## RANDOM DETERMINANTS, MIXED VOLUMES OF ELLIPSOIDS, AND ZEROS OF GAUSSIAN RANDOM FIELDS

## D. Zaporozhets\* and Z. Kabluchko<sup>†</sup>

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Consider a  $d \times d$  matrix M whose rows are independent, centered, nondegenerate Gaussian vectors  $\xi_1, \ldots, \xi_d$  with covariance matrices  $\Sigma_1, \ldots, \Sigma_d$ . Denote by  $\mathcal{E}_i$  the dispersion ellipsoid of  $\xi_i : \mathcal{E}_i = \{\mathbf{x} \in \mathbb{R}^d : \mathbf{x}^\top \Sigma_i^{-1} \mathbf{x} \leq 1\}$ . We show that

 $\mathbb{E} |\det M| = \frac{d!}{(2\pi)^{d/2}} V_d(\mathcal{E}_1, \dots, \mathcal{E}_d),$ 

where  $V_d(\cdot, \ldots, \cdot)$  denotes the mixed volume. We also generalize this result to the case of rectangular matrices. As a direct corollary, we get an analytic expression for the mixed volume of d arbitrary ellipsoids in  $\mathbb{R}^d$ .

As another application, we consider a smooth, centered, nondegenerate Gaussian random field  $X = (X_1, \ldots, X_k)^{\top}$ :  $\mathbb{R}^d \to \mathbb{R}^k$ . Using the Kac-Rice formula, we obtain a geometric interpretation of the intensity of zeros of X in terms of the mixed volume of dispersion ellipsoids of the gradients of  $X_i/\sqrt{\operatorname{Var} X_i}$ . This relates zero sets of equations to mixed volumes in a way which is reminiscent of the well-known Bernstein theorem about the number of solutions of a typical system of algebraic equations. Bibliography: 10 titles.

## 1. Main results

1.1. Random determinant and mixed volume of ellipsoids. Consider independent, centered, nondegenerate Gaussian random vectors  $\xi_1, \ldots, \xi_k \in \mathbb{R}^d$ ,  $k \leq d$ , with covariance matrices  $\Sigma_1, \ldots, \Sigma_k$ . Denote by  $\mathcal{E}_i$  the dispersion ellipsoid of  $\xi_i$ :

$$\mathcal{E}_i = \left\{ \mathbf{x} = (x_1, \dots, x_d)^\top \in \mathbb{R}^d : \mathbf{x}^\top \Sigma_i^{-1} \mathbf{x} \le 1 \right\}, \quad i = 1, \dots, k.$$
 (1.1)

Denote by M the  $k \times d$  matrix whose rows are  $\xi_1, \ldots, \xi_k$ .

**Theorem 1.1.** The following relation holds:

$$\mathbf{E}\sqrt{\det(MM^{\top})} = \frac{(d)_k}{(2\pi)^{k/2}\kappa_{d-k}} V_d(\mathcal{E}_1, \dots, \mathcal{E}_k, B, \dots, B), \tag{1.2}$$

where  $V_d(\cdot, \ldots, \cdot)$  denotes the mixed volume of d convex bodies in  $\mathbb{R}^d$  (see Sec. 2 for details), B is the unit ball in  $\mathbb{R}^d$ ,  $(d)_k = d(d-1)\cdots(d-k+1)$  is the Pochhammer symbol, and  $\kappa_n = \pi^{n/2}/\Gamma(1+n/2)$  denotes the volume of the unit ball in  $\mathbb{R}^n$ .

The left-hand side of (1.2) can be interpreted as the average k-dimensional volume of a Gaussian random parallelotope.

**Corollary 1.2.** In the case k = d, the following relation holds:

$$\mathbf{E} | \det M | = \frac{d!}{(2\pi)^{d/2}} V_d(\mathcal{E}_1, \dots, \mathcal{E}_d).$$

As another direct corollary, we can calculate the mixed volume of d arbitrary ellipsoids in  $\mathbb{R}^d$ .

Corollary 1.3. If  $\mathcal{E}_1, \ldots, \mathcal{E}_d$  are arbitrary ellipsoids defined by symmetric positive definite matrices  $\Sigma_1, \ldots, \Sigma_d$  as in (1.1), then

$$V_d(\mathcal{E}_1, \dots, \mathcal{E}_d) = \frac{1}{d!} \prod_{i=1}^d (\det \Sigma_i)^{-1/2} \int_{\mathbb{R}^{d^2}} |\det(x_{ij})| \prod_{i=1}^d \exp\left(-\frac{1}{2} \mathbf{x}_i^\top \Sigma_i^{-1} \mathbf{x}_i\right) dx_{11} \dots dx_{dd},$$

where

$$\mathbf{x}_i = (x_{i1}, \dots, x_{id})^\top.$$

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<sup>\*</sup>St.Petersburg Department of the Steklov Mathematical Institute, St.Petersburg, Russia, e-mail: zap1979@gmail.com.

<sup>&</sup>lt;sup>†</sup>Ulm University, Ulm, Germany, e-mail: zakhar.kabluchko@uni-ulm.de.

The only estimate of the mixed volume of ellipsoids which we know is due to Barvinok [2]. He showed that

$$\frac{\kappa_d}{3(d-1)/2}\sqrt{D_d(\Sigma_1,\ldots,\Sigma_d)} \le V_d(\mathcal{E}_1,\ldots,\mathcal{E}_d) \le \kappa_d\sqrt{D_d(\Sigma_1,\ldots,\Sigma_d)},$$

where  $D_d(\cdot,\ldots,\cdot)$  denotes the mixed discriminant of d symmetric  $d\times d$  matrices:

$$D_d(A_1, \dots, A_d) = \frac{1}{d!} \frac{\partial^d}{\partial \lambda_1 \dots \partial \lambda_d} \det(\lambda_1 A_1 + \dots + \lambda_d A_d) \Big|_{\lambda_1 = \dots = \lambda_d = 0}.$$

If  $\xi_1, \ldots, \xi_k$  are independent, standard Gaussian vectors, then  $MM^{\top}$  is a Wishart matrix, and (1.2) turns into (see [5, 10])

$$\mathbf{E}\,\sqrt{\det(MM^\top)} = \frac{(d)_k \kappa_d}{(2\pi)^{k/2} \kappa_{d-k}}.$$

**1.2. Intrinsic volumes.** If  $\xi_1, \xi_2, \dots, \xi_k \in \mathbb{R}^d, k \leq d$ , are identically distributed with the common covariance matrix  $\Sigma$  and dispersion ellipsoid  $\mathcal{E}$ , then (1.2) turns into

$$\mathbf{E}\sqrt{\det(MM^{\top})} = \frac{k!}{(2\pi)^{k/2}} V_k(\mathcal{E}),\tag{1.3}$$

where  $V_k(\cdot)$  denotes the kth intrinsic volume of a convex body in  $\mathbb{R}^d$ :

$$V_k(K) = \frac{\binom{d}{k}}{\kappa_{d-k}} V_d(\underbrace{K, \dots, K}_{k \text{ times}}, B, \dots, B).$$

The normalization is chosen so that  $V_k(K)$  depends only on K and not on the dimension of the surrounding space, i.e., if dim K < d, then the computation of  $V_k(K)$  in  $\mathbb{R}^d$  leads to the same result as the computation in the affine span of K. In particular, if dim K = k, then  $V_k(K) = \operatorname{Vol}_k(K)$ , the k-dimensional volume of K.

It is known that  $V_1(K)$  is proportional to the mean width of K:

$$V_1(K) = \frac{d\kappa_d}{2\kappa_{d-1}} w(K).$$

Taking k = 1 in (1.3), we see that for any centered Gaussian vector  $\xi$  with dispersion ellipsoid  $\mathcal{E}$ ,

$$\mathbf{E}\|\xi\| = \frac{1}{\sqrt{2\pi}} V_1(\mathcal{E}). \tag{1.4}$$

It was pointed out by M. Lifshits that (1.4) is a special case of the following remarkable result of Sudakov.

**1.3.** Connection with Sudakov's result. For our purposes, the following finite-dimensional version of Sudakov's theorem suffices. The result in full generality can be found in [9, Proposition 14].

**Proposition 1.4.** For an arbitrary subset  $A \subset \mathbb{R}^d$ ,

$$\mathbf{E} \sup_{\mathbf{x} \in A} \langle \mathbf{x}, \eta \rangle = \frac{1}{\sqrt{2\pi}} V_1(\text{conv}(A)), \tag{1.5}$$

where  $\eta$  is a standard Gaussian vector in  $\mathbb{R}^d$  and conv(A) is the convex hull of A.

Let us deduce (1.4) from (1.5). Consider a matrix U such that  $\Sigma = U^{-1}(U^{-1})^{\top}$  and  $U\xi$  is a standard Gaussian vector. Using (1.5) with  $A = \mathcal{E}$  and  $\eta = U\xi$ , we get

$$\mathbf{E}\|\xi\| = \mathbf{E} \sup_{\|\mathbf{x}\| \leq 1} \langle \mathbf{x}, \xi \rangle = \mathbf{E} \sup_{\|\mathbf{x}\| \leq 1} \langle (U^{-1})^{\top}\mathbf{x}, U\xi \rangle = \mathbf{E} \sup_{\|U^{\top}\mathbf{x}\| \leq 1} \langle \mathbf{x}, U\xi \rangle = \mathbf{E} \sup_{\mathbf{x} \in \mathcal{E}} \langle \mathbf{x}, U\xi \rangle = \frac{1}{\sqrt{2\pi}} V_1(\mathcal{E}).$$

- **1.4. Zeros of Gaussian random fields.** Let  $X(\mathbf{t}) = (X_1(\mathbf{t}), \dots, X_k(\mathbf{t}))^{\top} : \mathbb{R}^d \to \mathbb{R}^k$ ,  $k \leq d$ , be a random field. Following Azaïs and Wschebor [1], we always assume that the following conditions hold:
  - (a) X is Gaussian;
  - (b) almost surely, the function  $X(\cdot)$  is of class  $\mathcal{C}^1$ ;
  - (c) for all  $\mathbf{t} \in \mathbb{R}^d$ ,  $X(\mathbf{t})$  has a nondegenerate distribution;
  - (d) almost surely, if  $X(\mathbf{t}) = 0$ , then  $X'(\mathbf{t})$ , the Jacobian matrix of  $X(\mathbf{t})$ , has the full rank.

Then, almost surely, the level set  $X^{-1}(0)$  is a  $\mathcal{C}^1$ -manifold of dimension d-k, and for any Borel set F, the Lebesgue measure  $\operatorname{Vol}_{d-k}(X^{-1}(0) \cap F)$  is well-defined  $(\operatorname{Vol}_0(\cdot)$  denotes the counting measure).

It was shown in [1, p. 177] that

$$\mathbf{E}\operatorname{Vol}_{d-k}(X^{-1}(0)\cap F) = \int_{F} \mathbf{E}\left(\sqrt{\det\left(X'(\mathbf{t})X'(\mathbf{t})^{\top}\right)} \mid X(\mathbf{t}) = 0\right) p_{X(\mathbf{t})}(0) d\mathbf{t}, \tag{1.6}$$

where  $p_{X(\mathbf{t})}(\cdot)$  is the density of  $X(\mathbf{t})$ . Thus, the integrand in (1.6) can be interpreted as the intensity of zeros of X.

In this paper, we consider the special case where X is centered and its coordinates  $X_1, \ldots, X_k$  are independent. Denote by  $\mathcal{E}_i(\mathbf{t})$  the dispersion ellipsoid of  $\nabla [X_i(\mathbf{t})/\sqrt{\operatorname{Var} X_i(\mathbf{t})}]$ .

**Theorem 1.5.** Let X be a centered random field with independent coordinates defined as above and satisfying conditions (a)–(d). Then

$$\mathbf{E} \operatorname{Vol}_{d-k}(X^{-1}(0) \cap F) = \frac{(d)_k}{(2\pi)^k \kappa_{d-k}} \int_F V_d(\mathcal{E}_1(\mathbf{t}), \dots, \mathcal{E}_k(\mathbf{t}), B, \dots, B) d\mathbf{t}.$$
 (1.7)

Formula (1.7) relates zero sets of random equations to mixed volumes. In the case k = d, it is therefore reminiscent of the well-known fact from the algebraic geometry which we formulate in the next subsection.

**1.5.** Bernstein's theorem. Consider a complex polynomial in d variables,

$$f(z_1, \dots, z_d) = \sum_{j_1, \dots, j_d} z_1^{j_1} \dots z_d^{j_d}.$$

The Newton polytope of f is the subset of  $\mathbb{R}^d$  defined as follows:

$$Nw(f) = conv \{ (j_1, ..., j_d) \in \mathbb{Z}^d : c_{j_1,...,j_d} \neq 0 \}.$$

Let  $K_1, \ldots, K_d$  be compact convex polytopes in  $\mathbb{R}^d$  with vertices in  $\mathbb{Z}^d$ . Consider a system of algebraic equations

$$\begin{cases} f_1(z_1, \dots, z_d) = 0, \\ \dots \\ f_d(z_1, \dots, z_d) = 0, \end{cases}$$

such that  $Nw(f_i) = K_i$ . Bernstein showed [3] that for almost all such systems (with respect to Lebesgue measure in the space of coefficients of the polynomials), the number of nonzero solutions is equal to

$$\operatorname{Vol}_0(f_1^{-1}(0) \cap \cdots \cap f_d^{-1}(0) \setminus \{\mathbf{0}\}) = d!V_d(K_1, \dots, K_d).$$

2. Some essential tools from geometry

For the basic facts from integral and convex geometry we refer the reader to [4] and [8].

**2.1. Mixed volumes.** Consider arbitrary convex bodies  $K_1, \ldots, K_d \subset \mathbb{R}^d$ . Minkowski showed [7] that  $\operatorname{Vol}_d(\lambda_1 K_1 + \cdots + \lambda_d K_d)$ , where  $\lambda_1, \ldots, \lambda_d \geq 0$ , is a homogeneous polynomial of degree d with nonnegative coefficients:

$$Vol_{d}(\lambda_{1}K_{1} + \dots + \lambda_{d}K_{d}) = \sum_{i_{1}=1}^{d} \dots \sum_{i_{d}=1}^{d} \lambda_{i_{1}} \dots \lambda_{i_{d}}V_{d}(K_{i_{1}}, \dots, K_{i_{d}}).$$
(2.1)

The coefficients  $V_d(K_{i_1}, \ldots, K_{i_d})$  are uniquely determined by the assumption that they are symmetric with respect to permutations of  $K_{i_1}, \ldots, K_{i_d}$ . The coefficient  $V_d(K_1, \ldots, K_d)$  is called the mixed volume of  $K_1, \ldots, K_d$ . Differentiating (2.1), we get an alternative definition of the mixed volume:

$$V_d(K_1, \dots, K_d) = \frac{1}{d!} \frac{\partial^d}{\partial \lambda_1 \dots \partial \lambda_d} \operatorname{Vol}_d(\lambda_1 K_1 + \dots + \lambda_d K_d) \big|_{\lambda_1 = \dots = \lambda_d = 0}.$$

For any affine transformation L,

$$V_d(LK_1, \dots, LK_d) = |\det L| \cdot V_d(K_1, \dots, K_d).$$
 (2.2)

The following relation can also be stated:

$$\int_{\mathbb{R}^{d-1}} V_{d-1}(P_{\mathbf{u}}K_1, \dots, P_{\mathbf{u}}K_{d-1}) d\mathbf{u} = \frac{\kappa_{d-1}}{\kappa_d} V_d(K_1, \dots, K_{d-1}, B),$$
(2.3)

where  $d\mathbf{u}$  is the surface measure on  $\mathbb{S}^{d-1}$  normalized to have total mass 1 and  $P_{\mathbf{u}}$  denotes the orthogonal projection to the linear hyperplane  $\mathbf{u}^{\perp}$ .

**2.2. Volumes of parallelotopes.** For any  $A \subset \mathbb{R}^d$  and  $\mathbf{x}_1, \dots, \mathbf{x}_k \in \mathbb{R}^d$  denote by  $P_{\mathbf{x}_1, \dots, \mathbf{x}_k} A$  the orthogonal projection of A to span<sup> $\perp$ </sup> { $\mathbf{x}_1, \dots, \mathbf{x}_k$ } (the orthogonal complement of the linear span of  $\mathbf{x}_1, \dots, \mathbf{x}_k$ ). Denote by  $H_{\mathbf{x}_1, \dots, \mathbf{x}_k}$  the parallelotope generated by the vectors  $\mathbf{x}_1, \dots, \mathbf{x}_k$ . It is known that

$$Vol_k(H_{\mathbf{x}_1,\dots,\mathbf{x}_k}) = \sqrt{\det(AA^\top)},\tag{2.4}$$

where A is the matrix whose rows are  $\mathbf{x}_1, \dots, \mathbf{x}_k$ .

For any  $\mathbf{x}_1, \dots, \mathbf{x}_d \in \mathbb{R}^d$  and  $k = 1, \dots, d - 1$ ,

$$\operatorname{Vol}_{d}(H_{\mathbf{x}_{1},\dots,\mathbf{x}_{d}}) = \operatorname{Vol}_{k}(H_{\mathbf{x}_{1},\dots,\mathbf{x}_{k}}) \operatorname{Vol}_{d-k}(P_{\mathbf{x}_{1},\dots,\mathbf{x}_{k}} H_{\mathbf{x}_{k+1},\dots,\mathbf{x}_{d}}). \tag{2.5}$$

**2.3. Ellipsoids.** There is a bijection  $A \mapsto \mathcal{E}$  between  $d \times d$  symmetric positive definite matrices and d-dimensional nondegenerate ellipsoids centered at the origin (see [6] for details):

$$\mathcal{E} = \{ \mathbf{x} \in \mathbb{R}^d : \mathbf{x}^\top A^{-1} \mathbf{x} \le 1 \}.$$

Any nondegenerate linear coordinate transformation of the form  $\mathbf{x} \mapsto L\mathbf{x}$  is reflected by a change of the corresponding representing matrix A to the matrix  $A_L$  given by

$$A_L = LAL^{\top}. (2.6)$$

Let  $\mathcal{E}'$  be the orthogonal projection of  $\mathcal{E}$  onto an k-dimensional subspace with some orthonormal basis  $\mathbf{x}_1, \dots, \mathbf{x}_k \in \mathbb{R}^d$ . Denote by A' the  $k \times k$  matrix representing the ellipsoid  $\mathcal{E}'$  in this basis. If C is the  $k \times d$  matrix whose rows are  $\mathbf{x}_1, \dots, \mathbf{x}_k$ , then

$$A' = CAC^{\top}. (2.7)$$

3. Proofs

**3.1.** Proof of Theorem 1.1. Case k = d. We proceed by induction on d. First let us assume that  $\xi_d$  is a standard Gaussian vector. Denote by  $\chi_d$  a random variable having the chi distribution with d degrees of freedom and independent from  $\xi_1, \ldots, \xi_{d-1}$ . Using (2.4) and (2.5) with k = 1, we get the relations

$$\mathbf{E} | \det M | = \mathbf{E} \operatorname{Vol}_{d}(H_{\xi_{1},\dots,\xi_{d}}) = \int_{\mathbb{S}^{d-1}} \mathbf{E} \operatorname{Vol}_{d}(H_{\xi_{1},\dots,\xi_{d-1},\chi_{d}}\mathbf{u}) d\mathbf{u}$$

$$= \mathbf{E}\chi_{d} \int_{\mathbb{S}^{d-1}} \mathbf{E} \operatorname{Vol}_{d-1}(P_{\mathbf{u}}H_{\xi_{1},\dots,\xi_{d-1}}) d\mathbf{u}$$

$$= \frac{d\kappa_{d}}{\sqrt{2\pi}\kappa_{d-1}} \int_{\mathbb{S}^{d-1}} \mathbf{E} \operatorname{Vol}_{d-1}(H_{P_{\mathbf{u}}\xi_{1},\dots,P_{\mathbf{u}}\xi_{d-1}}) d\mathbf{u}.$$

It follows from (2.7) that  $P_{\mathbf{u}}\xi_i$  has dispersion ellipsoid  $P_{\mathbf{u}}\mathcal{E}_i$ . By the induction assumption,

$$\mathbf{E} \operatorname{Vol}_{d-1} \left( H_{P_{\mathbf{u}}\xi_{1},\dots,P_{\mathbf{u}}\xi_{d-1}} \right) = \frac{(d-1)!}{(2\pi)^{(d-1)/2}} V_{d-1} (P_{\mathbf{u}}\mathcal{E}_{1},\dots,P_{\mathbf{u}}\mathcal{E}_{d-1}).$$

Combining the latter two relations with (2.3), we obtain the equality

$$\mathbf{E} | \det M | = \frac{d!}{(2\pi)^{d/2}} V_d(\mathcal{E}_1, \dots, \mathcal{E}_{d-1}, B). \tag{3.1}$$

If  $\xi_d$  is an arbitrary nondegenerate Gaussian vector, then there exists a linear transformation L such that  $L\xi_d$  is a standard Gaussian vector. It follows from (2.6) that  $L\mathcal{E}_i$  is the dispersion ellipsoid of  $L\xi_i$ , and, in particular,  $L\mathcal{E}_d = B$ . Applying (3.1) to the matrix  $LM^{\top}$  and using (2.2), we get the equalities

$$\mathbf{E} |\det M| = |\det L|^{-1} \mathbf{E} |\det LM^{\top}| = \frac{d!}{(2\pi)^{d/2}} |\det L|^{-1} V_d(L\mathcal{E}_1, \dots, L\mathcal{E}_{d-1}, B)$$
$$= \frac{d!}{(2\pi)^{d/2}} V_d(\mathcal{E}_1, \dots, \mathcal{E}_{d-1}, \mathcal{E}_d).$$

**3.2.** Proof of Theorem 1.1. Case k < d. Consider a  $d \times d$  matrix M' whose first k rows form the matrix M and the last d - k rows are independent standard Gaussian vectors  $\xi_{k+1}, \ldots, \xi_d$  (independent from M). By the previous case,

$$\mathbf{E} | \det M' | = \frac{d!}{(2\pi)^{d/2}} V_d(\mathcal{E}_1, \dots, \mathcal{E}_k, B, \dots, B).$$

On the other hand, by (2.5),

$$\mathbf{E} | \det M' | = \mathbf{E} \operatorname{Vol}_d(H_{\xi_1, \dots, \xi_d}) = \mathbf{E} \operatorname{Vol}_k(H_{\xi_1, \dots, \xi_k}) \operatorname{Vol}_{d-k}(P_{\xi_1, \dots, \xi_k} H_{\xi_{k+1}, \dots, \xi_d})$$
$$= \mathbf{E} \sqrt{\det(MM^\top)} \mathbf{E} \operatorname{Vol}_{d-k}(H_{\eta_1, \dots, \eta_{d-k}}),$$

where  $\eta_1, \ldots, \eta_{d-k}$  are independent, standard Gaussian vectors in  $\mathbb{R}^{d-k}$ . By the previous case,

**E** Vol<sub>d-k</sub>
$$(H_{\eta_1,...,\eta_{d-k}}) = \frac{(d-k)!}{(2\pi)^{(d-k)/2}} \kappa_{d-k}.$$

Combining the latter three relations completes the proof.

**3.3.** Proof of Theorem 1.5. First we assume that  $X_j$  has a unit variance:  $\operatorname{Var} X_j(\mathbf{t}) \equiv 1$  for all  $j = 1, \dots, k$ . Differentiating the relation  $\mathbf{E} X_j(\mathbf{t}) X_j(\mathbf{t}) = 1$  with respect to  $t_i$ , we obtain the equality

$$\mathbf{E}\frac{\partial X_j}{\partial t_i}(\mathbf{t})X_j(\mathbf{t}) = 0,$$

which, together with the independence of the coordinates of X, implies that  $X'(\mathbf{t})$  and  $X(\mathbf{t})$  are independent. This means that the conditioning on  $X(\mathbf{t}) = 0$  in (1.6) may be dropped. To complete the proof of the theorem in the case  $\operatorname{Var} X_i(\mathbf{t}) \equiv 1$ , it remains to combine (1.6) with (1.2).

To cover the general case, it suffices to note that  $X_j/\sqrt{\operatorname{Var} X_j}$  has the same zero set as  $X_j$ .

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