AstroStatistics and Cosmology Homework

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Contents

Exercises 1–3 and 7[1] are in Jupyter notebooks in the folder `astrostat_homework`. They can be most easily accessed through the following links:

1. https://nbviewer.jupyter.org/github/jacopok/notes/blob/master/ap_third_semester/astrostat_homework/exercises_123.ipynb
2. https://nbviewer.jupyter.org/github/jacopok/notes/blob/master/ap_third_semester/astrostat_homework/exercise_7.ipynb.

1 November exercises

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

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

[1] It is not finished yet.

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 $V = C^{-1}$:

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

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 $V^{-1}(i\vec{k} - V\vec{\mu})$.[2]

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

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

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

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

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

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

Now, we only need to simplify ②:

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

inserting which into the exponent yields the desired result. □

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 $C = O^\top D O$, 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:

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

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:

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

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. □

Exercise 5

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

$$\mathbb{E}\left[x_\alpha^{n_\alpha} \dots x_\beta^{n_\beta}\right] = \left.\frac{\partial^{n_\alpha \dots n_\beta} \phi(\vec{k})}{\partial(-ik_\alpha)^{n_\alpha} \dots \partial(-ik_\beta)^{n_\beta}}\right|_{\vec{k}=0}. \tag{1.31}$$

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

$$\begin{aligned}
\mathbb{E}(x_\alpha) &= \left.\frac{\partial \phi(\vec{k})}{\partial(-ik_\alpha)}\right|_{\vec{k}=0} && (1.32)\\
&= \left.\frac{\partial}{\partial(-ik_\alpha)}\right|_{\vec{k}=0} \exp\left(-\frac{1}{2}\vec{k}^\top C\vec{k} - i\vec{k}\cdot\vec{\mu}\right) && (1.33)\\
&= \left[-i\sum_\beta k_\beta C_{\beta\alpha} + \mu_\alpha\right] \exp\left(-\frac{1}{2}\vec{k}^\top C\vec{k} - i\vec{k}\cdot\vec{\mu}\right)\Bigg|_{\vec{k}=0} && (1.34)\\
&= \mu_\alpha\,, && (1.35)
\end{aligned}$$

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

$$\frac{\partial}{\partial k_\alpha}\left(\sum_{\beta\gamma} k_\beta k_\gamma C_{\beta\gamma}\right) = 2\sum_{\beta\gamma} \delta_{\beta\alpha} k_\gamma C_{\beta\gamma} = 2\sum_\gamma k_\gamma C_{\alpha\gamma}\,. \tag{1.36}$$

The covariance matrix can be computed by linearity as

$$\widetilde{C}_{\alpha\beta} = \mathbb{E}\left[\left(x_\alpha - \mathbb{E}(x_\alpha)\right)\left(x_\beta - \mathbb{E}(x_\beta)\right)\right] = \mathbb{E}\left[x_\alpha x_\beta\right] - \mu_\alpha \mu_\beta\,, \tag{1.37}$$

the first term of which reads as follows:

$$\mathbb{E}[x_\alpha x_\beta] = \left.\frac{\partial^2 \phi(\vec{k})}{\partial(-ik_\beta)\partial(-ik_\alpha)}\right|_{\vec{k}=0} \tag{1.38}$$

$$= \frac{\partial}{\partial(-ik_\beta)}\bigg|_{\vec{k}=0} \left[-i\sum_\beta k_\beta C_{\beta\alpha} + \mu_\alpha\right] \exp\left(-\frac{1}{2}\vec{k}^\top C\vec{k} - i\vec{k}\cdot\vec{\mu}\right) \tag{1.39}$$

$$= C_{\alpha\beta} + \mu_\alpha\mu_\beta\,, \tag{1.40}$$

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

Exercise 6

Claim 1.2. *The characteristic function of a multivariate Gaussian is, up to normalization, a multivariate Gaussian.*

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

$$\frac{1}{2}\vec{k}^\top C\vec{k} + i\vec{k}\cdot\vec{\mu} = \frac{1}{2}\left(\vec{k} + iC^{-1}\vec{\mu}\right)^\top C\left(\vec{k} + iC^{-1}\vec{\mu}\right) + \frac{1}{2}\vec{\mu}^\top C^{-1}\vec{\mu}\,, \tag{1.41}$$

which means that the characteristic function is in the form

$$\phi(\vec{k}) = \text{const} \times \exp\left(-\frac{1}{2}(\vec{k}-\vec{m})^\top C(\vec{k}-\vec{m})\right), \tag{1.42}$$

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. □

Exercise 8

For clarity, we denote with Greek indices those ranging from 1 to N, the size of the vector of data; and with Latin indices those ranging from 1 to M, the number of templates.

We are assuming that the data have a Gaussian distribution with a covariance matrix C, and we are modelling their mean μ_α as a sum of templates $t_{i\alpha}$ with coefficients A_i:

$$\mu_\alpha = t_{i\alpha}A_i\,, \tag{1.43}$$

where the Einstein summation convention has been used. Therefore, the likelihood is proportional to

$$\mathscr{L}(d_\alpha|A_i) \propto \exp\left(-\frac{1}{2}(d_\alpha - A_i t_{i\alpha})C^{-1}_{\alpha\beta}\left(d_\beta - A_j t_{j\beta}\right)\right). \tag{1.44}$$

The normalization only depends on the covariance matrix $C_{\alpha\beta}$, which we assume is fixed. Therefore, maximizing the likelihood[3] is equivalent to minimizing the χ^2, which reads

$$\chi^2 = (d_\alpha - A_i t_{i\alpha})C^{-1}_{\alpha\beta}\left(d_\beta - A_j t_{j\beta}\right). \tag{1.45}$$

[3] Which is equivalent to maximizing the posterior if we are using a flat prior.

We want to maximize this as the amplitudes vary: therefore, we set the derivative with respect to A_k to zero,

$$\frac{\partial \chi^2}{\partial A_k} = -2 t_{k\alpha} C^{-1}_{\alpha\beta} \left(d_\beta - A_j t_{j\beta} \right) = 0 \,, \tag{1.46}$$

which means that

$$t_{k\alpha} C^{-1}_{\alpha\beta} d_\beta = (t_{k\alpha} C^{-1}_{\alpha\beta} t_{j\beta}) A_j \,, \tag{1.47}$$

a linear system of M equations (indexed by k) in the M variables A_j. If we denote the evaluations of bilinear forms in the data (N-dimensional) space with brackets, as $a_\alpha C_{\alpha\beta} b_\beta \overset{\text{def}}{=} (a|C|b)$, this reads

$$(t|C^{-1}|d)_k = (t|C^{-1}|t)_{kj} A_j \tag{1.48}$$

$$\left[(t|C^{-1}|t)^{-1} \right]_{mk} (t|C^{-1}|d)_k = \underbrace{\left[(t|C^{-1}|t)^{-1} \right]_{mk} (t|C^{-1}|t)_{kj}}_{=\delta_{mj}} A_j = A_m \tag{1.49}$$

$$A_m = \left[(t|C^{-1}|t)^{-1} \right]_{mk} (t|C^{-1}|d)_k \,, \tag{1.50}$$

where the inverse of $(t|C^{-1}|t)$ is to be computed in the M-dimensional vector space.

Exercise 9

Our model for the mean value is in the form $\mu(\Theta, A) = A\overline{x}(\Theta)$, where $\overline{x}$ is a generic function of Θ, while A is our scale parameter.[4] Our likelihood then reads

$$\mathscr{L}(x|\Theta, A) = \underbrace{\frac{1}{(2\pi)^{N/2}\sqrt{\det C}}}_{B_1} \exp\left(-\frac{1}{2} (x - A\overline{x}(\Theta))^\top C^{-1} (x - A\overline{x}(\Theta)) \right) . \tag{1.51}$$

If the priors for both A and Θ are flat, this corresponds to the joint posterior $P(\Theta, A|x)$. We want to marginalize over A, which amounts to integrating over it: dropping the dependence on Θ of $\overline{x}$ and defining $V = C^{-1}$ we find

$$P(\Theta|x) = B_1 \int \exp\left(-\frac{1}{2} (x - A\overline{x})^\top V (x - A\overline{x}) \right) \mathrm{d}A \tag{1.52}$$

$$= B_1 \int \exp\left(-\frac{1}{2} \left(x^\top V x - 2A\overline{x}^\top V x + A^2 \overline{x}^\top V \overline{x} \right) \right) \mathrm{d}A \, . \tag{1.53}$$

Used the symmetry of V.

Applying the formula for the single-variable Gaussian integral (1.29) (the bilinear forms are all evaluated to yield scalars, we are only integrating over the scalar A!) we then get

$$P(\Theta|x) = \underbrace{B_1 \exp\left(-\frac{1}{2} x^\top V x \right)}_{B_2} \exp\left(\frac{(\overline{x}^\top V x)^2}{4(\overline{x}^\top V \overline{x})} \right) \sqrt{\frac{\pi}{\overline{x}^\top V \overline{x}}} \tag{1.54}$$

[4] This is not specified in the problem, but it seems natural to think that $\left|\overline{x}(\Theta)\right|$ is a constant for varying Θ.

$$= B_2 \sqrt{\frac{\pi}{\overline{x}^\top V \overline{x}}} \exp\left(\frac{\overline{x}^\top \Omega \overline{x}}{4\overline{x}^\top V \overline{x}} \right), \tag{1.55}$$

where we defined the bilinear form $\Omega = V x x^\top V^\top$.[5]

Let us consider a simple example of this as a sanity check: suppose that x is two-dimensional, and $\overline{x}(\Theta) = (\cos\Theta, \sin\Theta)^\top$; further, suppose that V is diagonal, so that

$$V = \begin{bmatrix} \sigma_x^{-2} & 0 \\ 0 & \sigma_y^{-2} \end{bmatrix}. \tag{1.56}$$

Also, suppose that the observed data parameter is

$$x = A_x \begin{bmatrix} \cos\varphi \\ \sin\varphi \end{bmatrix}. \tag{1.57}$$

Then, the multiplicative constant in front of the marginalized posterior reads

$$B_2 = B_1 \exp\left(-\frac{1}{2} A_x^2 \left(\frac{\cos^2\varphi}{\sigma_x^2} + \frac{\sin^2\varphi}{\sigma_y^2} \right) \right); \tag{1.58}$$

while the bilinear form Ω is

$$\Omega = A_x^2 \begin{bmatrix} \sigma_x^{-2} & 0 \\ 0 & \sigma_y^{-2} \end{bmatrix} \begin{bmatrix} \cos^2\varphi & \cos\varphi\sin\varphi \\ \cos\varphi\sin\varphi & \sin^2\varphi \end{bmatrix} \begin{bmatrix} \sigma_x^{-2} & 0 \\ 0 & \sigma_y^{-2} \end{bmatrix} \tag{1.59}$$

$$= A_x^2 \begin{bmatrix} \cos^2\varphi/\sigma_x^4 & \cos\varphi\sin\varphi/\sigma_x^2\sigma_y^2 \\ \cos\varphi\sin\varphi/\sigma_x^2\sigma_y^2 & \sin^2\varphi/\sigma_y^4 \end{bmatrix}. \tag{1.60}$$

Then, when we evaluate the marginalized posterior we will find something in the form

$$P(\Theta|x) = B_1\sqrt{\pi} \left(\frac{\cos^2\Theta}{\sigma_x^2} + \frac{\sin^2\Theta}{\sigma_y^2} \right)^{-1/2} \exp\left(A_x^2 F(\Theta, \varphi) \right), \tag{1.61}$$

where $F(\Theta, \varphi)$ is some function whose specific form does not really matter;[6] the point is that the amplitude of the observed data vector, A_x, appears only as a multiplicative prefactor: its exact value will be taken care of by the evidence, and it cannot affect the shape of the distribution. Therefore, we see that by marginalizing over A we have "forgotten" any scaling information about x.

[5] With explicit indices, $\Omega_{im} = V_{ij} x_j x_k V_{km}$.

[6] For completeness, here is the full expression:

$$\begin{aligned} F(\Theta, \varphi) = &-\frac{1}{2} \left(\frac{\cos^2\varphi}{\sigma_x^2} + \frac{\sin^2\varphi}{\sigma_y^2} \right) + \\ &+ \frac{1}{4} \left(\frac{\cos^2\Theta}{\sigma_x^2} + \frac{\sin^2\Theta}{\sigma_y^2} \right)^{-1} \left[\frac{\cos^2\Theta\cos^2\varphi}{\sigma_x^4} + 2\frac{\cos\Theta\sin\Theta\cos\varphi\sin\varphi}{\sigma_x^2\sigma_y^2} + \frac{\sin^2\Theta\sin^2\varphi}{\sigma_y^4} \right]. \end{aligned} \tag{1.62}$$