)^k 2^{(n-k-2)/2} \Gamma\left(\frac{n-k}{2}\right) \int_{\partial V} \sigma_{n-k-1}(\theta) S(d\theta). \end{aligned}$$

A formula linking the surface integral of σ_{n-k-1} with the k th transverse measure is known (e.g., see [4, formula 21, p. 142]), which in our notation becomes

$$\mathcal{M}_k(V) = 2^{-(k+2)/2} \pi^{-n/2} k! \Gamma\left(\frac{n-k}{2}\right) \int_{\partial V} \sigma_{n-k-1}(\theta) S(d\theta).$$

We now have

$$\begin{aligned} & \int_{\mathbb{R}^n} \prod_{i=1}^n (1 + z\lambda_i(x)) \gamma_V(dx) \\ & = \frac{1}{n!} \mathcal{M}_n(V)(1+z)^n \\ & + (2\pi)^{-n/2} \sum_{k=0}^{n-1} (1+z)^k 2^{(n-k-2)/2} \Gamma\left(\frac{n-k}{2}\right) \frac{2^{(k+2)/2} \pi^{n/2}}{k! \Gamma((n-k)/2)} \mathcal{M}_k(V) \\ & = \sum_{k=0}^n \frac{1}{k!} \mathcal{M}_k(V)(1+z)^k. \end{aligned}$$

Remark 2. If the surface ∂V is piecewise C^2 -smooth, then the second derivatives of φ and their characteristic numbers $\lambda_i(x)$ are piecewise continuous. It is not hard

to show by an approximation that Lemma 1 is preserved for this case. Further, if one takes a polyhedron as V , then all the $\lambda_i(x)$ become zeros and ones, and our Lemma 1 yields Lemma 1 in [2].

LEMMA 2. For any $\theta \in V$, $\sigma > 0$ and $z > -1$,

$$\int \prod_{i=1}^n (1 + z\lambda_i(x)) \gamma_{\theta, \sigma}(dx) \leq \exp\left(\frac{1+z}{\sigma} \mathcal{M}_1(V)\right).$$

Proof. We can assume that $\theta = 0$ and $\sigma = 1$; the general case can be reduced to this one via a shift and a dilation. Applying Lemma 1 and inequality (1) we obtain

$$\begin{aligned} \int \prod_{i=1}^n (1 + z\lambda_i(x)) \gamma(dx) &\leq \int \prod_{i=1}^n (1 + z\lambda_i(x)) \gamma_V(dx) \\ &= \sum_{k=0}^n \frac{1}{k!} \mathcal{M}_k(V) (1+z)^k \\ &\leq \sum_{k=0}^n \frac{1}{k!} ((1+z)\mathcal{M}_1(V))^k \\ &\leq \exp((1+z)\mathcal{M}_1(V)), \end{aligned}$$

as required.

The following two lemmas estimate the distance of the maximum likelihood estimate (MLE) from the true value of the parameter. The space E can again be both finite-dimensional and infinite-dimensional.

LEMMA 3. Let $V \subset E_0$ be a convex GB-compact set, $\theta \in V$ and $\sigma > 0$. Then, for any $a \in [0, 1]$,

$$\int \exp\left(\frac{a(2-a)}{2\sigma^2} \|\hat{\theta}(x) - \theta\|^2\right) \gamma_{\theta, \sigma}(dx) \leq \exp\left(\frac{a}{\sigma} \mathcal{M}_1(V)\right).$$

Proof. We can assume that $\theta = 0$ and $\sigma = 1$. The general case can be reduced to this one via a shift and a dilation. Also, we can assume that V is finite-dimensional; for the general case can be reduced to this one by an approximation from the inside in view of Remark 3 in [1]. We apply inequality (6), formula (3) and Corollary 1 in [2]:

$$\begin{aligned} \int \exp\left(\frac{a(2-a)}{2} \|\hat{\theta}(x)\|^2\right) \gamma(dx) &= \int \exp\left(a\|\hat{\theta}(x)\|^2 - \frac{a^2}{2} \|\hat{\theta}(x)\|^2\right) \gamma(dx) \\ &\leq \int \exp\left(a\langle \hat{\theta}(x), x \rangle - \frac{a^2}{2} \|\hat{\theta}(x)\|^2\right) \gamma(dx) \\ &\leq \int \exp \sup_{\theta \in aV} \left(\langle \theta, x \rangle - \frac{1}{2} \|\theta\|^2\right) \gamma(dx) \\ &= \int \gamma_{aV}(dx) = \gamma_{aV}(E) \\ &\leq \exp(\mathcal{M}_1(aV)) = \exp(a\mathcal{M}_1(V)). \end{aligned}$$

COROLLARY 1. Under the hypotheses of Lemma 3,

$$\gamma_{\theta, \sigma}\{x \in E: \|\hat{\theta}(x) - \theta\| \geq r\} \leq e^{-u}$$

for any positive r and u such that

$$\sqrt{2u} = r/\sigma - \mathcal{M}_1(V)/r.$$

Proof. For any $a \in [0, 1]$ we have

$$\begin{aligned} \gamma_{\theta, \sigma} \{x \in E: \|\hat{\theta}(x) - \theta\| \geq r\} \\ \leq \exp\left(-\frac{a(2-a)}{2\sigma^2} r^2\right) \int \exp\left(\frac{a(2-a)}{2\sigma^2} \|\hat{\theta}(x) - \theta\|^2\right) \gamma_{\theta, \sigma}(dx) \\ \leq \exp\left(-\frac{a(2-a)}{2\sigma^2} r^2 + \frac{a}{\sigma} \mathcal{M}_1(V)\right). \end{aligned}$$

We assume that $\mathcal{M}_1(V) \leq \sigma r^2$ (otherwise there is nothing to prove). The minimum with respect to a is attained for $a = 1 - \mathcal{M}_1(V)/(\sigma r^2)$; substituting this a , we obtain on the right-hand side

$$\exp\left(-\frac{1}{2}\left(\frac{r}{\sigma} - \frac{\mathcal{M}_1(V)}{r}\right)^2\right).$$

Remark 3. For nonconvex V the corresponding weaker estimate is derived from different considerations in [1, Thm. 2(b)]; in the notation used here this estimate takes on the form

$$\sqrt{2u} = \frac{r}{R(V, \theta)} - \left(\frac{r}{2\sigma} - \frac{\mathcal{M}_1(V)}{r}\right).$$

LEMMA 4. Let $V \subset E_0$ be a closed convex set, $\theta \in V$, $\sigma > 0$, $\mathcal{M}_1(V \cap B(\theta, 1)) = C_2 < +\infty$. Then, for all $r \geq \max(\sigma C_2, \sqrt{\sigma C_2})$,

$$\gamma_{\theta, \sigma} \{x \in E: \|\hat{\theta}(x) - \theta\| \geq r\} \leq 9 \exp\left(-\frac{1}{2}\left(\frac{r}{\sigma} - \frac{C_2}{\min(r, 1)}\right)^2\right).$$

Proof. First step. Let $0 < r_0 < r_1 < \dots$, $r_n \rightarrow +\infty$, and $r_1 \geq 1$; applying Corollary 1 to the sets $V_{n+1} = V \cap B(\theta, r_{n+1})$ and noting that $\mathcal{M}_1(V_{n+1}) \leq r_{n+1} C_2$ according to (2) (it is here that the fact that $r_1 \geq 1$ is essential), we obtain

$$\begin{aligned} \gamma_{\theta, \sigma} \{x \in E: \|\hat{\theta}(x) - \theta\| \geq r_0\} &\leq \sum_{n=0}^{\infty} \gamma_{\theta, \sigma} \{x \in E: r_n \leq \|\hat{\theta}(x) - \theta\| \leq r_{n+1}\} \\ &\leq \sum_{n=0}^{\infty} \gamma_{\theta, \sigma} \{x \in E: \|\hat{\theta}(x, V_{n+1}) - \theta\| \geq r_n\} \\ &\leq \sum_{n=0}^{\infty} \exp\left(-\frac{1}{2}\left(\frac{r_n}{\sigma} - \frac{r_{n+1} C_2}{r_n}\right)^2\right). \end{aligned}$$

At the second step we shall prove that for any $r_0 \geq (C_2 + 2)\sigma$ one can choose r_1, r_2, \dots such that $r_0 < r_1 < r_2 < \dots$, $r_n \rightarrow +\infty$ and

$$\sum_{n=0}^{\infty} \exp\left(-\frac{1}{2}\left(\frac{r_n}{\sigma} - \frac{r_{n+1} C_2}{r_n}\right)^2\right) \leq 9 \exp\left(-\frac{1}{2}\left(\frac{r_0}{\sigma} - C\right)^2\right).$$

Let us convince ourselves that this implies the assertion of the lemma. For $r \leq (C_2 + 2)\sigma$ there is nothing to prove, for then

$$9 \exp\left(-\frac{1}{2}\left(\frac{r}{\sigma} - \frac{C_2}{\min(r, 1)}\right)^2\right) \geq 9 \exp(-2) > 1.$$

For $r \geq \max(1, (C_2 + 2)\sigma)$ we put $r_0 = r$ and obtain the desired at once. There remains only the case $(C_2 + 2)\sigma \leq r \leq 1$. It will become clear at the second step that $r_1 = f(r_0)$.

where f is a continuous function on $[(C_2+2)\sigma, +\infty)$. If $f(r_0) \geq 1$ for all $r_0 \in [(C_2+2)\sigma, 1]$, then we again put $r_0 = r$ and obtain

$$\begin{aligned} \gamma_{\theta, \sigma} \{x \in E: \|\hat{\theta}(x) - \theta\| \geq r\} &\leq 9 \exp\left(-\frac{1}{2}\left(\frac{r}{\sigma} - C_2\right)_+^2\right) \\ &\leq 9 \exp\left(-\frac{1}{2}\left(\frac{r}{\sigma} - \frac{C_2}{r}\right)_+^2\right). \end{aligned}$$

There remains the case where there exists an $r' \in [(C_2+2)\sigma, 1]$, such that $f(r'') \geq 1$ for all $r'' \in [r', 1]$, $f(r') = 1$, and $r \in [(C_2+2)\sigma, r']$. In this case we put $r_0 = r'$ and derive from the inequality

$$\sum_{n=0}^{\infty} \exp\left(-\frac{1}{2}\left(\frac{r_n}{\sigma} - \frac{r_{n+1}C_2}{r_n}\right)_+^2\right) \leq 9 \exp\left(-\frac{1}{2}\left(\frac{r_0}{\sigma} - C_2\right)^2\right)$$

that

$$\begin{aligned} \exp\left(-\frac{1}{2}\left(\frac{r_0}{\sigma} - \frac{C_2}{r_0}\right)_+^2\right) + \Sigma_1 &\leq 9 \exp\left(-\frac{1}{2}\left(\frac{r_0}{\sigma} - C_2\right)^2\right) \\ &\leq 9 \exp\left(-\frac{1}{2}\left(\frac{r_0}{\sigma} - \frac{C_2}{r_0}\right)_+^2\right), \end{aligned}$$

where

$$\Sigma_1 = \sum_{n=1}^{\infty} \exp\left(-\frac{1}{2}\left(\frac{r_n}{\sigma} - \frac{r_{n+1}C_2}{r_n}\right)_+^2\right);$$

thus,

$$\Sigma_1 \leq 8 \exp\left(-\frac{1}{2}\left(\frac{r_0}{\sigma} - \frac{C_2}{r_0}\right)_+^2\right).$$

We now have

$$\begin{aligned} \gamma_{\theta, \sigma} \{x \in E: \|\hat{\theta}(x) - \theta\| \geq r\} &\leq \exp\left(-\frac{1}{2}\left(\frac{r}{\sigma} - \frac{C_2}{r}\right)_+^2\right) + \Sigma_1 \\ &\leq \exp\left(-\frac{1}{2}\left(\frac{r}{\sigma} - \frac{C_2}{r}\right)_+^2\right) + 8 \exp\left(-\frac{1}{2}\left(\frac{r_0}{\sigma} - \frac{C_2}{r_0}\right)_+^2\right) \\ &\leq 9 \exp\left(-\frac{1}{2}\left(\frac{r}{\sigma} - \frac{C_2}{r}\right)_+^2\right), \end{aligned}$$

as required.

Second step. Given $r_0 \geq (C_2+2)\sigma$; it is required to construct r_1, r_2, \dots such that $r_0 < r_1 < r_2 < \dots$, $r_n \rightarrow +\infty$ and

$$\sum_{n=0}^{\infty} \exp\left(-\frac{1}{2}\left(\frac{r_n}{\sigma} - \frac{r_{n+1}C_2}{r_n}\right)_+^2\right) \leq 9 \exp\left(-\frac{1}{2}\left(\frac{r_0}{\sigma} - C_2\right)^2\right).$$

We make the substitution $r_n = (C_2 + t_n)\sigma$; and then we have

$$\begin{aligned} \frac{r_n}{\sigma} - \frac{r_{n+1}C_2}{r_n} &= t_n + C_2 - \frac{(t_{n+1} + C_2)C_2}{t_n + C_2} \\ &= t_n - \frac{C_2}{C_2 + t_n}(t_{n+1} - t_n) \\ &\geq t_n - (t_{n+1} - t_n) = 2t_n - t_{n+1}. \end{aligned}$$

Thus, for given $t_0 \geq 2$ it suffices to construct t_1, t_2, \dots , such that $t_0 < t_1 < t_2 < \dots, t_n \rightarrow +\infty$, and

$$\sum_{n=0}^{\infty} \exp\left(-\frac{1}{2}(2t_n - t_{n+1})_+^2\right) \leq 9 \exp\left(-\frac{1}{2}t_0^2\right).$$

Take $p_0 \geq 1$ such that $p_0 + 1/p_0 = t_0$. Further, take $p_n \geq 1$ such that

$$p_n \exp\left(-\frac{1}{2}p_n^2\right) = 2^{-n}p_0 \exp\left(-\frac{1}{2}p_0^2\right).$$

Then clearly p_n increases to $+\infty$. For $n = 1, 2, \dots$ set

$$t_n = 2^n t_0 - \sum_{k=0}^{n-1} 2^{n-k-1} p_k,$$

We then have $2t_n - t_{n+1} = p_n$. At the third step we shall see that $\sum_{n=0}^{\infty} 2^{-n}p_n < 2(p_0 + 1/p_0)$. We have

$$\begin{aligned} t_{n+1} - t_n &= 2^{n+1}t_0 - \sum_{k=0}^n 2^{n-k} p_k - 2^n t_0 + \sum_{k=0}^{n-1} 2^{n-k-1} p_k \\ &= 2^n t_0 - \sum_{k=0}^{n-1} 2^{n-k-1} p_k - p_n \geq 2^n t_0 - \sum_{k=0}^{\infty} 2^{n-k-1} p_k \\ &= 2^n \left(t_0 - \frac{1}{2} \sum_{k=0}^{\infty} 2^{-k} p_k \right), \end{aligned}$$

and the last expression in the parentheses is positive. It is now evident that t_n increases to $+\infty$. We have

$$\begin{aligned} \sum_{n=0}^{\infty} \exp\left(-\frac{1}{2}(2t_n - t_{n+1})_+^2\right) &= \sum_{n=0}^{\infty} \exp\left(-\frac{1}{2}p_n^2\right) \\ &= \sum_{n=0}^{\infty} 2^{-n} \frac{p_0}{p_n} \exp\left(-\frac{1}{2}p_0^2\right) \leq 2 \exp\left(-\frac{1}{2}p_0^2\right). \end{aligned}$$

But

$$\begin{aligned} 9 \exp\left(-\frac{1}{2}t_0^2\right) &= 9 \exp\left(-\frac{1}{2}(p_0^2 + 2 + p_0^{-2})\right) \geq 9 \exp\left(-\frac{1}{2}(p_0^2 + 3)\right) \\ &= 9 \exp\left(-\frac{3}{2}\right) \exp\left(-\frac{1}{2}p_0^2\right) > 2 \exp\left(-\frac{1}{2}p_0^2\right) \\ &\geq \sum_{n=0}^{\infty} \exp\left(-\frac{1}{2}(2t_n - t_{n+1})_+^2\right). \end{aligned}$$

Third step. Let us show that $\sum_{n=0}^{\infty} 2^{-n} p_n < 2(p_0 + 1/p_0)$. We have

$$\begin{aligned} \exp\left(-\frac{1}{2} p_n^2\right) - \exp\left(-\frac{1}{2} p_{n+1}^2\right) &= \int_{p_n}^{p_{n+1}} x \exp\left(-\frac{1}{2} x^2\right) dx \\ &> (p_{n+1} - p_n) p_{n+1} \exp\left(-\frac{1}{2} p_{n+1}^2\right) \\ &= (p_{n+1} - p_n) 2^{-n-1} p_0 \exp\left(-\frac{1}{2} p_0^2\right); \end{aligned}$$

and summing over $n = 0, 1, \dots$, we obtain

$$\begin{aligned} \exp\left(-\frac{1}{2} p_0^2\right) &> p_0 \exp\left(-\frac{1}{2} p_0^2\right) \left(-\frac{1}{2} p_0 + \frac{1}{2} \sum_{n=1}^{\infty} 2^{-n} p_n\right), \\ \frac{1}{p_0} &> -\frac{1}{2} p_0 + \frac{1}{2} \sum_{n=1}^{\infty} 2^{-n} p_n, \\ p_0 + \frac{1}{p_0} &> \frac{1}{2} \sum_{n=0}^{\infty} 2^{-n} p_n. \end{aligned}$$

Remark 4. The "9" in the statement of the lemma can of course be improved. Numerical computation shows that it can be made less than 4.

Remark 5. For nonconvex V the corresponding weaker estimate is derived from other considerations [1, Thm. 2(a)]; let us give both estimates in comparable notation:

$$\begin{aligned} u &= \frac{r^2}{32\sigma^2} - \frac{C_2}{10\sigma} - \frac{81}{32} \quad (\text{in [1]}); \\ u &= \frac{1}{2} \left(\frac{r}{\sigma} - \frac{C_2}{\min(r, 1)} \right)^2 - \log 9 \quad (\text{here}); \end{aligned}$$

but

$$\log 9 < \frac{81}{32}, \quad \text{and} \quad \frac{1}{2} \left(\frac{r}{\sigma} - \frac{C_2}{r} \right)^2 \geq -\frac{r^2}{32\sigma^2} - \frac{C_2}{10\sigma}$$

always, and

$$\frac{1}{2} \left(\frac{r}{\sigma} - C_2 \right)^2 \geq \frac{r^2}{32\sigma^2} - \frac{C_2}{10\sigma} \quad \text{for} \quad \sigma C_2 \leq \frac{1}{4};$$

these inequalities can be verified by reducing them to homogeneous quadratic inequalities with two variables by means of appropriate changes of variables.

Proof of Theorem 1 in [2]. Point (a) follows immediately from Lemma 1 in [2] and inequality (1); indeed, assuming that $\theta = 0$ and $\sigma = 1$ (the general case reduces to this one via a shift and a dilation), we obtain

$$\begin{aligned} P\{\hat{\theta}(\xi) \in F_k\} &= \gamma\{x: \hat{\theta}(x) \in F_k\} \leq \gamma_V\{x: \hat{\theta}(x) \in F_k\} = \frac{1}{k!} \mathcal{M}_k(V) \\ &\leq \frac{1}{k!} \mathcal{M}_1^k(V) = \frac{1}{k!} C^k. \end{aligned}$$

Let us prove point (b).

First step. From point (a) already proved, noting (2) we can derive that for any $r \geq 1$

$$P\{\hat{\theta}(\xi) \in F_k, \|\hat{\theta}(\xi) - \theta\| \leq r\} \leq \frac{1}{k!} \left(\frac{C_2 r}{\sigma} \right)^k;$$

$$P\{\hat{\theta}(\xi) \in F_k \cup F_{k+1} \cup \dots \cup F_n, \|\hat{\theta}(\xi) - \theta\| \leq r\} \leq \left(\frac{eC_2r}{k\sigma}\right)^k.$$

Indeed, assuming that $C_2r/(k\sigma) \leq 1$ (otherwise there is nothing to prove), we have

$$\begin{aligned} \sum_{l=k}^n \frac{1}{l!} \left(\frac{C_2r}{\sigma}\right)^l &\leq \min_{a \geq 1} a^{-k} \sum_{l=k}^{\infty} \frac{1}{l!} \left(\frac{C_2r}{\sigma} a\right)^l \\ &\leq \min_{a \geq 1} a^{-k} \exp\left(\frac{C_2r}{\sigma} a\right) \\ &= \left(\min_{a \geq 1} a^{-1} \exp\left(\frac{C_2r}{k\sigma} a\right)\right)^k = \left(\frac{eC_2r}{k\sigma}\right)^k. \end{aligned}$$

On the other hand,

$$P\{\|\hat{\theta}(\xi) - \theta\| \geq r\} \leq 9 \exp\left(-\frac{1}{2}\left(\frac{r}{\sigma} - C_2\right)_+^2\right)$$

for $r \geq 1$ by Lemma 4; thus,

$$P\{\hat{\theta}(\xi) \in F_k \cup F_{k+1} \cup \dots \cup F_n\} \leq \left(\frac{eC_2r}{k\sigma}\right)^k + 9 \exp\left(-\frac{1}{2}\left(\frac{r}{\sigma} - C_2\right)_+^2\right)$$

for any $r \geq 1$.

Second step. Let us show that

$$\min_{r \geq 1} \left(\frac{eC_2r}{k\sigma}\right)^k + 9 \exp\left(-\frac{1}{2}\left(\frac{r}{\sigma} - C_2\right)_+^2\right) \leq 10 \left(\frac{e^2 C_2^2}{k} \log \frac{k}{C_2^2}\right)^{k/2}$$

for $k > C_2^2$ and $\sigma^2 k \log(k/C_2^2) \geq 1$. For this we put $a = \sqrt{k}/C_2$ and take $r = \sigma \sqrt{k \log a^2}$. We then have

$$\begin{aligned} \left(\frac{eC_2r}{k\sigma}\right)^k &= \left(\frac{e^2 \log a^2}{a^2}\right)^{k/2}, \\ \exp\left(-\frac{1}{2}\left(\frac{r}{\sigma} - C_2\right)_+^2\right) &= \exp\left(-\frac{k}{2}\left(\sqrt{2 \log a} - \frac{1}{a}\right)_+^2\right). \end{aligned}$$

It is not hard to check that

$$\frac{1}{2}\left(\sqrt{2 \log a} - \frac{1}{a}\right)_+^2 \geq \log a - \frac{1}{2} \log(2 \log a) - 1$$

for all $a > 1$; hence

$$\begin{aligned} \exp\left(-\frac{1}{2}\left(\frac{r}{\sigma} - C_2\right)_+^2\right) &\leq \exp\left(-k\left(\log a - \frac{1}{2} \log(2 \log a) - 1\right)\right) \\ &= \left(\frac{e^2 \log a^2}{a^2}\right)^{k/2}, \end{aligned}$$

which yields the required result.

Remark 6. If all the hypotheses of Theorem 1(b) are satisfied aside from the inequality $\sigma^2 k \log(k/C_2^2) \geq 1$, then we can use the estimate

$$P\{\hat{\theta}(\xi) \in F_k \cup F_{k+1} \cup \dots \cup F_n\} \leq \left(\frac{eC_2}{k\sigma}\right)^k + 9 \exp\left(-\frac{1}{2}\left(\frac{1}{\sigma} - C_2\right)_+^2\right);$$

it is derived from the reasoning given above for $r = 1$.

The next two lemmas (one is for the finite-dimensional case, the other for the infinite-dimensional case) are directed towards the proof of Theorem 3.

LEMMA 5. Let $V (V \subset \mathbb{R}^n)$ be a convex compact set with piecewise C^2 -smooth boundary and $\theta \in V$; then, for any $\sigma > 0$ and $a > 0$,

$$\int \exp(a\Delta\varphi(x))\gamma_{\theta,\sigma}(dx) \leq \exp\left(\frac{e^a}{\sigma}\mathcal{M}_1(V)\right)$$

(here Δ is the differential Laplace operator).

Proof. The Laplacian is the sum of the characteristic numbers of the second differential: $\Delta\varphi(x) = \lambda_1(x) + \dots + \lambda_n(x)$ (note incidentally that this is the trace of the differential of the mapping $\hat{\theta}$, see (8)). Using the inequality $\exp(a\lambda) \leq 1 + (e^a - 1)\lambda$, which is valid for $0 \leq \lambda \leq 1$, and Lemma 2, we obtain

$$\begin{aligned} \int \exp(a\Delta\varphi(x))\gamma_{\theta,\sigma}(dx) &\leq \int \prod_{i=1}^n (1 + (e^a - 1)\lambda_i(x))\gamma_{\theta,\sigma}(dx) \\ &\leq \exp\left(\frac{e^a}{\sigma}\mathcal{M}_1(V)\right). \end{aligned}$$

LEMMA 6. Let $V \subset E_0$ be a convex GB-compact set and $\theta \in V$. Then, for any positive σ, δ and a ,

$$\int \exp\left(\frac{2a}{\delta^2}(\varphi_\delta(x) - \varphi(x))\right)\gamma_{\theta,\sigma}(dx) \leq \exp\left(\frac{e^a}{\sigma}\mathcal{M}_1(V)\right),$$

where $\varphi_\delta(x) = \int \varphi(x + \delta y)\gamma(dy)$.

Proof. We can assume that V is a finite-dimensional convex solid with piecewise smooth boundary; the general case is derived from this one by means of an approximation from the inside. We shall assume that $(E, \gamma) = (\mathbb{R}^n, \gamma^n)$. We shall need the formula

$$\varphi_\delta(x) - \varphi(x) = \frac{1}{2} \int_0^{\delta^2} dt \int \gamma(dy) \Delta\varphi(x + \sqrt{t}y).$$

It can be checked by routine calculations (passage to polar coordinates in the integral with respect to y) or by application of Itô's formula to the stochastic differential $d\varphi(w_n(t))$, where w_n is an n -dimensional Wiener process. Let us use this formula, the convexity of the exponential function and Lemma 5:

$$\begin{aligned} &\int \exp\left(\frac{2a}{\delta^2}(\varphi_\delta(x) - \varphi(x))\right)\gamma_{\theta,\sigma}(dx) \\ &= \int \gamma_{\theta,\sigma}(dx) \exp\left(a\frac{1}{\delta^2} \int_0^{\delta^2} dt \int \gamma(dy) \Delta\varphi(x + \sqrt{t}y)\right) \\ &\leq \int \gamma_{\theta,\sigma}(dx) \frac{1}{\delta^2} \int_0^{\delta^2} dt \int \gamma(dy) \exp(a\Delta\varphi(x + \sqrt{t}y)) \\ &= \frac{1}{\delta^2} \int_0^{\delta^2} dt \int \gamma_{\theta,\sqrt{\sigma^2+t}}(dx) \exp(a\Delta\varphi(x)) \\ &\leq \frac{1}{\delta^2} \int_0^{\delta^2} dt \exp\left(\frac{e^a}{\sqrt{\sigma^2+t}}\mathcal{M}_1(V)\right) \leq \exp\left(\frac{e^a}{\sigma}\mathcal{M}_1(V)\right). \end{aligned}$$

Proof of Theorem 3 in [2]. First step. As will be proved at the second step,

$$\lim_{\delta \rightarrow 0+} \frac{2}{\delta^2} (\varphi_\delta(x) - \varphi(x)) \cong K(\hat{\theta}(x))$$

for $\gamma_{\theta, \sigma}$ -almost all $x \in E$. Because of this, point (a) reduces to Lemma 6:

$$\begin{aligned} E \exp(aK(\hat{\theta}(\xi))) &\leq \int \exp\left(a \lim_{\delta \rightarrow 0+} \frac{2}{\delta^2} (\varphi_\delta(x) - \varphi(x))\right) \gamma_{\theta, \sigma}(dx) \\ &\leq \lim_{\delta \rightarrow 0+} \int \exp\left(\frac{2a}{\delta^2} (\varphi_\delta(x) - \varphi(x))\right) \gamma_{\theta, \sigma}(dx) \\ &\leq \exp\left(\frac{e^a}{\sigma} \mathcal{M}_1(V)\right) = \exp\left(\frac{e^a}{\sigma} C\right). \end{aligned}$$

From point (a), for $a = \log(k\sigma/C)$ it follows that

$$P\{K(\hat{\theta}(x)) \geq k\} \leq \left(\frac{eC}{\sigma k}\right)^k;$$

and now it remains to apply Lemma 4 and the second step in the proof of Theorem 1.

Second step. Let us prove that

$$\lim_{\delta \rightarrow 0+} \frac{2}{\delta^2} (\varphi_\delta(x) - \varphi(x)) \cong K(\hat{\theta}(x))$$

for $\gamma_{\theta, \sigma}$ -almost all $x \in E$. Let $K(\hat{\theta}(x)) \geq k$, $k < +\infty$. There exist a k -dimensional subspace $H_k \subset E_0$ and an $\varepsilon > 0$ such that $\hat{\theta}(x) + \eta \in V$ for all $\eta \in H_k$ such that $\|\eta\| \leq \varepsilon$. Consider the orthogonal projector $P_k: E_0 \rightarrow H_k$ and extend it to a measurable linear operator $P_k: E \rightarrow H_k$. For $\eta \in H_k$ put $Q(\eta) = \eta$ if $\|\eta\| \leq \varepsilon$ and $Q(\eta) = 0$ if $\|\eta\| > \varepsilon$; for $y \in E$ put $Q(y) = Q(P_k(y))$. We recall the definition of φ , note that $\hat{\theta}(x) + Q(\delta y) \in V$, drop the odd terms with respect to y (their integral is zero), and discard inessential measurements:

$$\begin{aligned} \varphi_\delta(x) - \varphi(x) &= \int (\varphi(x + \delta y) - \varphi(x)) \gamma(dy) \\ &\cong \int \left(\langle \hat{\theta}(x) + Q(\delta y), x + \delta y \rangle - \frac{1}{2} \|\hat{\theta}(x) + Q(\delta y)\|^2 \right. \\ &\quad \left. - \langle \hat{\theta}(x), x \rangle + \frac{1}{2} \|\hat{\theta}(x)\|^2 \right) \gamma(dy) \\ &= \int \left(\langle Q(\delta y), \delta y \rangle - \frac{1}{2} \|Q(\delta y)\|^2 \right) \gamma(dy) \\ &= \int_{H_k} \left(\langle Q(\delta \eta), \delta \eta \rangle - \frac{1}{2} \|Q(\delta \eta)\|^2 \right) \gamma^k(d\eta) \\ &= \frac{\delta^2}{2} \int_{\|\eta\| \leq \varepsilon/\delta} \|\eta\|^2 \gamma^k(d\eta); \end{aligned}$$

thus,

$$\begin{aligned} \lim_{\delta \rightarrow 0+} \frac{2}{\delta^2} (\varphi_\delta(x) - \varphi(x)) &\cong \lim_{\delta \rightarrow 0+} \int_{\|\eta\| \leq \varepsilon/\delta} \|\eta\|^2 \gamma^k(d\eta) \\ &= \int_{H_k} \|\eta\|^2 \gamma^k(d\eta) = k. \end{aligned}$$

The next two lemmas pertaining to the finite-dimensional case set the stage for the proof of Theorem 2.

LEMMA 7. Suppose that the quadratic form A on \mathbf{R}^n has characteristic values $\lambda_1 \geq \dots \geq \lambda_n \geq 0$. Then, for any $m \in \mathbf{R}^n$, $\sigma \in (0, 1/\sqrt{2\lambda_1})$,

$$\int \exp A(m + \sigma x) \gamma^n(dx) \leq \left(\prod_{i=1}^n (1 - 2\sigma^2 \lambda_i) \right)^{-1/2} \exp \frac{A(m)}{1 - 2\sigma^2 \lambda_1}.$$

Proof. We can assume that A has been reduced to the principal axes: $A(x_1, \dots, x_n) = \sum \lambda_i x_i^2$. Then the integral decomposes into the product of one-dimensional integrals that are easy to compute:

$$\int_{-\infty}^{+\infty} \exp (\lambda_i (m_i + \sigma x_i)^2) \gamma^1(dx_i) = (1 - 2\lambda_i \sigma^2)^{-1/2} \exp \left(\frac{\lambda_i m_i^2}{1 - 2\lambda_i \sigma^2} \right).$$

LEMMA 8. Let $V (V \subset \mathbf{R}^n)$ be a convex compact set, $0 \subset V$, and $\|\theta\| \leq r$ for all θ in V . Then, for any $a, b > 0$, $c \in (0, \frac{1}{2})$,

$$\begin{aligned} \iint \exp \left(c \left(\frac{\|\hat{\theta}(ax + by) - \hat{\theta}(ax - by)\|}{2b} \right)^2 \right) \gamma^n(dx) \gamma^n(dy) \\ \leq \exp \left(\frac{\mathcal{M}_1(V)}{a\sqrt{1-2c}} + \frac{cb^2 r^2}{a^4(1-2c)} \right). \end{aligned}$$

Proof. We can assume that V is a convex solid with piecewise smooth boundary. We use formulas (5) and (8):

$$\begin{aligned} \|\hat{\theta}(ax + by) - \hat{\theta}(ax - by)\|^2 &\leq (\hat{\theta}(ax + by) - \hat{\theta}(ax - by), 2by) \\ &= D\varphi(ax + by, 2by) - D\varphi(ax - by, 2by) \\ &= 2 \frac{d}{dt} \varphi(ax + tby) \Big|_{t=-1}^{t=+1} \\ &= 2 \int_{-1}^{+1} \frac{d^2}{dt^2} \varphi(ax + tby) dt \\ &= 2 \int_{-1}^{+1} D^2 \varphi(ax + tby, by) dt. \end{aligned}$$

We take into account the convexity of the exponential function:

$$\begin{aligned} \iint \exp \left(c \left(\frac{\|\hat{\theta}(ax + by) - \hat{\theta}(ax - by)\|}{2b} \right)^2 \right) \gamma^n(dx) \gamma^n(dy) \\ \leq \iint \exp \left(\frac{c}{b^2} \frac{1}{2} \int_{-1}^{+1} D^2 \varphi(ax + tby, by) dt \right) \gamma^n(dx) \gamma^n(dy) \\ \leq \iint \int_{-1}^{+1} \frac{1}{2} \exp \left(\frac{c}{b^2} D^2 \varphi(ax + tby, by) \right) dt \gamma^n(dx) \gamma^n(dy). \end{aligned}$$

Changing the order of integration, we obtain $\frac{1}{2} \int_{-1}^{+1} J(t) dt$, where

$$J(t) = \iint \exp (cD^2 \varphi(ax + tby, y)) \gamma^n(dx) \gamma^n(dy).$$

It suffices to prove that, for all $t \in [-1, 1]$,

$$J(t) \leq \exp \left(\frac{\mathcal{M}_1(V)}{a\sqrt{1-2c}} + \frac{cb^2 r^2}{a^4(1-2c)} \right).$$

We cannot apply Lemma 7 to the integral for $J(t)$ directly due to the fact that y appears in the expression $ax + tby$. We switch from the variables x, y to the new variables $v = (ax + tby)s^{-1}$, $w = (tbx - ay)s^{-1}$, where $s = (a^2 + t^2b^2)^{1/2}$, and then $\gamma^n(dx)\gamma^n(dy) = \gamma^n(dv)\gamma^n(dw)$. We apply Lemma 7 to the integral with respect to w and note that the characteristic values $\lambda_i(x)$ of the quadratic form $D^2(x, h)$ do not exceed one:

$$J(t) = \iint \exp(cD^2\varphi(sv, (tbv - aw)s^{-1}))\gamma^n(dv)\gamma^n(dw) \\ \cong \int \left(\prod_{i=1}^n \left(1 - 2\left(\frac{a}{s}\right)^2 c\lambda_i(sv) \right) \right)^{-1/2} \exp\left(\frac{cD^2\varphi(sv, tbvs^{-1})}{1 - 2(a/s)^2c}\right)\gamma^n(dv).$$

Note that $D^2\varphi(sv, sv) \leq r^2$. Indeed, if $sv \in V$, then $D^2\varphi(sv, sv) = \|sv\|^2 \leq r^2$; but if $sv \notin V$, then the quadratic form $D^2\varphi(sv, h)$ is degenerate in the direction of the vector $h = sv - \hat{\theta}(sv)$, and therefore $D^2\varphi(sv, sv) = D^2\varphi(sv, \hat{\theta}(sv)) \leq \|\hat{\theta}(sv)\|^2 \leq r^2$. Using this estimate, the routine inequality

$$(1 - \delta\lambda)^{-1/2} \leq 1 + \left(\frac{1}{\sqrt{1-\delta}} - 1\right)\lambda \quad \text{for } \lambda \in [0, 1], \quad \delta = \frac{2a^2c}{s^2} < 1,$$

as well as Lemma 2 for $z = 1/\sqrt{1-\delta} - 1$, we obtain

$$J(t) \leq \exp\left(\frac{ct^2b^2r^2}{s^4(1-\delta)}\right) \int \left(\prod_{i=1}^n (1 + z\lambda_i(sv))\right)\gamma^n(dv) \\ \leq \exp\left(\frac{ct^2b^2r^2}{s^4(1-\delta)}\right) \exp\left(\frac{\mathcal{M}_1(V)}{s\sqrt{1-\delta}}\right) \\ \leq \exp\left(\frac{\mathcal{M}_1(V)}{a\sqrt{1-\delta}} + \frac{cb^2r^2}{a^4(1-\delta)}\right);$$

it remains to note that $\delta \leq 2c$.

Proof of Theorem 2 in [2]. Let us first prove point (a). We can assume that $\theta = 0$. The correlated vectors ξ_1 and ξ_2 can be represented in the form $\xi_1 = a\zeta_1 + b\zeta_2$, $\xi_2 = a\zeta_1 - b\zeta_2$, where $a = \sigma\sqrt{(1+\rho)}/2$, $b = \sigma\sqrt{(1-\rho)}/2$, and ζ_1 and ζ_2 are independent random vectors with standard Gaussian distribution. Let us apply Lemma 8 for $c = \frac{1}{2}$:

$$\mathbf{E} \exp\left(\frac{\|\hat{\theta}(\xi_1) - \hat{\theta}(\xi_2)\|^2}{4b}\right) = \iint \exp\left(\frac{\|\hat{\theta}(ax + by) - \hat{\theta}(ax - by)\|^2}{4b}\right)\gamma^n(dx)\gamma^n(dy) \\ \leq \exp\left(\frac{\sqrt{2}C}{a} + \frac{b^2r^2}{2a^4}\right).$$

But $r \leq \sqrt{2\pi}C$, and so

$$\frac{\sqrt{2}C}{a} + \frac{b^2r^2}{2a^4} \leq \frac{C}{a}\left(\sqrt{2} + \frac{\pi b^2C}{a^3}\right) \\ = \frac{C}{a}\left(\sqrt{2} + \frac{\pi\sqrt{2}C}{\sigma(1+\rho)^{3/2}(1-\rho)}\right) \\ \leq \frac{C}{a}\left(\sqrt{2} \frac{\pi\sqrt{2}C}{\sigma(\frac{3}{2})^{3/2}} \frac{\sigma}{5C}\right) \leq 1.9 \frac{C}{a}.$$

Hence

$$\begin{aligned} & \mathbf{P} \left\{ \frac{\|\hat{\theta}(\xi_1) - \hat{\theta}(\xi_2)\|}{\sqrt{\sigma(1-\rho)}} \geq 3\sqrt{\sigma u + 2C} \right\} \\ & \leq \exp \left(- \left(\frac{\sqrt{\sigma(1-\rho)} 3\sqrt{\sigma u + 2C}}{4b} \right)^2 \right) \mathbf{E} \exp \left(\left(\frac{\|\hat{\theta}(\xi_1) - \hat{\theta}(\xi_2)\|}{4b} \right)^2 \right) \\ & \leq \exp \left(- \frac{9\sigma(1-\rho)(\sigma u + 2C)}{16b^2} + \frac{1.9C}{a} \right) \\ & = \exp \left(- \frac{9}{8}u - \frac{9C}{4\sigma} + \frac{1.9\sqrt{2}C}{\sigma\sqrt{1+\rho}} \right) \\ & \leq \exp \left(-u - \frac{C}{\sigma} \left(\frac{9}{4} - \frac{1.9\sqrt{2}}{\sqrt{1+\rho}} \right) \right) \leq \exp(-u). \end{aligned}$$

This proves point (a). Substituting $u = q^2/(9\sigma) - 2C/\sigma$, we rewrite it as

$$\mathbf{P} \left\{ \frac{\|\hat{\theta}(\xi_1) - \hat{\theta}(\xi_2)\|}{\sqrt{\sigma(1-\rho)}} \geq q \right\} \leq \exp \left(- \frac{q^2}{9\sigma} + \frac{2C}{\sigma} \right).$$

In order to prove point (b), we apply the last inequality to the set $V \cap B(\theta, r)$; using Lemma 4 and (2) we have, for any $r \geq 1$,

$$\begin{aligned} & \mathbf{P} \left\{ \frac{\|\hat{\theta}(\xi_1) - \hat{\theta}(\xi_2)\|}{\sqrt{\sigma(1-\rho)}} \geq q \right\} \\ & \leq \mathbf{P} \left\{ \frac{\|\hat{\theta}(\xi_1) - \hat{\theta}(\xi_2)\|}{\sqrt{\sigma(1-\rho)}} \geq q, \|\hat{\theta}(\xi_1) - \theta\| \leq r, \|\hat{\theta}(\xi_2) - \theta\| \leq r \right\} \\ & \quad + \mathbf{P}\{\|\hat{\theta}(\xi_1) - \theta\| \geq r\} + \mathbf{P}\{\|\hat{\theta}(\xi_2) - \theta\| \geq r\} \\ & \leq \exp \left(- \frac{q^2}{9\sigma} + \frac{2C_2 r}{\sigma} \right) + 18 \exp \left(- \frac{1}{2} \left(\frac{r}{\sigma} - C_2 \right)_+^2 \right). \end{aligned}$$

It suffices to choose $r \geq 1$ such that

$$- \frac{q^2}{9\sigma} + \frac{2C_2 r}{\sigma} \leq -(u+3) \quad \text{and} \quad - \frac{1}{2} \left(\frac{r}{\sigma} - C_2 \right)_+^2 \leq -(u+3),$$

for $\exp(-u-3) + 18 \exp(-u-3) < \exp(-u)$. Take $r = \max(1, \sigma(\sqrt{2(u+3)} + C_2))$; it is not hard to check that for $r = \sigma(\sqrt{2(u+3)} + C_2)$ we have $q = 3\sqrt{\sigma}(\sqrt{u+3} + \sqrt{2C_2})$ (the first case), while for $r = 1$ we have $q = 3\sqrt{\sigma(u+3) + 2C_2}$ (the second case). In the first case we simply have $-q^2/(9\sigma) + 2C_2 r/\sigma = -(u+3)$ and $-\frac{1}{2}(r/\sigma - C_2)^2 = -(u+3)$. In the second case we again have $-q^2/(9\sigma) + 2C_2 r/\sigma = -(u+3)$ and, moreover,

$$- \frac{1}{2} \left(\frac{r}{\sigma} - C_2 \right)^2 = - \frac{1}{2} \left(\frac{1}{\sigma} - C_2 \right)^2 \leq -(u+3),$$

since $\sigma(\sqrt{2(u+3)} + C_2) \leq 1$.

Proof of Theorem 4 in [2]. For a finite-dimensional V , the desired assertions follow from Theorem 2. The passage to the limit for the general case is carried out via Remark 3 in [1].

REFERENCES

[1] B. S. TSIREL'SON, *A geometric approach to a maximum likelihood estimation for infinite-dimensional location. I*, Theory Probab. Appl., 27 (1982), pp. 411-418.
 [2] ———, *A geometric approach to a maximum likelihood estimation for infinite-dimensional location. II*, Theory Probab. Appl., 30 (1985), pp. 820-828.
 [3] S. CHEVET, *Processus Gaussiens et volumes mixtes*, Z. Wahrsch. Verw. Gebiete, 36 (1976), pp. 47-65.
 [4] YU. D. BURAGO AND V. A. ZALGALLER, *Geometric Inequalities*, Nauka, Leningrad, 1980. (In Russian.)