AstroStatistics and Cosmology Homework

Jacopo Tissino

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Exercises 1–3 are in a Jupyter notebook in this same folder.

1 Exercise 4

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

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

Claim 1.1. *A multivariate normal distribution*

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

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

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

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 $V = C^{-1}$:

$$
\begin{aligned}
i\vec{k}\cdot\vec{x} + \frac{1}{2}\vec{y}^\top V\vec{y} &= i\vec{k}\cdot\vec{x} + \frac{1}{2}\vec{x}^\top V\vec{x} - \vec{x}^\top V\vec{\mu} + \frac{1}{2}\vec{\mu}^\top V\vec{\mu} \qquad (1.5)\\
&= \frac{1}{2}\vec{x}^\top V\vec{x} + \vec{x}^\top\left(i\vec{k} - V\vec{\mu}\right) + \frac{1}{2}\vec{\mu}^\top V\vec{\mu} \qquad (1.6)\\
&= \underbrace{\frac{1}{2}\left(\vec{x} + V^{-1}(i\vec{k} - V\vec{\mu})\right)^\top V\left(\vec{x} + V^{-1}(i\vec{k} - V\vec{\mu})\right)}_{①} + \\
&\quad \underbrace{-\frac{1}{2}\left(i\vec{k} - V\vec{\mu}\right)^\top V^{-1}\left(i\vec{k} - V\vec{\mu}\right) + \frac{1}{2}\vec{\mu}^\top V\vec{\mu}}_{②}, \qquad (1.7)
\end{aligned}
$$

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 $V^{-1}(i\vec{k} - V\vec{\mu})$.[1]

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

$$
\begin{aligned}
\phi(\vec{k}) &= N\int \mathrm{d}^n(x+p)\exp\left(-① - ②\right) \qquad (1.12)\\
&= N\sqrt{\frac{(2\pi)^n}{\det V}}\exp\left(-②\right) \qquad (1.13)\\
&= \underbrace{\frac{1}{\sqrt{\det V \det C}}}_{=1}\exp\left(-②\right), \qquad (1.14)
\end{aligned}
$$

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

Now, we only need to simplify ②:

$$
\begin{aligned}
② &= -\frac{1}{2}\left[-\vec{k}^\top V^{-1}\vec{k} - 2i\vec{\mu}^\top V V^{-1}\vec{k} + \vec{\mu}^\top V V^{-1} V\vec{\mu}\right] + \frac{1}{2}\vec{\mu}^\top V\vec{\mu} \qquad (1.15)\\
&= \frac{1}{2}\vec{k}^\top C\vec{k} + i\vec{\mu}^\top\vec{k}, \qquad (1.16)
\end{aligned}
$$

inserting which into the exponent yields the desired result. □

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

$$
\begin{aligned}
&\frac{1}{2}\left(\vec{x} + A^{-1}\vec{b}\right)^\top A\left(\vec{x} + A^{-1}\vec{b}\right) - \frac{1}{2}\vec{b}^\top A^{-1}\vec{b} = \qquad (1.8)\\
&= \frac{1}{2}\left[\vec{x}^\top A\vec{x} + \vec{x}^\top A A^{-1}\vec{b} + \left(A^{-1}\vec{b}\right)^\top A\vec{x} + \left(A^{-1}\vec{b}\right)^\top A A^{-1}\vec{b} - \vec{b}^\top A^{-1}\vec{b}\right] \qquad (1.9)\\
&= \frac{1}{2}\left[\vec{x}^\top A\vec{x} + \vec{x}^\top\vec{b} + \vec{b}^\top (A^{-1})^\top A\vec{x} + \vec{b}^\top (A^{-1})^\top\vec{b} - \vec{b}^\top A^{-1}\vec{b}\right] \qquad (1.10)\\
&= \frac{1}{2}\vec{x}^\top A\vec{x} + \vec{b}^\top\vec{x}, \qquad (1.11)
\end{aligned}
$$

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

Proof: 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 $C = O^\top D O$, 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 λ_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:

$$
\begin{aligned}
i\vec{k}\cdot\vec{x} + \frac{1}{2}\left(\vec{x}-\vec{\mu}\right)^\top C^{-1}\left(\vec{x}-\vec{\mu}\right) &= i\vec{u}\cdot\vec{z} + \frac{1}{2}(\vec{z}-\vec{m})^\top D^{-1}(\vec{z}-\vec{m}) && (1.17)\\
&= i\vec{u}\cdot\vec{z} + \frac{1}{2}\sum_i d_i (z_i - m_i)^2 && (1.18)\\
&= \sum_i \left[i u_i z_i + \frac{d_i}{2}\left(z_i^2 + m_i^2 - 2 m_i z_i\right)\right] && (1.19)\\
&= \sum_i \left[z_i^2 \frac{d_i}{2} + z_i (i u_i - m_i d_i) + \frac{d_i}{2} m_i^2 \right]. && (1.20)
\end{aligned}
$$

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

$$
\begin{aligned}
\phi(\vec{k}) &= N \int \mathrm{d}^n x \exp\left(-i\vec{k}\cdot\vec{x} - \frac{1}{2}\left(\vec{x}-\vec{\mu}\right)^\top C^{-1}\left(\vec{x}-\vec{\mu}\right)\right) && (1.21)\\
&= N \int \mathrm{d}^n z \exp\left(-\sum_i \left[z_i^2 \frac{d_i}{2} + z_i (i u_i - m_i d_i) + \frac{d_i}{2} m_i^2 \right]\right) && (1.22)\\
&= N \prod_i \int \mathrm{d} z_i \exp\left(-z_i^2 \frac{d_i}{2} - z_i (i u_i - m_i d_i) - \frac{d_i}{2} m_i^2\right) && (1.23)\\
&= N \prod_i \sqrt{\frac{2\pi}{d_i}} \exp\left(\frac{(i u_i - m_i d_i)^2}{2 d_i} - \frac{d_i m_i^2}{2}\right) && (1.24)\\
&= \frac{1}{\sqrt{\det C \det V}} \prod_i \exp\left(\frac{-u_i^2 + m_i^2 d_i^2 - 2 i u_i m_i d_i}{2 d_i} - \frac{d_i m_i^2}{2}\right) && (1.25)\\
&= \exp\left(\sum_i \left[-\frac{u_i^2}{2 d_i} - i u_i m_i\right]\right) && (1.26)\\
&= \exp\left(-\frac{1}{2}\vec{u}^\top C \vec{u} - i\vec{u}\cdot\vec{m}\right) && (1.27)\\
&= \exp\left(-\frac{1}{2}\vec{k}^\top C \vec{k} - i\vec{k}\cdot\vec{\mu}\right), && (1.28)
\end{aligned}
$$

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

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

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

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

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

2 Exercise 5

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

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

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

$$\begin{aligned}
\mathbb{E}(x_\alpha) &= \left.\frac{\partial\phi(\vec{k})}{\partial(-ik_\alpha)}\right|_{\vec{k}=0} && (2.2)\\
&= \left.\frac{\partial}{\partial(-ik_\alpha)}\right|_{\vec{k}=0} \exp\left(-\frac{1}{2}\vec{k}^\top C\vec{k} - i\vec{k}\cdot\vec{\mu}\right) && (2.3)\\
&= \left[-i\sum_\beta k_\beta C_{\beta\alpha} + \mu_\alpha\right] \exp\left(-\frac{1}{2}\vec{k}^\top C\vec{k} - i\vec{k}\cdot\vec{\mu}\right)\Bigg|_{\vec{k}=0} && (2.4)\\
&= \mu_\alpha , && (2.5)
\end{aligned}$$

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:

$$\begin{aligned}
\mathbb{E}[x_\alpha x_\beta] &= \left.\frac{\partial^2\phi(\vec{k})}{\partial(-ik_\beta)\partial(-ik_\alpha)}\right|_{\vec{k}=0} && (2.8)\\
&= \left.\frac{\partial}{\partial(-ik_\beta)}\right|_{\vec{k}=0} \left[-i\sum_\beta k_\beta C_{\beta\alpha} + \mu_\alpha\right] \exp\left(-\frac{1}{2}\vec{k}^\top C\vec{k} - i\vec{k}\cdot\vec{\mu}\right) && (2.9)\\
&= C_{\alpha\beta} + \mu_\alpha\mu_\beta , && (2.10)
\end{aligned}$$

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. □