STAT 3690 Lecture 07

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Useful properties of MVN

- $\mathbf{X} \sim MVN_p(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \Leftrightarrow \mathbf{Z} = \boldsymbol{\Sigma}^{-1/2}(\mathbf{X} \boldsymbol{\mu}) \sim MVN_p(\mathbf{0}, \mathbf{I})$. So, we have a stochastic representation of arbitrary $\mathbf{X} \sim MVN_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$: $\mathbf{X} = \boldsymbol{\Sigma}^{1/2}\mathbf{Z} + \boldsymbol{\mu}$, where $\mathbf{Z} \sim MVN_p(\mathbf{0}, \mathbf{I})$.
- $\mathbf{X} \sim MVN$ iff, for all $a \in \mathbb{R}^p$, $a^{\mathsf{T}}\mathbf{X}$ has a (univariate) normal distribution.
- If $\mathbf{X} \sim MVN_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, then $\mathbf{A}\mathbf{X} + \boldsymbol{b} \sim MVN_q(\mathbf{A}\boldsymbol{\mu} + \boldsymbol{b}, \mathbf{A}\boldsymbol{\Sigma}\mathbf{A}^\top)$ for $\mathbf{A} \in \mathbb{R}^{q \times p}$ and $\mathrm{rk}(\mathbf{A}) = q$.
- Exercise: Generate six iid samples following bivariate normal $MVN_2(\mu, \Sigma)$ with

$$\boldsymbol{\mu} = [3, 6]^{\top}, \quad \boldsymbol{\Sigma} = \left[\begin{array}{cc} 10 & 2 \\ 2 & 5 \end{array} \right].$$

- Exercise:
 - 1. Prove that $(\mathbf{X} \boldsymbol{\mu})^{\top} \boldsymbol{\Sigma}^{-1} (\mathbf{X} \boldsymbol{\mu}) \sim \chi^2(p)$ if $\mathbf{X} \sim MVN_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$.
 - 2. Suppose $X_1 \sim N(0,1)$. In the following two cases, verify that $X_2 \sim N(0,1)$ as well. Does $\mathbf{X} = [X_1, X_2]^{\top}$ follow an MVN in both cases?

a.
$$X_2 = -X_1$$
;
b. $X_2 = (2Y - 1)X_1$, where $Y \sim Ber(p)$ and $\mathbf{Y} \perp \!\!\! \perp \mathbf{X}$.
- P.S.: $\mathbf{Y} \perp \!\!\! \perp \mathbf{X} \Leftrightarrow f_{\mathbf{Z}}(\mathbf{z}) = f_{\mathbf{X}}(\mathbf{x})f_{\mathbf{Y}}(\mathbf{y})$, where $\mathbf{Z} = [\mathbf{X}^{\top}, \mathbf{Y}^{\top}]^{\top}$

Joint, marginal and conditional MVN

• If $\mathbf{X} \sim MVN_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ and

$$\mathbf{X} = \left[egin{array}{c} \mathbf{X}_1 \\ \mathbf{X}_2 \end{array}
ight], \quad oldsymbol{\mu} = \left[egin{array}{c} oldsymbol{\mu}_1 \\ oldsymbol{\mu}_2 \end{array}
ight] \quad ext{and} \quad oldsymbol{\Sigma} = \left[egin{array}{c} oldsymbol{\Sigma}_{11} & oldsymbol{\Sigma}_{12} \\ oldsymbol{\Sigma}_{21} & oldsymbol{\Sigma}_{22} \end{array}
ight]$$

with $\Sigma_{11} > 0$ and $\Sigma_{22} > 0$, then

- $\mathbf{X}_i \sim MVN_{p_i}(\boldsymbol{\mu}_i,\boldsymbol{\Sigma}_{ii}),$ i.e., marginals of MVN are MVN.
- $-\mathbf{X}_i \mid \mathbf{X}_j = \mathbf{x}_j \sim MVN_{p_i}(\boldsymbol{\mu}_{i|j}, \boldsymbol{\Sigma}_{i|j})$, i.e., conditionals of MVN are MVN.
- $-oldsymbol{\mu}_{i|j} = oldsymbol{\mu}_i + oldsymbol{\Sigma}_{ij} oldsymbol{\Sigma}_{jj}^{-1} (oldsymbol{x}_j oldsymbol{\mu}_j)$
- $\Sigma_{i|j} = \Sigma_{ii} \Sigma_{ij} \widetilde{\Sigma}_{jj}^{-1} \Sigma_{ji}$
- $-\mathbf{X}_{1} \perp \mathbf{X}_{2} \Leftrightarrow \mathbf{\Sigma}_{12} = \mathbf{0}$

[•] Exercise: The argument $\mathbf{X}_1 \perp \!\!\! \perp \mathbf{X}_2 \Leftrightarrow \mathbf{\Sigma}_{12} = 0$ is based on the assumption that $\mathbf{X} = [\mathbf{X}_1^\top, \mathbf{X}_2^\top]^\top$ is of MVN. That is, if \mathbf{X}_1 and \mathbf{X}_2 are both MVN BUT they are not jointly normal, a zero $\mathbf{\Sigma}_{12}$ doesn't suffice for the independence between \mathbf{X}_1 and \mathbf{X}_2 . A counter-example will be part of Assignment 1.

Checking normality (J&W Sec 4.6)

- Checking the univariate marginal distributions
 - Normal Q-Q plot
 - * qqnorm(); car::qqPlot()
 - Normality test
 - * shapiro.test()
- Checking the quadratic form
 - $-\chi^2$ Q-Q plot
 - * $D_i^2 = (\mathbf{X}_i \bar{\mathbf{X}})^{\top} \mathbf{S}^{-1} (\mathbf{X}_i \bar{\mathbf{X}}) \approx \chi^2(p) \text{ if } \mathbf{X}_i \stackrel{\text{iid}}{\sim} MVN_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$
 - * qqplot(); car::qqPlot()

Detecting outliers (J&W Sec 4.7)

- Scatter plot of standardized values
- Check the points farthest from the origin in χ^2 Q-Q plot

Improving normality (J&W Sec 4.8)

• Box-cox transformation: for x > 0,

$$x^*(\lambda) = \begin{cases} (x^{\lambda} - 1)/\lambda & \lambda \neq 0\\ \ln(x) & \lambda = 0 \end{cases}$$

- If $x \leq 0$, change it to be positive first.
- Exploratory data analysis (EDA)
 - J. Tukey (1977). Exploratory Data Analysis. Addison-Wesley. ISBN 978-0-201-07616-5.

R package "MVN"