Multivariate Statistical Analysis

Lecture 04

Fudan University

luoluo@fudan.edu.cn

Outline

Outline

Singular Normal Distributions

In previous section, we focus on non-singular normal normally distributed variate $\mathbf{x} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ with $\boldsymbol{\Sigma} \succ \mathbf{0}$ whose density function is

$$n(\mathbf{x} \mid \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{\sqrt{(2\pi)^p \det(\boldsymbol{\Sigma})}} \exp\left(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\right).$$

What about the case of singular $\boldsymbol{\Sigma}$?

General Linear Transformation

1. Let $\mathbf{x} \sim \mathcal{N}_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, with $\boldsymbol{\Sigma} \succ \mathbf{0}$. Then
$$\mathbf{y} = \mathbf{C}\mathbf{x}$$
is distributed according to $\mathcal{N}_p(\mathbf{C}\boldsymbol{\mu}, \mathbf{C}\boldsymbol{\Sigma}\mathbf{C}^\top)$ for non-singular $\mathbf{C} \in \mathbb{R}^{p\times p}$.

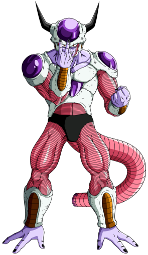
2. Let $\mathbf{x} \sim \mathcal{N}_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, with $\boldsymbol{\Sigma} \succ \mathbf{0}$. Then
$$\mathbf{y} = \mathbf{C}\mathbf{x}$$
is distributed according to $\mathcal{N}_q(\mathbf{C}\boldsymbol{\mu}, \mathbf{C}\boldsymbol{\Sigma}\mathbf{C}^\top)$ for $\mathbf{C} \in \mathbb{R}^{q\times p}$ of rank $q \le p$.

3. Let $\mathbf{x} \sim \mathcal{N}_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$. Then
$$\mathbf{y} = \mathbf{C}\mathbf{x}$$
is distributed according to $\mathcal{N}_q(\mathbf{C}\boldsymbol{\mu}, \mathbf{C}\boldsymbol{\Sigma}\mathbf{C}^\top)$ for any $\mathbf{C} \in \mathbb{R}^{q\times p}$.

5.3×10^5

$c \neq 0$

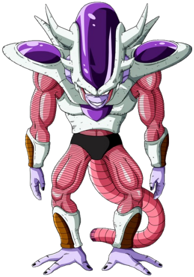
$\sigma^2 > 0$



$> 1.0 \times 10^6$

$\mathbf{C} \in \mathbb{R}^{p \times p}$ is non-singular

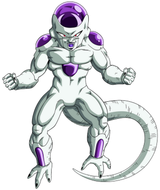
$\boldsymbol{\Sigma} \succ \mathbf{0}$



$2.0 \times 10^6 \sim 3.0 \times 10^6$

$\mathbf{C} \in \mathbb{R}^{q \times p}$ of rank $q \leq p$

$\boldsymbol{\Sigma} \succ \mathbf{0}$



$> 3.0 \times 10^7$

$\mathbf{C} \in \mathbb{R}^{q \times p}$

$\boldsymbol{\Sigma} \succeq \mathbf{0}$

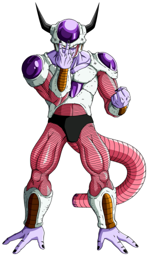
General Linear Transformation

Theorem

Let $\mathbf{x} \sim \mathcal{N}_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$*, with* $\boldsymbol{\Sigma} \succ \mathbf{0}$*. Then*

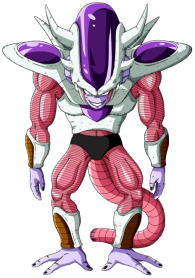
$$\mathbf{z} = \mathbf{D}\mathbf{x}$$

is distributed according to $\mathcal{N}_q(\mathbf{D}\boldsymbol{\mu}, \mathbf{D}\boldsymbol{\Sigma}\mathbf{D}^\top)$ *for* $\mathbf{D} \in \mathbb{R}^{q\times p}$ *of rank* $q \leq p$*.*



non-singular

$$\Longrightarrow$$



full-rank

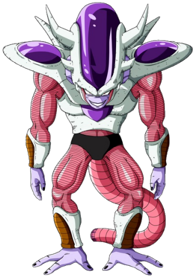
General Linear Transformation

Theorem

Let $\mathbf{x} \sim \mathcal{N}_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$. *Then*

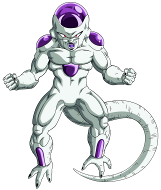
$$\mathbf{z} = \mathbf{D}\mathbf{x}$$

is distributed according to $\mathcal{N}_q(\mathbf{D}\boldsymbol{\mu}, \mathbf{D}\boldsymbol{\Sigma}\mathbf{D}^\top)$ *for any* $\mathbf{D} \in \mathbb{R}^{q \times p}$.



full-rank

$$\xRightarrow{\text{understand the singular normal distribution}}$$



no limitation

Singular Normal Distribution

Singular normal distribution:

1. The mass is concentrated on a given lower dimensional set.
2. The probability associated with any set that does not intersecting the given low-dimensional set is 0.

For example, consider that

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \right).$$

1. Probability of any set that does not intersecting the x_2-axis is 0.
2. The measure of x_2-axis in the space of $\mathbb{R}^2$ is zero.
3. The random vector $\mathbf{x}$ has no density, but its distribution exists.

Singular Normal Distributions

Suppose that $\mathbf{y} \sim \mathcal{N}_q(\boldsymbol{\nu}, \mathbf{T})$, $\boldsymbol{\lambda} \in \mathbb{R}^p$, and $\mathbf{A} \in \mathbb{R}^{p \times q}$ with $\mathbf{T} \succ \mathbf{0}$ and $p > q$; then we say that

$$\mathbf{x} = \mathbf{A}\mathbf{y} + \boldsymbol{\lambda}$$

has a singular (degenerate) normal distribution in p-space.

We have $\boldsymbol{\mu} = \mathbb{E}[\mathbf{x}] = \mathbf{A}\boldsymbol{\nu} + \boldsymbol{\lambda}$ and

$$\boldsymbol{\mu} = \mathbb{E}[\mathbf{x}] = \mathbf{A}\boldsymbol{\nu} + \boldsymbol{\lambda} \quad \text{and} \quad \boldsymbol{\Sigma} = \mathrm{Cov}[\mathbf{x}] = \mathbf{A}\mathbf{T}\mathbf{A}^\top.$$

The matrix $\boldsymbol{\Sigma}$ is singular and we cannot write density for $\mathbf{x}$.

Singular Normal Distributions

Now we give a formal definition of a normal distribution that includes the singular distribution.

Definition

A p-dimensional random vector $\mathbf{x}$ with $\mathbb{E}[\mathbf{x}] = \boldsymbol{\mu}$ and $\mathrm{Cov}[\mathbf{x}] = \boldsymbol{\Sigma}$ is said to be normally distributed if there is a transformation

$$\mathbf{x} = \mathbf{A}\mathbf{y} + \boldsymbol{\lambda},$$

where $\mathbf{A} \in \mathbb{R}^{p \times r}$, $\boldsymbol{\lambda} \in \mathbb{R}^{p}$, r is the rank of $\boldsymbol{\Sigma}$ and $\mathbf{y}$ has r-dimensional non-singular normal distribution, e.g., $\mathbf{y} \sim \mathcal{N}_r(\boldsymbol{\nu}, \mathbf{T})$ with $\mathbf{T} \succ \mathbf{0}$.

We also use the notation $\mathcal{N}_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ even if $\boldsymbol{\Sigma}$ is singular.

If $\boldsymbol{\Sigma}$ has rank p, we can take $\mathbf{A} = \mathbf{I}$ and $\boldsymbol{\lambda} = \mathbf{0}$.

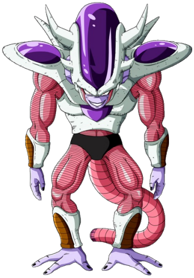
General Linear Transformation

Theorem

Let $\mathbf{x} \sim \mathcal{N}_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$. *Then*

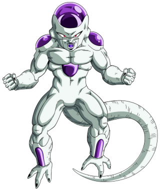
$$\mathbf{z} = \mathbf{D}\mathbf{x}$$

is distributed according to $\mathcal{N}_q(\mathbf{D}\boldsymbol{\mu}, \mathbf{D}\boldsymbol{\Sigma}\mathbf{D}^\top)$ *for any* $\mathbf{D} \in \mathbb{R}^{q \times p}$.



full-rank

only use the definition (without density) $\Longrightarrow$



no limitation

Examples

Theorem

Let $\mathbf{U}$ *be a* $d \times k$ *random matrix* $(k \leq d)$ *and each of its entry is independent distributed according to* $\mathcal{N}(0,1)$*, then it holds that*

$$\mathbb{E}\left[\mathbf{U}(\mathbf{U}^\top\mathbf{U})^{-1}\mathbf{U}^\top\right] = \frac{k}{d}\mathbf{I}_d.$$

Lemma

Assume $\mathbf{P} \in \mathbb{R}^{d\times r}$ *is column orthonormal* $(r \leq d)$ *and* $\mathbf{v} \sim \mathcal{N}_d(\mathbf{0}, \mathbf{P}\mathbf{P}^\top)$ *is a* d*-dimensional multivariate normal distributed vector. Then we have*

$$\mathbb{E}\left[\frac{\mathbf{v}\mathbf{v}^\top}{\mathbf{v}^\top\mathbf{v}}\right] = \frac{1}{r}\mathbf{P}\mathbf{P}^\top.$$

Outline

Conditional Distribution

Let $\mathbf{x}$ be distributed according to $\mathcal{N}_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ with $\boldsymbol{\Sigma} \succ \mathbf{0}$.

We partition

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}^{(1)} \\ \mathbf{x}^{(2)} \end{bmatrix} \quad \text{with } \mathbf{x}^{(1)} \in \mathbb{R}^q \text{ and } \mathbf{x}^{(2)} \in \mathbb{R}^{p-q},$$

$$\boldsymbol{\mu} = \begin{bmatrix} \boldsymbol{\mu}^{(1)} \\ \boldsymbol{\mu}^{(2)} \end{bmatrix} \quad \text{with } \boldsymbol{\mu}^{(1)} \in \mathbb{R}^q \text{ and } \boldsymbol{\mu}^{(2)} \in \mathbb{R}^{p-q},$$

and

$$\boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{21} & \boldsymbol{\Sigma}_{22} \end{bmatrix}$$

with $\boldsymbol{\Sigma}_{11} \in \mathbb{R}^{q \times q}$, $\boldsymbol{\Sigma}_{12} \in \mathbb{R}^{q \times (p-q)}$, $\boldsymbol{\Sigma}_{21} \in \mathbb{R}^{(p-q) \times q}$ and $\boldsymbol{\Sigma}_{22} \in \mathbb{R}^{(p-q) \times (p-q)}$.

Conditional Distribution

The conditional density of $\mathbf{x}^{(1)}$ given that $\mathbf{x}^{(2)}$ is

$$\begin{aligned} f(\mathbf{x}^{(1)} \mid \mathbf{x}^{(2)}) &= \frac{f(\mathbf{x}^{(1)}, \mathbf{x}^{(2)})}{f(\mathbf{x}^{(2)})} \\ &= \frac{1}{\sqrt{(2\pi)^q \det(\boldsymbol{\Sigma}_{11.2})}} \exp\left(-\frac{1}{2}\left(\mathbf{x}_{11.2} - \boldsymbol{\mu}_{11.2}\right)^\top \boldsymbol{\Sigma}_{11.2}^{-1}\left(\mathbf{x}_{11.2} - \boldsymbol{\mu}_{11.2}\right)\right), \end{aligned}$$

where

$$\mathbf{x}_{11.2} = \mathbf{x}^{(1)} - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\mathbf{x}^{(2)}, \qquad \boldsymbol{\mu}_{11.2} = \boldsymbol{\mu}^{(1)} - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\boldsymbol{\mu}^{(2)}$$

and

$$\boldsymbol{\Sigma}_{11.2} = \boldsymbol{\Sigma}_{11} - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\boldsymbol{\Sigma}_{21}.$$

Hence, the conditional density of $\mathbf{x}^{(1)}$ given that $\mathbf{x}^{(2)}$ is

$$\mathbf{x}^{(1)} \mid \mathbf{x}^{(2)} \sim \mathcal{N}\left(\boldsymbol{\mu}^{(1)} + \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}(\mathbf{x}^{(2)} - \boldsymbol{\mu}^{(2)}), \boldsymbol{\Sigma}_{11} - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\boldsymbol{\Sigma}_{21}\right)$$