

STAT151A Homework 3: Due February 23rd

Your name here

Normal intervals

For these problems, assume I give you a computer program that can compute the function $\Phi(z) = \mathbb{P}(\tilde{z} \leq z)$ where \tilde{z} is a standard scalar-valued random variable.

Let \tilde{x} denote a scalar-valued $N(\mu, \sigma^2)$ random variable. Using only $\Phi(z)$ and elementary arithmetic, construct functions that evaluate the following:

(a)

$$a \mapsto \mathbb{P}(\tilde{x} \leq a)$$

A solution:

$$\mathbb{P}(\tilde{x} \leq a) = \mathbb{P}\left(\frac{\tilde{x} - \mu}{\sigma} \leq \frac{a - \mu}{\sigma}\right) = \mathbb{P}\left(\tilde{z} \leq \frac{a - \mu}{\sigma}\right) = \Phi\left(\frac{a - \mu}{\sigma}\right)$$

(b)

$$b \mapsto \mathbb{P}(\tilde{x} \geq b)$$

A solution:

$$\mathbb{P}(\tilde{x} \geq b) = \mathbb{P}\left(\frac{\tilde{x} - \mu}{\sigma} \geq \frac{b - \mu}{\sigma}\right) = \mathbb{P}\left(\tilde{z} \geq \frac{b - \mu}{\sigma}\right) = \mathbb{P}\left(\tilde{z} \leq -\frac{b - \mu}{\sigma}\right) = \Phi\left(-\frac{b - \mu}{\sigma}\right)$$

(c)

$$a, b \mapsto \mathbb{P}(b \leq \tilde{x} \leq a)$$

A solution:

$$\mathbb{P}(\tilde{x} \leq a) = \mathbb{P}(b \leq \tilde{x} \leq a) + \mathbb{P}(\tilde{x} \leq b) \quad \Rightarrow \quad \mathbb{P}(b \leq \tilde{x} \leq a) = \mathbb{P}(\tilde{x} \leq a) - \mathbb{P}(\tilde{x} \leq b)$$

and use (a).

(d)

$$a \mapsto \mathbb{P}(|\tilde{x}| \leq a)$$

A solution:

$$\mathbb{P}(|\tilde{x}| \leq a) = \mathbb{P}(-a \leq \tilde{x} \leq a) \text{ and use (c).}$$

(e)

$$a \mapsto \mathbb{P}(|\tilde{x}| \geq a)$$

A solution:

$$\mathbb{P}(|\tilde{x}| \geq a) = 1 - \mathbb{P}(|\tilde{x}| \leq a) \text{ and use (d).}$$

(f)

$$a \mapsto \mathbb{P}(|\tilde{x}| > a)$$

A solution:

$$\tilde{x} \text{ is continuous, so } \mathbb{P}(\tilde{x} = a) = 0 \text{ and } \mathbb{P}(|\tilde{x}| > a) = \mathbb{P}(|\tilde{x}| \geq a). \text{ Use (e).}$$

(g)

$$a \mapsto \mathbb{P}(|\tilde{x}| = a)$$

A solution: $\mathbb{P}(|\tilde{x}| = a) = 0$.

Multivariate CLT

Let $\tilde{\mathbf{x}}_n$ denote an IID sequence of random variables in \mathbb{R}^P (not necessarily normal), each with zero mean and finite covariance matrix Σ . Let $\mathbf{a} \in \mathbb{R}^P$ denote a fixed vector.

(a)

Using the univariate CLT, find the limiting distribution of

$$\frac{1}{\sqrt{N}} \sum_{n=1}^N \mathbf{a}^\top \tilde{\mathbf{x}}_n.$$

Solution:

Since \mathbf{a} is constant, $\mathbb{E}[\mathbf{a}^\top \tilde{\mathbf{x}}_n] = 0$, so we can apply the CLT. We also have $\text{Cov}(\mathbf{a}^\top \tilde{\mathbf{x}}_n) = \mathbf{a}^\top \Sigma \mathbf{a}$, so the limiting distribution is $\mathcal{N}(0, \mathbf{a}^\top \Sigma \mathbf{a})$.

(b)

Using the multivariate CLT and the continuous mapping theorem, find the limiting distribution of

$$\mathbf{a}^\top \left(\frac{1}{\sqrt{N}} \sum_{n=1}^N \tilde{\mathbf{x}}_n \right).$$

Solution: By the multivariate CLT, $\frac{1}{\sqrt{N}} \sum_{n=1}^N \tilde{\mathbf{x}}_n \rightarrow \tilde{\mathbf{z}}$ where $\tilde{\mathbf{z}} \sim \mathcal{N}(\mathbf{0}, \Sigma)$. By the continuous mapping theorem, the distribution of the given expression converges to the distribution of $\mathbf{a}^\top \tilde{\mathbf{z}}$, which is $\mathcal{N}(0, \mathbf{a}^\top \Sigma \mathbf{a})$ as in (a). (As must be the case.)

(c)

Now, suppose that $P = 2$ and

$$\Sigma = \begin{pmatrix} 1 & -1 \\ -1 & 1 \end{pmatrix}.$$

Note that we can write

$$\tilde{\mathbf{x}}_n = \begin{pmatrix} \tilde{\mathbf{x}}_{n1} \\ \tilde{\mathbf{x}}_{n2} \end{pmatrix},$$

where $\tilde{\mathbf{x}}_{n1}$ and $\tilde{\mathbf{x}}_{n2}$ are scalars. Find the limiting distributions of each of the following expressions:

$$\begin{aligned}\frac{1}{\sqrt{N}} \sum_{n=1}^N \tilde{\mathbf{x}}_{n1} &\rightarrow? \\ \frac{1}{\sqrt{N}} \sum_{n=1}^N \tilde{\mathbf{x}}_{n2} &\rightarrow? \\ \frac{1}{\sqrt{N}} \sum_{n=1}^N (\tilde{\mathbf{x}}_{n1} + \tilde{\mathbf{x}}_{n2}) &\rightarrow?\end{aligned}$$

(This result demonstrates why it's not enough to only look at the marginal distribution of the vector components when using a multivariate CLT.)

Solution: The first two go to $\mathcal{N}(0, 1)$, but the last goes to $\mathcal{N}(0, 0)$, since

$$\tilde{\mathbf{x}}_{n1} + \tilde{\mathbf{x}}_{n2} = (1, 1)\tilde{\mathbf{x}} \quad \Rightarrow \quad \text{Var}(\tilde{\mathbf{x}}_{n1} + \tilde{\mathbf{x}}_{n2}) = (1, 1) \begin{pmatrix} 1 & -1 \\ -1 & 1 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} = 0.$$

Valid covariance matrices

Suppose I were to tell you that the vector-valued random variable \mathbf{x} has a covariance matrix $\text{Cov}(\mathbf{x}) = \mathbf{\Sigma}$ where $\mathbf{\Sigma}$ is not positive semi-definite (i.e., $\mathbf{\Sigma}$ has at least one negative eigenvalue). Show that, if this were true, you could construct a scalar-valued random variable with *negative* variance, which is impossible.

(It follows from this argument every covariance matrix must be positive semi-definite.)

Solution:

Let \mathbf{u} denote an eigenvector of $\mathbf{\Sigma}$ with a negative eigenvalue. Then $\text{Var}(\mathbf{u}^\top \mathbf{x}) = \mathbf{u}^\top \mathbf{\Sigma} \mathbf{u} < 0$.