Multivariate Analysis Lecture 5: Multivariate Normal, MGF, and Independence

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Section 1

The Big Picture

The Big Picture: Univariate vs Multivariate

- Review: A random sample, denoted by $X_1, \cdots, X_n$, from a (univariate) normal distribution $N(\mu, \sigma^2)$
  - What are the distributions of $\bar{X}, s^2$? What useful statistics can be constructed?
- New material: A random sample, denoted by $\mathbf{X}_1, \cdots, \mathbf{X}_n$, from a multivariate normal distribution $N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$
  - What are the distributions of $\bar{\mathbf{X}}, \mathbf{S}$? What useful statistics can be constructed?

The Big Picture: Univariate

- A random sample, denoted by $X_1, \cdots, X_n$, from a (univariate) normal distribution $N(\mu, \sigma^2)$
- Let $\mathbf{X}_{n\times 1} = (X_1, \cdots, X_n)^T$. It is random vector with a multivarite normal distribution, i.e.,

$$\mathbf{X}_{n\times 1} = (X_1, \cdots, X_n)^T \sim \mathbf{N}(\mu\mathbf{1}, \sigma^2\mathbf{I})$$

1. $\bar{X} \sim N(\mu, \sigma^2/n)$
2. $\frac{(n-1)s^2}{\sigma^2} \sim \chi^2_{n-1}$
3. Independence between $\bar{X}$ and s^2.
4. a t-statistic is

$$\frac{\frac{\bar{X}-\mu}{\sqrt{\sigma^2/n}}}{\sqrt{\frac{(n-1)s^2/\sigma^2}{n-1}}} = \frac{\sqrt{n}(\bar{X}-\mu)}{s} \sim t_{n-1}$$

The Big Picture: Multivariate

- A random sample $\mathbf{X}_1, \cdots, \mathbf{X}_n$ from a multivariate normal distribution $\mathbf{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$.
- Let

$$\mathbf{X}_{n\times p} = \begin{pmatrix} \mathbf{X}_1^T \\ \vdots \\ \mathbf{X}_n^T \end{pmatrix}$$

$\mathbf{X}$ follows a matrix normal distribution.

1. Sample mean vector follows a multivariate normal, i.e., $\bar{\mathbf{X}} \sim \mathbf{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}/n)$
2. Sample covariance matrix $(n-1)\mathbf{S}$ follows a Wishart distribution, i.e., $(n-1)\mathbf{S} \sim Wishart_p(n-1, \Sigma)$
3. Independence between $\bar{\mathbf{X}}$ and S.
4. Hoetelling's T^2: $T^2 = (\bar{\mathbf{X}} - \boldsymbol{\mu})^T \left(\frac{\mathbf{S}}{n}\right)^{-1} (\bar{\mathbf{X}} - \boldsymbol{\mu})$

Outline

- Multivariate normal distribution (MVN)
- Moment generating function (MGF)
  - Apply MGF to univariate normal
  - Apply MGF to multivariate normal (MVN)
- Zero-Cov vs Independence
- MVN: $\bar{\mathbf{X}}$ and $\mathbf{S}$

Section 2

MVN

PDF of Normal of Distributions

- Univariate normal distribution:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

- Bivariate normal distribution:

$$f(x, y) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)}\left(\frac{(x-\mu_1)^2}{\sigma_1^2}+\frac{(y-\mu_2)^2}{\sigma_2^2}-2\rho\frac{(x-\mu_1)(y-\mu_2)}{\sigma_1\sigma_2}\right)}$$

  The formula for a $p \geq 3$-dimensional multivariate normal distribution is much messier, so we use a compact way:

- Multivariate normal distribution:

$$f(\mathbf{x}) = \frac{1}{\sqrt{(2\pi)^p|\boldsymbol{\Sigma}|}} e^{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^T\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})}$$

Section 3

MGF

Tools to Characterize a Distribution

- Probability density function (PDF) or probability mass function (PMF)
- Cumulative distribution (CDF)
- Characteristic function (CF)
- Moment generating function (MGF)
- ... ...

Moment Generating Function (MGF)

- The moment generating function of random variable X is defined
$$M_X(t) = \mathbb{E}[e^{tX}]$$
- Like a PDF/PMF or CDF, a MGF uniquely determines/identifies a distribution
- The definition can be extended to random vectors and random matrices
  - Consider a random vector $\mathbf{X}_{p\times 1}$. Let t be a $p \times 1$ vector.
$$M_{\mathbf{X}} = \mathbb{E}[t^T\mathbf{X}]$$
  - Consider a random matrix $\mathbf{X}_{n\times p}$. Let t be a $n \times p$ matrix.
$$M_{\mathbf{X}} = \mathbb{E}[trace(t^T\mathbf{X})]$$

Moment Generating Function: Univariate

- Where does the name of MGF come from?

$$
\begin{aligned}
M_X(t) = \mathbb{E}[e^{tX}] &= \int_{-\infty}^{\infty} e^{tx} f(x) dx \\
&= \int_{-\infty}^{\infty} [1 + tx + \frac{(tx)^2}{2!} + \frac{(tx)^3}{3!} + \cdots] f(x) dx \\
&= 1 + t\mathbb{E}[X] + \frac{t^2}{2!}\mathbb{E}[X^2] + \cdots
\end{aligned}
$$

- $M_X^{(k)}(0) = E[X^K]$, where $M_X^{(k)}(t)$ is the kth derivative of $M_X(t)$.

Subsection 1

MGF: Univariate Normal

MGF of Univariate Normal

- Recall that the MGF of a random variable X is defined as: $M_X(t) = \mathbb{E}[e^{tX}]$.
- For the normal distribution with mean μ and variance σ^2, the MGF is given by:

$$M_X(t) = e^{\mu t + \frac{1}{2}\sigma^2 t^2}$$

- The mean is $\mathbb{E}[X] = M_X'(0) = \mu$.
- The variance is

$$\begin{aligned} \mathrm{Var}(X) &= E[(X-\mu)^2] = \ldots = E[X^2] - (E[X])^2 \\ &= M_X''(0) - M_X'(0)^2 = \sigma^2 \end{aligned}$$

MGF of Univariate Normal: Examples

- Recall that $M_X(t) = exp\{\mu t + \frac{1}{2}\sigma^2 t^2\}$ for $X \sim N(0, \sigma^2)$.

What is the distribution corresponding to each of the following MGFs?

1. $$M_X(t) = \exp\left(\frac{1}{2}t^2\right)$$
2. $$M_X(t) = \exp\left(2t + \frac{9}{2}t^2\right)$$
3. $$M_X(t) = \exp\left(-t + \frac{1}{8}t^2\right)$$

MGF of Univariate Normal: Examples (continued)

1. Standard normal distribution, i.e., $\mu = 0, \sigma^2 = 1$:

$$M_X(t) = \exp\left(\frac{1}{2}t^2\right)$$

2. Normal distribution with mean $\mu = 2$ and standard deviation $\sigma = 3$:

$$M_X(t) = \exp\left(2t + \frac{9}{2}t^2\right)$$

3. Normal distribution with mean $\mu = -1$ and standard deviation $\sigma = 0.5$:

$$M_X(t) = \exp\left(-t + \frac{1}{8}t^2\right)$$

MGF of Univariate Normal: A Linear Function

- Let $X \sim N(\mu, \sigma^2)$. We know that $M_X(t) = \exp\left(\mu t + \frac{1}{2}\sigma^2 t^2\right)$
- Let $Y = aX + b$, where a and b are constants.
- We now find $M_Y(t)$:

$$M_Y(t) = \mathbb{E}[e^{tY}] = \mathbb{E}[e^{t(aX+b)}] = e^{bt}\mathbb{E}[e^{(at)X}]$$

Since at is just another constant, we can treat it as a new variable, say $s = at$. Then:

$$\begin{aligned} M_Y(t) &= e^{bt} M_X(s) = e^{bt} \exp\{\mu s + \frac{1}{2}\sigma^2 s^2\} \\ &= \exp\{bt + a\mu t + \frac{1}{2}\sigma^2 a^2 t^2\} = \exp\{(a\mu + b)t + \frac{1}{2}(a\sigma)^2 t^2\} \end{aligned}$$

- $M_Y(t)$ has the form of the MGF of a normal distribution: $Y = aX + b \sim N(a\mu + b, a^2\sigma^2)$.

MGF of Univariate Normal: Sum of Two Independent Normal

- Let X and Y be two independent and $X \sim N(\mu_X, \sigma_X^2)$ and $Y \sim N(\mu_Y, \sigma_Y^2)$.

$$M_X(t) = \exp\{\mu_X t + \frac{1}{2}\sigma_X^2 t^2\}, M_Y(t) = \exp\{\mu_Y t + \frac{1}{2}\sigma_Y^2 t^2\}$$

- Let $Z = X + Y$.

$$\begin{aligned} M_Z(t) &\overset{X \perp Y}{=} M_X(t)M_Y(t) = \exp\{\mu_X t + \frac{1}{2}\sigma_X^2 t^2\}\exp\{\mu_Y t + \frac{1}{2}\sigma_Y^2 t^2\} \\ &= \exp\{(\mu_X + \mu_Y)t + \frac{1}{2}(\sigma_X^2 + \sigma_Y^2)t^2\} \end{aligned}$$

Which indicates that $Z \sim N(\mu_X + \mu_Y, \sigma_X^2 + \sigma_Y^2)$

MGF of Univariate Normal: Sample Mean

- If $X_1, \cdots, X_n \overset{iid}{\sim} N(\mu, \sigma^2)$.
- We have showed that $E[\bar{X}] = \mu$ and $Var[\bar{X}] = \sigma^2/n$.
- How to prove $\bar{X}$ follows a normal distribution?
- A short proof:

$$M_{\bar{X}}(t) = \prod_{i=1}^{n} M_{X_i}(\frac{t}{n}) = \left(\exp\{\mu\frac{t}{n} + \frac{1}{2}\sigma^2\frac{t^2}{n^2}\}\right)^n = \exp\{\mu t + \frac{1}{2}\frac{\sigma^2}{n}t^2\}$$

Based on the $M_{\bar{X}}(t)$, $\bar{X} \sim N(\mu, \frac{\sigma^2}{n})$.

MGF of Univariate Normal: Sample Mean

- A proof with more details explained

$$
\begin{aligned}
M_{\bar{X}}(t) &= E[e^{t\bar{X}}] = E[e^{\frac{t}{n}\sum_{i=1}^{n} X_i}] = E[e^{\frac{t}{n}X_1+\frac{t}{n}X_2+\cdots+\frac{t}{n}X_n}] \\
&\stackrel{iid}{=} E[e^{\frac{t}{n}X_1}]\cdots E[e^{\frac{t}{n}X_n}] = M_{X_1}(\frac{t}{n})\cdots M_{X_n}(\frac{t}{n}) \\
&= \exp\{\mu\frac{t}{n} + \frac{1}{2}\sigma^2\frac{t}{n}\}\cdots\exp\{\mu\frac{t}{n} + \frac{1}{2}\sigma^2\frac{t}{n}\} \\
&= \exp\{\mu t + \frac{1}{2}\frac{\sigma^2}{n}t\}
\end{aligned}
$$

Based on the $M_{\bar{X}}(t)$, $\bar{X} \sim N(\mu, \frac{\sigma^2}{n})$.

Subsection 2

MGF of MVN

MGF of Multivariate Normal

- The moment generating function (MGF) of a random vector $\mathbf{X}_{p\times 1}$ is defined as: $M_{\mathbf{X}}(\mathbf{t}) = \mathbb{E}[e^{\mathbf{t}^T\mathbf{X}}]$.
- Here t is a $p \times 1$ vector.
- For the multivariate normal distribution with mean vector $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$, the MGF is given by:

$$M_{\mathbf{X}}(\mathbf{t}) = \exp\left(\boldsymbol{\mu}^T\mathbf{t} + \frac{1}{2}\mathbf{t}^T\boldsymbol{\Sigma}\mathbf{t}\right)$$

MGF of MVN: Examples

1. Bivariate standard normal distribution:

$$\boldsymbol{\mu} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \boldsymbol{\Sigma} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, M_{\mathbf{X}}(\mathbf{t}) = \exp\left(\frac{1}{2}\mathbf{t}^T\boldsymbol{\Sigma}\mathbf{t}\right)$$

2. Bivariate normal distribution with specific mean vector and covariance matrix:

$$\boldsymbol{\mu} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}, \boldsymbol{\Sigma} = \begin{pmatrix} 4 & 1 \\ 1 & 9 \end{pmatrix}, M_{\mathbf{X}}(\mathbf{t}) = \exp\left(\boldsymbol{\mu}^T\mathbf{t} + \frac{1}{2}\mathbf{t}^T\boldsymbol{\Sigma}\mathbf{t}\right)$$

MGF of MVN: A Linear Combination

- Let $\mathbf{X}_{p\times 1} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$.
- The MGF of $\mathbf{X}$ is

$$M_{\mathbf{X}}(\mathbf{t}) = E[e^{\mathbf{t}^T\mathbf{X}}] = \exp\left(\boldsymbol{\mu}^T\mathbf{t} + \frac{1}{2}\mathbf{t}^T\boldsymbol{\Sigma}\mathbf{t}\right)$$

- We want to show that the linear combination $\mathbf{Y} = \mathbf{A}_{q\times p}\mathbf{X}$ also follows a MVN.

MGF of MVN: A Linear Combination

- To find the distribution of Y, we derive the MGF of Y.

$$M_{\mathbf{Y}}(\mathbf{t}) = E[e^{t^T AX}] = M_{\mathbf{X}}(\mathbf{A}^T\mathbf{t}) = \exp\left(\boldsymbol{\mu}^T\mathbf{A}^T\mathbf{t} + \frac{1}{2}\mathbf{t}^T\mathbf{A}\boldsymbol{\Sigma}\mathbf{A}^T\mathbf{t}\right)$$
$$= \exp\left((\mathbf{A}\boldsymbol{\mu})^T\mathbf{t} + \frac{1}{2}\mathbf{t}^T(\mathbf{A}\boldsymbol{\Sigma}\mathbf{A}^T)\mathbf{t}\right),$$

- $M_{\mathbf{Y}}(\mathbf{t})$ has the form of the MGF of a multivariate normal distribution with mean vector $\mathbf{A}\boldsymbol{\mu}$ and covariance matrix $\mathbf{A}\boldsymbol{\Sigma}\mathbf{A}^T$.
- As a result, the linear combination

$$\mathbf{Y} = \mathbf{AX} \sim N(\mathbf{A}\boldsymbol{\mu}, \mathbf{A}\boldsymbol{\Sigma}\mathbf{A}^T)$$

MGF of MVN: The Sample Mean Vector

- Let $\mathbf{X}_1, \cdots \mathbf{X}_n$ be a random sample from $N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$.
- We have defined the sample mean vector $\bar{\mathbf{X}}$
- We have shown that
  - $\mathbb{E}[\bar{\mathbf{X}}] = \boldsymbol{\mu}$
  - $Cov[\bar{\mathbf{X}}] = \frac{\boldsymbol{\Sigma}}{n}$
- Next, we will show that it follows a multivariate normal distribution.

MGF of MVN: The Sample Mean Vector

- We first calculate its MGF:

$$M_{\bar{\mathbf{X}}}(\mathbf{t}) \overset{iid}{=} \prod_{i=1}^{n} M_{\mathbf{X}_i}(\frac{1}{n}\mathbf{t}) = \left(\exp\left(\boldsymbol{\mu}^T \frac{1}{n}\mathbf{t} + \frac{1}{2}\left(\frac{1}{n}\mathbf{t}\right)^T \boldsymbol{\Sigma}\left(\frac{1}{n}\mathbf{t}\right)\right)\right)^n$$
$$= \exp\left(n\left(\boldsymbol{\mu}^T \frac{1}{n}\mathbf{t} + \frac{1}{2n}\mathbf{t}^T \boldsymbol{\Sigma}\mathbf{t}\right)\right)$$
$$= \exp\left(\boldsymbol{\mu}^T \mathbf{t} + \frac{1}{2}\mathbf{t}^T \frac{1}{n}\boldsymbol{\Sigma}\mathbf{t}\right)$$

- $M_{\bar{\mathbf{X}}}(\mathbf{t})$ has the form of the MGF of a multivariate normal distribution with mean vector $\boldsymbol{\mu}$ and covariance matrix $\frac{1}{n}\boldsymbol{\Sigma}$, i.e, $\bar{\mathbf{X}} \sim N(\boldsymbol{\mu}, \frac{\boldsymbol{\Sigma}}{n})$

Section 4

Zero-Covariance

Independence of Normals Under Jointly Normal

- In general, zero-correlation does not guarantee independence
- **Theorem** If the joint distribution of $\mathbf{X}_1$ (a $p \times 1$ random vector) and $\mathbf{X}_2$ is multivariate normal, i.e.,

$$\begin{pmatrix} \mathbf{X}_1 \\ \mathbf{X}_2 \end{pmatrix} \sim N(\begin{pmatrix} \boldsymbol{\mu}_1 \\ \boldsymbol{\mu}_2 \end{pmatrix}, \begin{pmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{21} & \boldsymbol{\Sigma}_{22} \end{pmatrix}),$$

  then $\mathbf{X}_1 \perp \mathbf{X}_2 \Leftrightarrow \boldsymbol{\Sigma}_{12} = 2$
- Proof: omitted. A result about MGF can be used to prove independence.

The Joint Distribution of Two Linear Functions

- Let $\mathbf{X}_{p\times 1} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$.
- Let $\mathbf{Y} = \mathbf{AX}$ and $\mathbf{Z} = \mathbf{BX}$.
- What is the joint distribution of Y and Z?
- Note that

$$\begin{pmatrix} \mathbf{Y} \\ \mathbf{Z} \end{pmatrix} = \begin{pmatrix} A \\ B \end{pmatrix} \mathbf{X},$$

i.e., the new random vector $\begin{pmatrix} \mathbf{Y} \\ \mathbf{Z} \end{pmatrix}$ is a linear combination of $\mathbf{X}$ that follows a MVN.

The Joint Distribution of Two Linear Functions

- As a result, the joint distribution of two linear functions, namely $\mathbf{Y}$ and $\mathbf{Z}$ are jointly normal (i.e, MVN).

$$\begin{pmatrix} \mathbf{Y} \\ \mathbf{Z} \end{pmatrix} \sim N(\begin{pmatrix} A \\ B \end{pmatrix} \boldsymbol{\mu}, \begin{pmatrix} A \\ B \end{pmatrix} \boldsymbol{\Sigma} \begin{pmatrix} A^T & B^T \end{pmatrix})$$
$$\sim N(\begin{pmatrix} A\boldsymbol{\mu} \\ B\boldsymbol{\mu} \end{pmatrix}, \begin{pmatrix} A\boldsymbol{\Sigma}A^T & A\boldsymbol{\Sigma}B^T \\ B\boldsymbol{\Sigma}A^T & B\boldsymbol{\Sigma}B^T \end{pmatrix})$$

By the Theorem on the slide titled "Independence of Normals Under Jointly Normal",

$$\mathbf{Y} \perp \mathbf{Z} \Leftrightarrow A\Sigma B^T = 0$$

Subsection 1

Sample Mean and Sample Variance

The Independence Between Sample Mean and Sample Variance

- Let $\mathbf{X} = (X_1, X_2, ..., X_n)^T$ be a random sample from a normal distribution with mean μ and variance σ^2.
- The sample mean and sample variance are defined as:
  - Sample mean: $\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$
  - Sample variance: $s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2$
- We want to show that $\bar{X}$ and s^2 are independent.

Proof

- We first rewrite the sample mean:

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i = \frac{1}{n}\mathbf{1}^T\mathbf{X}$$

- We have shown that $s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2 = \frac{1}{n-1}X^T\mathbb{C}X$, where $\mathbb{C} = \mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T$. In addition, it is easy to verify that $\mathbb{C} = \mathbb{C}^T, \mathbb{C}^2 = \mathbb{C}$. Thus, the distribution of s^2 can be rewritten to

$$s^2 = \frac{1}{n-1}(\mathbb{C}\mathbf{X})^T(\mathbb{C}\mathbf{X}),$$

which indicates that the distribution s^2 is determined by the distribution of $\mathbb{C}X$.

Proof (continued)

- Clearly $\bar{X}$ and $\mathbb{C}\mathbf{X}$ are linear combinations of $\mathbf{X}$, which follows a multivariate normal with covariance $\mathbf{\Sigma} = \mathbf{I}$. Thus,

$$cov(\bar{X}, \mathbb{C}) = \frac{1}{n}\mathbf{1}^T \Sigma \mathbb{C}\mathbf{X} = \frac{1}{n}\mathbf{1}^T \mathbb{C} = 0$$

  Please verify that last step.
- By Theorem on "Independence of Normals Under Jointly Normal", we have $\bar{X}$ and $\mathbb{C}\mathbf{X}$ are independent.
- Now we can conclude the $\bar{X}$ and s^2 are independent.

Section 5

MVN: $\bar{\mathbf{X}}$ and S

The Independence Between Sample Mean Vector and Sample Covariance Matrix

- Consider a random sample from $N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ (MVN). Let $\bar{\boldsymbol{X}}$ be the sample mean vector.
- We have shown that $\mathbb{E}[\bar{\mathbf{X}}] = \boldsymbol{\mu}$ and $Cov[\bar{\mathbf{X}}] = \boldsymbol{\Sigma}$.
- How to prove that the sample mean vector and the sample covariance matrix are independent?
- Messier way: vectorize the $n \times p$ matrix $\mathbf{X}$ to a $(np) \times 1$ vector and then apply the condition for independent linear combinations under MVN
- Neater way: use properties of Matrix Normal Distribution

Sample Mean Vector and Sample Covariance Matrix

- If we have a random sample from MVN, we will show that $\bar{\mathbf{X}}$ and S are independent
- Proof outline
  1. Vectorize $\mathbf{X}_{n\times p}$ to a vector $\tilde{\mathbf{X}}_{(np)\times 1}$, which follows a MVN
  2. Show that the distribution of $\bar{\mathbf{X}}$ is determined by a linear function of $\tilde{\mathbf{X}}_{(np)\times 1}$
  3. Show that the distribution of S is determined by a linear function of $\tilde{\mathbf{X}}_{(np)\times 1}$
  4. Find the covariance of the two linear functions
  5. Conclude that the two linear functions are independent, which indicates that the sample mean vector and the sample covariance matrix are independent

Step 1a: Vectorize

- We vectorize $\mathbf{X}_{n\times p}$ such that
  - the first n random variables are for the first feature
  - ... ...
  - the last n random variables are for the last feature

$$\tilde{\mathbf{X}}_{(np)\times 1} = \begin{pmatrix} \mathbf{X}_{(1)} \\ \vdots \\ \mathbf{X}_{(p)} \end{pmatrix}$$

- What is the distribution of $\mathbf{X}_{(1)}$?

Step 1b: The distribution of $\mathbf{x}_{n\times p}$

$$\tilde{\mathbf{X}}_{(np)\times 1} = \begin{pmatrix} \mathbf{X}_{(1)} \\ \vdots \\ \mathbf{X}_{(p)} \end{pmatrix} \sim N(\boldsymbol{\mu} \otimes \mathbf{1}_n, \boldsymbol{\Sigma} \otimes \mathbf{I}_n)$$

$$\sim N(\begin{pmatrix} \mu_1 \mathbf{1}_n \\ \vdots \\ \mu_p \mathbf{1}_n \end{pmatrix}, \begin{pmatrix} \sigma_{11}\mathbf{I}_n & \cdots & \sigma_{1p}\mathbf{I}_n \\ \vdots & \ddots & \vdots \\ \sigma_{p1}\mathbf{I}_n & \cdots & \sigma_{pp}\mathbf{I}_n \end{pmatrix})$$

Step 2: The sample mean vector

- The sample mean vector can be written as linear functions of $\tilde{\mathbf{X}}$:

$$\bar{\mathbf{X}} = \frac{1}{n} \begin{pmatrix} \mathbf{1}_n^T & \mathbf{0}_n^T & \cdots & \mathbf{0}_n^T \\ \mathbf{0}_n^T & \mathbf{1}_n^T & \cdots & \mathbf{0}_n^T \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0}_n^T & \mathbf{0}_n^T & \cdots & \mathbf{1}_n^T \end{pmatrix}_{p\times(np)} \tilde{\mathbf{X}}$$

Step 3: The sample covariance matrix

- Recall that we have shown the following result

$$S = \frac{1}{n-1}\mathbf{X}^T\mathbb{C}\mathbf{X} = \frac{1}{n-1}(\mathbb{C}\mathbf{X})^T\mathbb{C}\mathbf{X}$$

- So we only need to focus on $\mathbb{C}\mathbf{X}$, the centered random matrix.
- The vectorized version of the centered random matrix is

$$vec(\mathbb{C}\mathbf{X}) = \begin{pmatrix} \mathbb{C} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbb{C} & \cdots & \mathbf{0} \\ \cdots & \cdots & \cdots & \cdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbb{C} \end{pmatrix}_{(np)\times(np)} \tilde{\mathbf{X}}$$

Step 4: The covariance of the two linear functions

So we have the following results -

$$\tilde{\mathbf{X}}_{(np)\times 1} \sim N(\boldsymbol{\mu}\otimes\mathbf{1}_n, \boldsymbol{\Sigma}\otimes\mathbf{I}_n) \sim N(\begin{pmatrix}\mu_1\mathbf{1}_n \\ \vdots \\ \mu_p\mathbf{1}_n\end{pmatrix}, \begin{pmatrix}\sigma_{11}\mathbf{I}_n & \cdots & \sigma_{1p}\mathbf{I}_n \\ \cdots & \cdots & \cdots \\ \sigma_{p1}\mathbf{I}_n & \cdots & \sigma_{pp}\mathbf{I}_n\end{pmatrix})$$

- The distribution of $\bar{\mathbf{X}}$ and S depend on

$$\bar{\mathbf{X}} = \frac{1}{n}\begin{pmatrix}\mathbf{1}_n^T & \mathbf{0}_n^T & \cdots & \mathbf{0}_n^T \\ \mathbf{0}_n^T & \mathbf{1}_n^T & \cdots & \mathbf{0}_n^T \\ \cdots & \cdots & \cdots & \cdots \\ \mathbf{0}_n^T & \mathbf{0}_n^T & \cdots & \mathbf{1}_n^T\end{pmatrix}\tilde{\mathbf{X}}, vec(\mathbb{C}\mathbf{X}) = \begin{pmatrix}\mathbb{C} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbb{C} & \cdots & \mathbf{0} \\ \cdots & \cdots & \cdots & \cdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbb{C}\end{pmatrix}\tilde{\mathbf{X}}$$

Step 4: The covariance of the two linear functions

- Let $\tilde{\boldsymbol{\Sigma}}$ denote the covariance matrix of $\tilde{\mathbf{x}}$
- Let $\mathbb{A}$ denote the matrix such that $\bar{\mathbf{X}} = \mathbb{A}\tilde{\mathbf{x}}$
- Let $\mathbb{B}$ denote the matrix such that $vec(\mathbb{C}\mathbf{X}) = \mathbb{B}\tilde{\mathbf{X}}$
- It can be verified that $\mathbb{A}\tilde{\boldsymbol{\Sigma}}\mathbb{B}^T = \mathbf{0}$.

Step 5: The independnece of the two linear functions

- Both $\bar{\mathbf{X}}$ and $vec(\mathbb{C}\mathbf{X})$ are linear function of the same MVN-distributed random vector $\tilde{\mathbf{X}}$
- Their covariance matrix is zero, which indicates that they are independent by Theorem on "Independence of Normals Under Jointly Normal".
- The sample covariance matrix only depends on the centered data, $vec(\mathbb{C}\mathbf{X})$ (the vector form) up to a constant
- Therefor, if we have a random sample from a MVN, the sample mean vector and the sample covariance matrix are independent
- The proof is lengthy. It can be more compact if we introduce matrix normal distribution.

A Simulation Study

- Suppose we have a random sample from a normal distribution.
- How to use a simulation study to show that sample mean and sample variance are uncorrelated (in fact they are also independent)?