# AstroStatistics and Cosmology Homework

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#### 1 Exercise 4

After being given a probability distribution  $\mathbb{P}(x)$ , we define the *characteristic function*  $\phi$  as its Fourier transform, which can also be expressed as the expectation value of  $\exp(-i\vec{k}\cdot\vec{x})$ :

$$\phi(\vec{k}) = \int d^n x \exp\left(-i\vec{k} \cdot \vec{x}\right) \mathbb{P}(x) = \mathbb{E}\left[\exp\left(-i\vec{k} \cdot \vec{x}\right)\right]. \tag{1.1}$$

Claim 1.1. A multivariate normal distribution

$$\mathcal{N}(\vec{x}|\vec{\mu},C) = \frac{1}{(2\pi)^{n/2}\sqrt{\det C}} \exp\left(-\frac{1}{2}\vec{y}^{\top}C^{-1}\vec{y}\right)\Big|_{\vec{y}=\vec{x}-\vec{\mu}},$$
(1.2)

has a characteristic function equal to

$$\phi(\vec{k}) = \exp\left(-i\vec{\mu}\cdot\vec{k} - \frac{1}{2}\vec{k}^{\top}C\vec{k}\right). \tag{1.3}$$

*Proof: completing the square.* The integral we need to compute is given, absorbing the normalization into a factor N, by

$$\phi(\vec{k}) = N \int d^n x \, \exp\left(-i\vec{k} \cdot \vec{x} - \frac{1}{2} \vec{y}^\top C^{-1} \vec{y}\right) \bigg|_{\vec{y} = \vec{x} - \vec{\mu}} \,. \tag{1.4}$$

The only integrals we really know how to do are Gaussian ones, so we want to rewrite the argument of the exponential so that it is a quadratic form. The manipulation goes as follows, considering the opposite of the argument the exponential in order to have less minus signs and defining the symmetric matrix  $V = C^{-1}$ :

$$i\vec{k} \cdot \vec{x} + \frac{1}{2}\vec{y}^{\top}V\vec{y} = i\vec{k} \cdot \vec{x} + \frac{1}{2}\vec{x}^{\top}V\vec{x} - \vec{x}^{\top}V\vec{\mu} + \frac{1}{2}\vec{\mu}^{\top}V\vec{\mu}$$

$$= \frac{1}{2}\vec{x}^{\top}V\vec{x} + \vec{x}^{\top}(i\vec{k} - V\vec{\mu}) + \frac{1}{2}\vec{\mu}^{\top}V\vec{\mu}$$
(1.5)

$$= \frac{1}{2} (\vec{x} + V^{-1} (i\vec{k} - V\vec{\mu})) + \frac{1}{2} \vec{\mu} V \vec{\mu}$$

$$= \underbrace{\frac{1}{2} (\vec{x} + V^{-1} (i\vec{k} - V\vec{\mu}))^{\top} V (\vec{x} + V^{-1} (i\vec{k} - V\vec{\mu}))}_{\text{(1.6)}} +$$

$$\underbrace{-\frac{1}{2}\left(i\vec{k} - V\vec{\mu}\right)^{\top}V^{-1}\left(i\vec{k} - V\vec{\mu}\right) + \frac{1}{2}\vec{\mu}^{\top}V\vec{\mu}}_{(2)},$$
(1.7)

which we can now integrate, since it is now a quadratic form in terms of a shifted variable,  $\vec{x} + \vec{p}$ , where the constant (with respect to  $\vec{x}$ ) vector  $\vec{p}$  is given by  $V^{-1}(i\vec{k} - V\vec{\mu})$ .

Now, shifting the integral from one in  $d^n x$  to one in  $d^n (x + p)$  does not change the measure, since the Jacobian of a shift is the identity. Then, we have

$$\phi(\vec{k}) = N \int d^n(x+p) \exp\left(-(1) - (2)\right)$$
(1.12)

$$= N\sqrt{\frac{(2\pi)^n}{\det V}}\exp\left(-2\right) \tag{1.13}$$

$$= \underbrace{\frac{1}{\sqrt{\det V \det C}}}_{=1} \exp\left(-2\right), \tag{1.14}$$

since the determinant of the inverse is the inverse of the determinant.

Now, we only need to simplify 2:

$$=\frac{1}{2}\vec{k}^{\top}C\vec{k}+i\vec{\mu}^{\top}\vec{k}\,,\tag{1.16}$$

inserting which into the exponent yields the desired result.

$$\frac{1}{2} \left( \vec{x} + A^{-1} \vec{b} \right)^{\top} A \left( \vec{x} + A^{-1} \vec{b} \right) - \frac{1}{2} \vec{b}^{\top} A^{-1} \vec{b} = \tag{1.8}$$

$$= \frac{1}{2} \left[ \vec{x}^{\top} A \vec{x} + \vec{x}^{\top} A A^{-1} \vec{b} + \left( A^{-1} \vec{b} \right)^{\top} A \vec{x} + \left( A^{-1} \vec{b} \right)^{\top} A A^{-1} \vec{b} - \vec{b}^{\top} A^{-1} \vec{b} \right]$$
(1.9)

$$= \frac{1}{2} \left[ \vec{x}^{\top} A \vec{x} + \vec{x}^{\top} \vec{b} + \vec{b}^{\top} (A^{-1})^{\top} A \vec{x} + \vec{b}^{\top} (A^{-1})^{\top} \vec{b} - \vec{b}^{\top} A^{-1} \vec{b} \right]$$
(1.10)

$$= \frac{1}{2}\vec{x}^{\top}A\vec{x} + \vec{b}^{\top}\vec{x}, \tag{1.11}$$

which we used with  $\vec{b} = i\vec{k} - V\vec{\mu}$ .

In the last step we applied the matrix square completion formula: for a symmetric matrix A and vectors  $\vec{x}$ ,  $\vec{b}$  we have

*Proof: by diagonalization.* We now follow a different approach: the covariance matrix C is symmetric, so we will always be able to find an orthogonal matrix O (satisfying  $O^{\top} = O^{-1}$ ) such that  $C = O^{\top}DO$ , where D is diagonal. We will then also have  $V = C^{-1} = O^{\top}D^{-1}O$ . Let us denote the eigenvalues of D as  $\lambda_i$ , and the eigenvalues of  $D^{-1}$  as  $d_i = \lambda_i^{-1}$ .

Defining  $\vec{z} = O\vec{x}$ ,  $\vec{m} = O\vec{\mu}$ ,  $\vec{u} = O\vec{k}$  the negative of the argument of the integral becomes:

$$i\vec{k} \cdot \vec{x} + \frac{1}{2} (\vec{x} - \vec{\mu})^{\top} C^{-1} (\vec{x} - \vec{\mu}) = i\vec{u} \cdot \vec{z} + \frac{1}{2} (\vec{z} - \vec{m})^{\top} D^{-1} (\vec{z} - \vec{m})$$
(1.17)

$$= i\vec{u} \cdot \vec{z} + \frac{1}{2} \sum_{i} d_{i} (z_{i} - m_{i})^{2}$$
 (1.18)

$$= \sum_{i} \left[ i u_{i} z_{i} + \frac{d_{i}}{2} \left( z_{i}^{2} + m_{i}^{2} - 2 m_{i} z_{i} \right) \right]$$
 (1.19)

$$= \sum_{i} \left[ z_i^2 \frac{d_i}{2} + z_i (iu_i - m_i d_i) + \frac{d_i}{2} m_i^2 \right]. \tag{1.20}$$

With this, and since by  $\det O = 1$  we have  $d^n z = d^n x$ , we can decompose our Gaussian integral into a product of Gaussian integrals:

$$\phi(\vec{k}) = N \int d^n x \exp\left(-i\vec{k} \cdot \vec{x} - \frac{1}{2}(\vec{x} - \vec{\mu})^{\top} C^{-1}(\vec{x} - \vec{\mu})\right)$$
(1.21)

$$= N \int d^{n}z \exp\left(-\sum_{i} \left[z_{i}^{2} \frac{d_{i}}{2} + z_{i}(iu_{i} - m_{i}d_{i}) + \frac{d_{i}}{2}m_{i}^{2}\right]\right)$$
(1.22)

$$= N \prod_{i} \int dz_{i} \exp\left(-z_{i}^{2} \frac{d_{i}}{2} - z_{i} (iu_{i} - m_{i}d_{i}) - \frac{d_{i}}{2} m_{i}^{2}\right)$$
(1.23)

$$= N \prod_{i} \sqrt{\frac{2\pi}{d_{i}}} \exp\left(\frac{(iu_{i} - m_{i}d_{i})^{2}}{2d_{i}} - \frac{d_{i}m_{i}^{2}}{2}\right)$$
(1.24)

$$= \frac{1}{\sqrt{\det C \det V}} \prod_{i} \exp\left(\frac{-u_i^2 + m_i^2 d_i^2 - 2iu_i m_i d_i}{2d_i} - \frac{d_i m_i^2}{2}\right)$$
(1.25)

$$= \exp\left(\sum_{i} \left[ -\frac{u_i^2}{2d_i} - iu_i m_i \right] \right) \tag{1.26}$$

$$= \exp\left(-\frac{1}{2}\vec{u}^{\top}C\vec{u} - i\vec{u}\cdot\vec{m}\right) \tag{1.27}$$

$$= \exp\left(-\frac{1}{2}\vec{k}^{\top}C\vec{k} - i\vec{k}\cdot\vec{\mu}\right),\tag{1.28}$$

where we have used the expression for the single-variable Gaussian integral:

$$\int dz \exp\left(-az^2 + bz + c\right) = \sqrt{\frac{\pi}{a}} \exp\left(\frac{b^2}{4a} + c\right), \tag{1.29}$$

which comes from the one-variable completion of the square:

$$-az^{2} + bz + c = -a\left(z - \frac{b}{2a}\right)^{2} + \frac{b^{2}}{4a} + c.$$
 (1.30)

Also, we used the fact that orthogonal transformation do not change fully-contracted objects, such as scalar products or bilinear forms.  $\Box$ 

### 2 Exercise 5

We can calculate the moments of a distribution through its characteristic function:

$$\mathbb{E}\left[x_{\alpha}^{n_{\alpha}} \dots x_{\beta}^{n_{\beta}}\right] = \left. \frac{\partial^{n_{\alpha} \dots n_{\beta}} \phi(\vec{k})}{\partial (-ik_{\alpha})^{n_{\alpha}} \dots \partial (-ik_{\beta})^{n_{\beta}}} \right|_{\vec{k}=0}.$$
 (2.1)

In the multivariate Gaussian case we can then calculate the mean (component by component) as

$$\mathbb{E}(x_{\alpha}) = \left. \frac{\partial \phi(\vec{k})}{\partial (-ik_{\alpha})} \right|_{\vec{k}=0} \tag{2.2}$$

$$= \frac{\partial}{\partial(-ik_{\alpha})} \Big|_{\vec{k}=0} \exp\left(-\frac{1}{2}\vec{k}^{\top}C\vec{k} - i\vec{k} \cdot \vec{\mu}\right)$$
 (2.3)

$$= \left[ -i \sum_{\beta} k_{\beta} C_{\beta\alpha} + \mu_{\alpha} \right] \exp \left( -\frac{1}{2} \vec{k}^{\top} C \vec{k} - i \vec{k} \cdot \vec{\mu} \right) \bigg|_{\vec{k}=0}$$
 (2.4)

$$=\mu_{\alpha}$$
, (2.5)

where we used the fact that the differentiation of a symmetric bilinear form is as follows:

$$\frac{\partial}{\partial k_{\alpha}} \left( \sum_{\beta \gamma} k_{\beta} k_{\gamma} C_{\beta \gamma} \right) = 2 \sum_{\beta \gamma} \delta_{\beta \alpha} k_{\gamma} C_{\beta \gamma} = 2 \sum_{\gamma} k_{\gamma} C_{\alpha \gamma}. \tag{2.6}$$

The covariance matrix can be computed by linearity as

$$\widetilde{C}_{\alpha\beta} = \mathbb{E}\left[\left(x_{\alpha} - \mathbb{E}(x_{\alpha})\right)\left(x_{\beta} - \mathbb{E}(x_{\beta})\right)\right] = \mathbb{E}\left[x_{\alpha}x_{\beta}\right] - \mu_{\alpha}\mu_{\beta}, \tag{2.7}$$

the first term of which reads as follows:

$$\mathbb{E}[x_{\alpha}x_{\beta}] = \left. \frac{\partial^2 \phi(\vec{k})}{\partial (-ik_{\beta})\partial (-ik_{\alpha})} \right|_{\vec{k}=0}$$
(2.8)

$$= \frac{\partial}{\partial (-ik_{\beta})} \bigg|_{\vec{k}=0} \left[ -i\sum_{\beta} k_{\beta} C_{\beta\alpha} + \mu_{\alpha} \right] \exp\left( -\frac{1}{2} \vec{k}^{\top} C \vec{k} - i \vec{k} \cdot \vec{\mu} \right)$$
 (2.9)

$$=C_{\alpha\beta}+\mu_{\alpha}\mu_{\beta}\,,\tag{2.10}$$

therefore, as expected,  $\widetilde{C}_{\alpha\beta}$  is indeed  $C_{\alpha\beta}$ .

## 3 Exercise 6

**Claim 3.1.** The characteristic function of a multivariate Gaussian is, up to normalization, a multivariate Gaussian.

*Proof.* The characteristic function is the exponential of (minus)

$$\frac{1}{2}\vec{k}^{\top}C\vec{k} + i\vec{k} \cdot \vec{\mu} = \frac{1}{2} \left( \vec{k} + iC^{-1}\vec{\mu} \right)^{\top} C \left( \vec{k} + iC^{-1}\vec{\mu} \right) + \frac{1}{2}\vec{\mu}^{\top}C^{-1}\vec{\mu} , \tag{3.1}$$

which means that the characteristic function is in the form

$$\phi(\vec{k}) = \text{const} \times \exp\left(-\frac{1}{2}(\vec{k} - \vec{m})^{\top}C(\vec{k} - \vec{m})\right), \tag{3.2}$$

a multivariate normal with mean  $\vec{m} = -iC^{-1}\vec{\mu}$  and covariance matrix  $C^{-1}$ , the inverse of the covariance matrix of the corresponding MVN.