Techniques and Applications of Multivariate statistics (I)

Department of Statistics

Professor Yong-Seok Choi

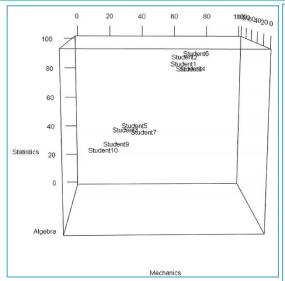
E-mail: yschoi@pusan.ac.kr

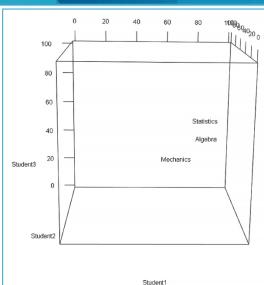
Home: yschoi.pusan.ac.kr

Contents

Multivariate Statistics (I) in Spring

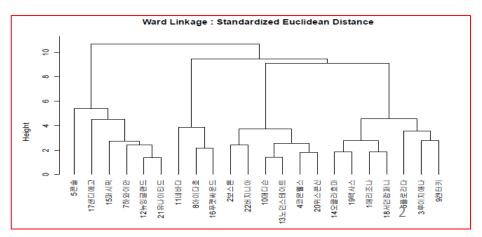
- 1. Multivariate Data Analysis
- 2. Principal Component Analysis (PCA)
- 3. Factor Analysis (FA)
- 4. Canonical Correlation Analysis (CCA)
- 5. Cluster Analysis (CA)





Multivariate Statistics (II) in Autumn

- 6. Discrimination and Classification Tree (DCT)
- 7. Multidimensional Scaling (MDS)
- 8. Correspondence Analysis (CRA)
- 9. Biplot
- 10. Shape Analysis



Multivariate Statistics (I)

1. Multivariate Data Analysis (MDA)

Contents

- 1.1. Multivariate data analysis
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- 1.3 Introduction and visualization of multivariate data
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- 1.6 Multivariate normal distribution and its useful property
- 1.7 Wishart dist and Hotelling's T^2 -dist
- 1.8 Test of multivariate normality
- 1.9 R for EDA: Practice Time

1.1 Multivariate data analysis

Summarizing Data

[Example 1.1.1] 3 subjects' marks of 10 students

[Table 1.1.1] (3subjects.txt)

| Students | Mechanics | | Statistics |
|---------------|-----------|----|------------|
| Student1 | 65 | 85 | 85 |
| Student2 | 65 | 80 | 90 |
| Student3 | 30 | 40 | 50 |
| Student4 | 70 | 83 | 82 |
| Student5 | 35 | 43 | 52 |
| Student6 | 72 | 82 | 92 |
| Student7 | 40 | 43 | 48 |
| Student8 | 68 | 83 | 82 |
| Student9 | 25 | 32 | 43 |
| Student10 | 17 | 51 | 35 |
| [5] Stem-and- | Leaf Plot | | |
| 0 7 | 2 2 | | 2 5 |
| 2 505 | 4 0331 | l | 4 3802 |
| 4 0 | 6 | | 6 |
| 6 55802 | 8 0233 | 35 | 8 22502 |
| Mechanics | Algebra | | Statistics |

[1] Descriptive Statistics

| Mechanics | Algebra | Statistics |
|----------------|----------------|----------------|
| Min. :17.00 | Min.:32.00 | Min. :35.00 |
| 1st Qu. :31.25 | 1st Qu .:43.00 | 1st Qu. :48.50 |
| Median :52.50 | Median :65.50 | Median:67.00 |
| Mean :48.70 | Mean :62.20 | Mean :65.90 |
| 3rd Qu. :67.25 | 3rd Qu. :82.75 | 3rd Qu. :84.25 |
| Max.:72.00 | Max.:85.00 | Max. :92.00 |

[2] Covariance Matrix

Mechanics Algebra Statistics

Mechanics 453.3444 431.5111 459.0778

Algebra 431.5111 484.6222 450.2444

Statistics 459.0778 450.2444 487.8778

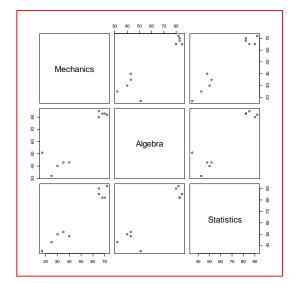
[3] Correlation Matrix

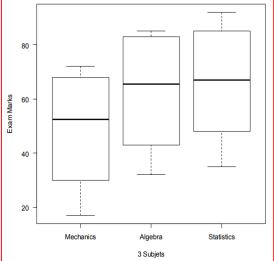
Mechanics 1.0000000 0.9206110 0.9761501

Algebra 0.9206110 1.0000000 0.9259578

Statistics 0.9761501 0.9259578 1.0000000

Mechanics Algebra Statistics





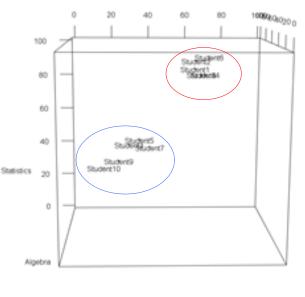
[4] Multiple Scatter Plot

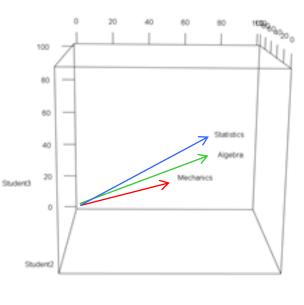
[5] Box Plot

1.1 Multivariate data analysis

❖ Geometrical Representations of 3-dimensinal space

| Students | Mechanics | Algebra | Statistics |
|-----------|-----------|---------|------------|
| Student1 | 65 | 85 | 85 |
| Student2 | 65 | 80 | 90 |
| Student3 | 30 | 40 | 50 |
| Student4 | 70 | 83 | 82 |
| Student5 | 35 | 43 | 52 |
| Student6 | 72 | 82 | 92 |
| Student7 | 40 | 43 | 48 |
| Student8 | 68 | 83 | 82 |
| Student9 | 25 | 32 | 43 |
| Student10 | 17 | 51 | 35 |





a) n = 10 points in p-space

b) p = 3 points in n-space

[R-code 1.1.2] 3subjects-3d.R

```
Data1.1.1<-read.table("3subjects.txt", header=T) X<-Data1.1.1 library(rgl)
```

```
# Observations in Variables Space lim<-c(0, 100) plot3d(X[,1], X[,2], X[,3],xlim=lim, ylim=lim, zlim=lim, xlab="Mechanics", ylab="Algebra", zlab="Statistics") text3d(X[,1], X[,2], X[,3],rownames(X)) # Variables in Observations Space plot3d(X[1,], X[2,], X[3,], xlim=lim, ylim=lim, zlim=lim, xlab="Student1", ylab="Student2", zlab="Student3") text3d(X[1,], X[2,], X[3,], colnames(X))
```

1.2 Types of multivariate analysis techniques

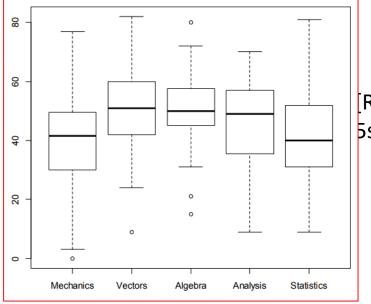
- Definition of Multivariate Analysis
- A collection of techniques dealing with data containing observations on two or more variables.
- Multivariate data contain the *n* observations and *p* variables

❖ Techniques based on the geometrical ideas

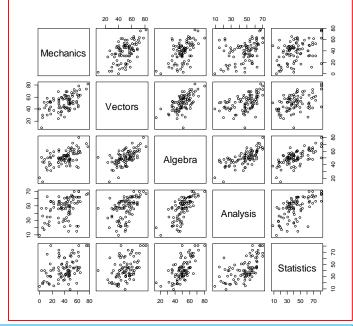
- ✓ **R-Techniques**: Analyses based on the matrix of covariance or correlations between variables.
 - PCA/FA/CCA/Biplot
- ✓ Q-Techniques: Analyses based on the matrix of distances between observations.
 - CA/DA/MDS/SCA/MCA/Biplot
- ✓ V-Techniques: Visualization techniques based on relationships among variables or observations.
 - Biplot/SCA/MCA/MDS/Stars Plot/Mosaic Plot

P [Data 1.3.1] Examination marks on 5 subjects (Mardia et al., 1979, pp. 3-4)

| | Closed | I-DOOK | Open-book | | |
|---------|--------------|------------|------------|-------------|---------------|
| Student | Mechanics(c) | Vectors(c) | Algebra(o) | Analysis(o) | Statistics(o) |
| 1 | 77 | 82 | 67 | 67 | 81 |
| 2 | 63 | 78 | 80 | 70 | 81 |
| 3 | 75 | 73 | 71 | 66 | 81 |
| 4 | 55 | 72 | 63 | 70 | 68 |
| 5 | 63 | 63 | 65 | 70 | 63 |
| | | | • | | |
| 87 | 5 | 26 | 15 | 20 | 20 |
| 88 | 0 | 40 | 21 | 9 | 14 |



Classed-back



[R-code 1.3.1] 5subjects-boxsctter.R

Questions:

Multiple Scatter Plot plot(X)

Box Plot boxplot(X)

- How to combine or average these marks?
- Relationship between open-book and closed-book?

Applications: PCA/FA/CCA

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• [Data 1.3.2] KLPGA player's grades (www.klpga.com, 2006) [R-code 1.3.2] klpga-boxscatter.R

Putting average, Green in regulation % , Par save % , Par break % , Scoring average, Prize rate

| | | | | <u> </u> | | |
|---|---|---|---|---|--|---|
| 선수 | 평균퍼팅수 | 그린적중율 | 파세이브율 | 파브레이크율 | 평균타수 | 상금율 |
| 1 2 3 4 5 6 7 8 9 10 | 30.36 30.85 31.364 30.97 31.09 31.25 29.86 31.91 | 82.72 76.94 79.632 79.636 78.559 77.47 69.57 78.28 | 90.129.25 85.55.57 86.59.084 86.69.57 86.69.95 86.77 | 23,77 23,69 19,26 21,30 17,17 20,48 16,82 15,63 15,32 | 69,58 70,85 70,47 70,47 71,23 71,61 71,84 71,73 | 100.0 63.7 59.4 50.2 44.0 38.0 30.5 21.1 19.2 |
| 46 47 48 49 50 | 30,79 31,70 31,20 32,50 31,07 | 63,07 65,66 70,19 71,35 68,72 | 78,59 76,26 80,19 78,13 80,36 | 11,76 12,63 14,44 12,67 14,88 | 74,06 74,52 73,53 74,06 73,39 | 6,5 6,3 6,2 5,9 5,1 |

Data1.3.2<-read.table("klpga.txt", header=T)
X<-Data1.3.2[, -1]

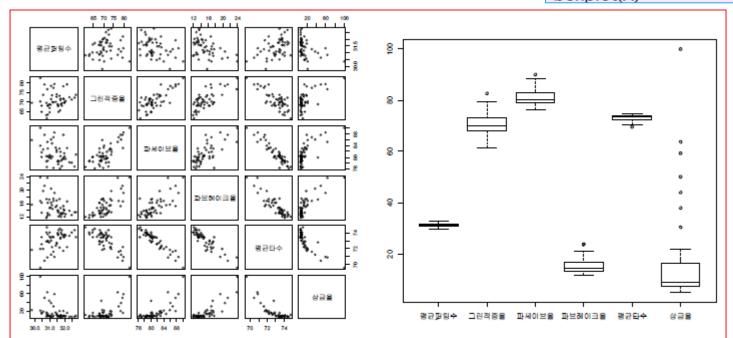
Descriptive Statistics
summary(X)

Covariance Matrix
cov(X)

Correlation Matrix
cor(X)

Multiple Scatter Plot
plot(X)

Boxplot of 3 Subjects
boxplot(X)



Applications : CCA/CA/DCT

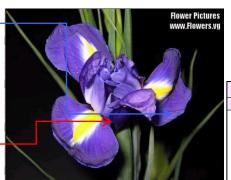
• [Data 1.3.4] Fisher's Iris flower data(Johnson & Wichern, 2002, p. 657)

X1: Sepal length

X2: Sepal width

X3: Petal length

X4: Petal width



Questions:

- Ask to which species a new iris of unknown species belongs?
- How to find the criteria for classifying?



Sir Ronald Aylmer Fisher (17 February 1890 – 29 July 1962) English statistician, evolutionary biologist, and geneticis

Applications : DCT/CA







Iris Versicolor

Iris Setosa

Iris Virginica

Multiple Scatter Plot and Box Plot for Iris flower data

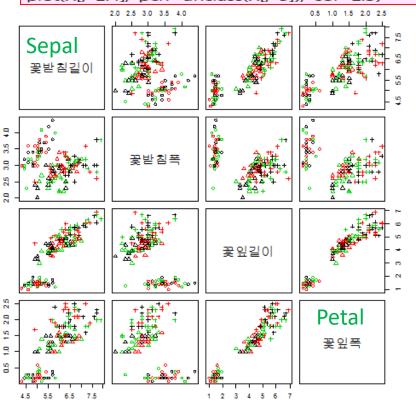
[R-code 1.3.4] irisflower-boxscatter.R

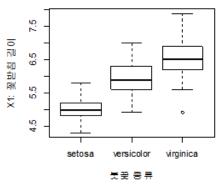
```
Data1.3.4<-read.table("irisflower.txt", header=T)
X<-Data1.3.4[, -1]

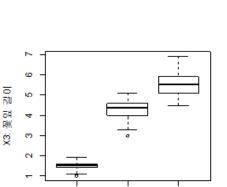
# Box Plot
par(mfrow=c(2, 2))
boxplot(꽃받침길이~group, data=X, xlab="붓꽃 종류", ylab="X1: 꽃받침 길이")
boxplot(꽃받침폭~group, data=X, xlab="붓꽃 종류", ylab="X2: 꽃받침 폭")
boxplot(꽃받침폭~group, data=X, xlab="붓꽃 종류", ylab="X2: 꽃받침 폭")
boxplot(꽃잎길이~group, data=X, xlab="붓꽃 종류", ylab="X3: 꽃잎 길이")
boxplot(꽃잎꼭~group, data=X, xlab="붓꽃 종류", ylab="X4: 꽃잎 폭")

# Multiple Scatter Plot
plot(X[, 1:4], pch=unclass(X[, 5]), col=1:3)
```

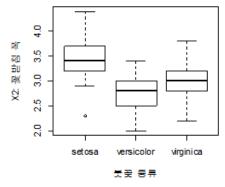


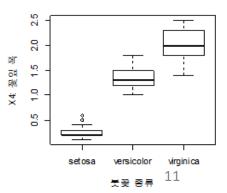






붗꽃 종류





[Data 1.3.5] Economic Views Data of the 1990

| 기관 | 성장률 | GNP | 수출 | 수입 | 국제 흑자 | 연말 외채 | 연말 환 율 | 실업률 | 소비 물가 | 임금 상승 |
|---------|-----|------|-----|-----|----------|----------|----------------------|-----|----------|----------|
| 한국은행 | 8.2 | 1950 | 698 | 650 | 98 | 280 | 630 | 3.0 | 5.7 | 12.0 |
| 대우증권 | 9.5 | 2100 | 710 | 620 | 110 | 270 | 640 | 2.7 | 4.5 | 12.0 |
| 동서증권 | 9.0 | 2000 | 690 | 630 | 100 | 290 | 630 | 2.6 | 6.0 | 12.0 |
| 전경련 | 7.8 | 1850 | 668 | 660 | 88 | 280 | 620 | 3.0 | 6.4 | 13.8 |
| 대한상공회의소 | 8.5 | 1928 | 710 | 670 | 90 | 290 | 620 | 3.0 | 6.0 | 10.0 |
| 중소기업중앙회 | 9.0 | 1958 | 710 | 615 | 95 | 280 | 603 | 4.0 | 6.0 | 10.0 |
| 현대자동차 | 8.5 | 1900 | 700 | 610 | 100 | 250 | 620 | 3.2 | 5.5 | 14.0 |
| 삼성물산 | 8.0 | 1900 | 700 | 640 | 100 | 280 | 640 | 2.7 | 5.5 | 10.0 |
| 선경 | 8.5 | 1950 | 700 | 620 | 120 | 300 | 630 | 2.7 | 7.0 | 12.0 |
| 대우경제연구소 | 7.9 | 1900 | 697 | 645 | 95 | 280 | 610 | 2.9 | 6.8 | 15.0 |
| 신한종합연구소 | 9.0 | 2030 | 700 | 620 | 100 | 275 | 630 | 3.0 | 7.0 | 13.0 |
| 동서경제연구소 | 8.5 | 1950 | 690 | 630 | 90 | 290 | 630 | 2.9 | 6.0 | 12.0 |
| 고려대학교 | 9.9 | 1870 | 729 | 649 | 123 | 260 | 616 | 3.4 | 6.1 | 15.8 |
| 중앙대학교 | 8.5 | 1700 | 700 | 630 | 90 | 260 | 620 | 4.0 | 6.0 | 14.0 |

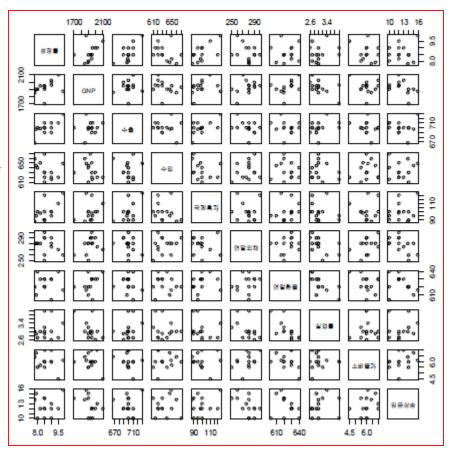
한국은행 대우증권 동서중권 전경련

대한상공회의소 중소기업중앙회 현대자동차 상성불산

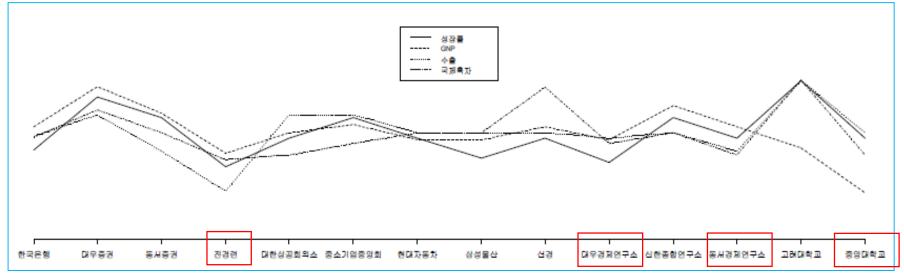
선경 대우경제연구소 신한종합연구소 동서경제연구소

고려대학교 중앙대학교 국제회자 성장를

Growth /Export/Import/ Black-ink balance/ Foreign debt /Exchange rate/ Unemployed rate /Consumer price rate /Wage increase rate



❖ [Data 1.3.5] Economic Views Data



```
Data1.3.5 <- read.table("economicview.txt", header=T)
X<-Data1.3.5[, -1]
                                            [R-code 1.3.5] economicview-starscatterparcoord.R
# Multiple Scatter Plot
plot(X)
# Star Plot
X < -scale(as.matrix(X[, c(1,2,3,5)]))
rownames(X) < - Data1.3.5[, 1]
stars(X,key.loc=c(8,2), full = FALSE)
# Parallel Coordinate Plot
library(gclus)
parcoordlabel < -function(x, col = 1, lty = 1, var.label = F,...)
     rx < -lapply(X, range, na.rm = TRUE)
    matplot(1L:ncol(x), t(x), type = "l", col = col, lty = 1:nrow(X), lwd=1.5,
        xlab = "", ylab = "", axes = FALSE,
            ylim=c(-4, 4), xlim=c(1, nrow(X)), ...)
    axis(1, at = 1L:ncol(x), labels = colnames(x))
    legend("top", horiz=F, legend=colnames(X), lty=1:nrow(X),
          col=1, cex=0.8, lwd=1.5)
    for (i in 1L:ncol(x))
      invisible()
windows(height=5, width=12)
parcoordlabel(t(X))
```

Representation

$$\checkmark n \times p$$
 data matrix

$$X = \begin{bmatrix} x_{11} \cdots x_{1j} \cdots x_{1p} \\ \vdots & \vdots & \vdots \\ x_{i1} \cdots x_{ij} \cdots & x_{ip} \\ \vdots & \vdots & \vdots \\ x_{n1} \cdots x_{nj} \cdots & x_{np} \end{bmatrix} = (x_{ij}), \ i = 1, \ ..., \ n; \ j = 1, \ ..., \ p$$

80

10x3 Data Matrix from [Data 1.1.1]

$$HX$$
 X

✓ Centred data matrix :
$$Y = X - \frac{1}{n}JX = HX$$
 $X = \begin{bmatrix} \vdots \\ x_i^t \\ \vdots \\ x_n^t \end{bmatrix} = [x_{(1)}, ..., x_{(j)}, ..., x_{(p)}]$ Standardized data matrix : $Z = HXD_s^{-1/2}$

$$\checkmark$$
 Standardized data matrix : $Z = HXD_s^{-1/2}$

where $H = I - \frac{1}{n}J$: centring matrix and symmetric idempotent

J =Square matrix with all elements 1, I =unit matrix

$$D_s^{1/2} = diag(\sqrt{s_{11}}\,,\,...,\,\sqrt{s_{pp}})$$
 : SD matrix

Representation of Data in Space: $|x_{(i)} \in \mathbb{R}^n$, j = 1, ..., p

$$x_i \in \mathbb{Q}^p$$
, $i = 1, ..., n$
 $x_{(i)} \in \mathbb{R}^n$, $j = 1, ..., p$

Sample Summary Statistics

- (Sample) mean vector $\overline{x} = [\overline{x}_1,...,\overline{x}_j,...,\overline{x}_p]^t = \frac{X^t 1_n}{n}$

- (Sample variance-) covariance matrix

$$s_{jj} = s_j^2 = \frac{1}{n-1} \sum_{i=1}^n (x_{ij} - \overline{x_j})^2$$

$$s_{kj} = s_{jk} = \frac{1}{n-1} \sum_{i=1}^n (x_{ik} - \overline{x_k})(x_{ij} - \overline{x_j})$$

- Algebraic relationship:

$$S = \frac{1}{n-1} Y^t Y = \frac{1}{n-1} X^t H X.$$

- Correlation matrix

$$\boldsymbol{y}_{(j)} = (y_{1j}, \ ..., \ y_{nj})^t = (x_{1j} - \overline{x}_j, \ ..., \ x_{nj} - \overline{x}_j)^t, \ j = 1, \ \cdots, \ p$$

 $=\frac{\sum\limits_{i=1}^{n}(x_{ik}-\overline{x_{k}}\,)(x_{ij}-\overline{x_{j}}\,)}{\sqrt{\sum\limits_{i=1}^{n}(x_{ik}-\overline{x_{k}}\,)^{2}}\,\sqrt{\sum\limits_{i=1}^{n}(x_{ij}-\overline{x_{j}}\,)^{2}}}$

 $\cos\theta_{kj} = \frac{\boldsymbol{y}_{(k)}^{t}\boldsymbol{y}_{(j)}}{||\boldsymbol{y}_{(k)}||\;||\boldsymbol{y}_{(i)}||}$

$$r_{kj} = \frac{s_{kj}}{\sqrt{s_{kk}} \sqrt{s_{jj}}} = \frac{\sum\limits_{i=1}^{n} (x_{ik} - \overline{x_k})(x_{ij} - \overline{x_j})}{\sqrt{\sum\limits_{i=1}^{n} (x_{ik} - \overline{x_k})^2} \sqrt{\sum\limits_{i=1}^{n} (x_{ij} - \overline{x_j})^2}} \quad \text{if } k \neq j$$

$$R = (r_{kj}) = \begin{bmatrix} 1 & r_{12} & \cdots & r_{1j} \cdots & r_{1p} \\ & 1 & \cdots & r_{2j} \cdots & r_{2p} \\ & & \ddots & & \ddots \\ & & & 1 & \cdots & r_{jp} \\ & & & \ddots & & \\ & & & 1 & \cdots & r_{jp} \\ & & & & 1 & \end{bmatrix}$$

- Algebraic relationship :

$$R = D_s^{-1/2} S D_s^{-1/2}$$
 where $D_s^{-1/2} = (D_s^{1/2})^{-1}$, $D_s^{1/2} = diag(\sqrt{s_{11}}, ..., \sqrt{s_{pp}})$: standard deviation matrix (squared root matrix)

Note:

The measurement units of variables are different or some variables have widely differing variances \Rightarrow correlation matrix R

- Measures for amount of variation from the centroid:

- generalized variance = |S| or |R|
- total variance = $tr(S) = s_{11} + \cdots + s_{pp}$, or tr(R)

Notes:

- Large values indicate a high degree of scatter about mean vector and low values represent concentration about mean vector
- |S|=0 : collinearity among variables
- |R|=0 : correlation among variables
- |S| or |R| plays an important role in MLE/FA(Sec 3.4 MLFA)/DCT
- tr(S) or tr(R) is a useful concept in PCA(Sec 2.4)/FA(Sec 3.4) :

goodness-of-fit

• [Example 1.4.1] S and R for examination marks on 3 subjects

$$\frac{-}{x}$$
 = (48.70, 62.20, 65.90)

• **Results of** [R-code 1.4.1] 3subjects-covcorr.R

| | 자료 | 행렬 X | | | 중심화 | 자료행렬 | Y | | 표준화 | 자료행렬 | Z |
|----|-----------|---------|------------|------|-----------|---------|------------|------|------------|------------|------------|
| | Mechanics | Algebra | Statistics | | Mechanics | Algebra | Statistics | | Mechanics | Algebra | Statistics |
| 1 | 65 | 85 | 85 | [1,] | 16.3 | 22.8 | 19.1 | [1,] | 0.7655498 | 1.0356981 | 0.8647247 |
| 2 | 65 | 80 | 90 | [2,] | 16.3 | 17.8 | 24.1 | [2,] | 0.7655498 | 0.8085713 | 1.0910924 |
| 3 | 30 | 40 | 50 | [3,] | -18.7 | -22.2 | -15.9 | [3,] | -0.8782688 | -1.0084429 | -0.7198493 |
| 4 | 70 | 83 | 82 | [4,] | 21.3 | 20.8 | 16.1 | [4,] | 1.0003810 | 0.9448474 | 0.7289040 |
| 5 | 35 | 43 | 52 | [5,] | -13.7 | -19.2 | -13.9 | [5,] | -0.6434376 | -0.8721668 | -0.6293022 |
| 6 | 72 | 82 | 92 | [6,] | 23.3 | 19.8 | 26.1 | [6,] | 1.0943135 | 0.8994220 | 1.1816395 |
| 7 | 40 | 43 | 48 | [7,] | -8.7 | -19.2 | -17.9 | [7,] | -0.4086063 | -0.8721668 | -0.8103964 |
| 8 | 68 | 83 | 82 | [8,] | 19.3 | 20.8 | 16.1 | [8,] | 0.9064486 | 0.9448474 | 0.7289040 |
| 9 | 25 | 32 | 43 | [9,] | -23.7 | -30.2 | -22.9 | [9,] | -1.1131000 | -1.3718457 | -1.0367641 |
| 10 | 17 | 51 | 35 | [10, | -31.7 | -11.2 | -30.9 | [10 | -1.4888300 | -0.5087640 | -1.3989525 |

| | 공분산 | 행렬 S | | | 상관형 | det R | |
|------------|-----------|----------|------------|------------|-----------|-----------|------------|
| | Mechanics | Algebra | Statistics | | Mechanics | Algebra | Statistics |
| Mechanics | 453.3444 | 431.5111 | 459.0778 | Mechanics | 1.0000000 | 0.9206110 | 0.9761501 |
| Algebra | 431.5111 | 484.6222 | 450.2444 | Algebra | 0.9206110 | 1.0000000 | 0.9259578 |
| Statistics | 459.0778 | 450.2444 | 487.8778 | Statistics | 0.9761501 | 0.9259578 | 1.0000000 |

| | 변동량척도 |
|------------------------|---------------------------|
| 일반화분산 $ S $ = 690375.8 | 일반화분산 $ R = 0.006440846$ |
| 총분산 $tr(S)$ = 1425.844 | 총분산 $tr(R) = 3$ |

- [Example 1.4.2] S and R for iris flower data
- **Results of** [R-code 1.4.2] irisflower-covcorr.R

| | | Å | S | | R | | | S | tr(S) | R | tr(R) | |
|------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------|----------|----------|----------|
| setosa | 0.124 0.099 0.016 0.010 | 0.099 0.144 0.012 0.009 | 0.016 0.012 0.030 0.006 | 0.010 0.009 0.006 0.011 | 1.000 0.743 0.267 0.278 | 0.743 1.000 0.178 0.233 | 0.267 0.178 1.000 0.332 | 0.278 0.233 0.332 1.000 | 0.000002 | 0.309204 | 0.353359 | 4.000000 |
| versicolor | 0.266 0.085 0.183 0.056 | 0.085 0.098 0.083 0.041 | 0.183 0.083 0.221 0.073 | 0.056 0.041 0.073 0.039 | 1.000 0.526 0.754 0.546 | 0.526 1.000 0.561 0.664 | 0.754 0.561 1.000 0.787 | 0.546 0.664 0.787 1.000 | 0.000019 | 0.624824 | 0.083594 | 4.000000 |
| virginica | 0.404 0.094 0.303 0.049 | 0.094 0.104 0.071 0.048 | 0.303 0.071 0.305 0.049 | 0.049 0.048 0.049 0.075 | 1.000 0.457 0.864 0.281 | 0.457 1.000 0.401 0.538 | 0.864 0.401 1.000 0.322 | 0.281 0.538 0.322 1.000 | 0.000133 | 0.888367 | 0.137390 | 4.000000 |

1.5 Multivariate data distance

(1) Euclidean Distance

$$d_{r,s} = ||\boldsymbol{x}_r - \boldsymbol{x}_s|| = \left[(\boldsymbol{x}_r - \boldsymbol{x}_s)^t (\boldsymbol{x}_r - \boldsymbol{x}_s) \right]^{1/2} = \left[\sum_{i=1}^p (x_{ri} - x_{si})^2 \right]^{1/2}$$

(2) Weighted Euclidean Distance

$$d_{T.S} = \|\boldsymbol{x}_r - \boldsymbol{x}_s\|_{D_v} = \left[(\boldsymbol{x}_r - \boldsymbol{x}_s)^{\dagger} D_w (\boldsymbol{x}_r - \boldsymbol{x}_s) \right]^{1/2} = \left[\sum_{j=1}^p w_j (\boldsymbol{x}_{rj} - \boldsymbol{x}_{sj})^2 \right]^{\frac{1}{2}}$$

(3) Nomalized Eucliean Distance

$$d_r = \|\boldsymbol{x}_r - \boldsymbol{x}_s\|_{D_s^{-1}} = \left[(\boldsymbol{x}_r - \boldsymbol{x}_s)^t D_s^{-1} (\boldsymbol{x}_r - \boldsymbol{x}_s) \right]^{1/2} = \left[\sum_{i=1}^p \frac{1}{s_{ij}} (x_{rj} - x_{sj})^2 \right]^{\frac{1}{2}}$$

(4) Mahalanobis Distance

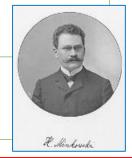
$$d_r = || \boldsymbol{x}_r - \boldsymbol{x}_s ||_{S^{-1}} = [(\boldsymbol{x}_r - \boldsymbol{x}_s)^t S^{-1} (\boldsymbol{x}_r - \boldsymbol{x}_s)]^{1/2}$$

(5) City-Block Distance

$$d_{rs} = \sum_{j=1}^{p} |x_{rj} - x_{sj}|$$

(6) Minkowski Distance

$$d_{r_{\xi}} = \left[\sum_{i=1}^{p} w_{i} | x_{r_{i}} - x_{s_{i}} |^{m} \right]^{1/m}, \quad m \ge 1$$



Hermann Minkowski (1864–1909): Russian mathematician

1.5 Multivariate data distance

• [Example 1.5.1][DATA 1.1.1]

Result of [R-code 1.5.1] 3subjects-distances.R

```
Data1.1.1<-read.table("3subjects.txt", header=T)
X<-Data1.1.1[,-1]
X<-as.matrix(Data1.1.1[,-1])
n < -nrow(X)
xbar<-t(X)%*%matrix(1,n,1)/n # 평균벡터
I<-diag(n)
J < -matrix(1,n,n)
H < -I - 1/n*J
                          # 중심화행렬
                          # 중심화 자료행렬
Y<-H%*%X
S<-t(Y)%*%Y/(n-1)
                          # 공분산행렬
D<-diag(1/sqrt(diag(S)))
                             # 표준편차행렬의 역
                             # 표준화자료행렬
Z<-Y%*%D
colnames(Z) < -colnames(X)
# 유클리드 거리
de <- as.matrix(dist(X, method="euclidean"))</pre>
de <- as.dist(de)
round(de, 3)
```

```
# 표준화 유클리드 거리
ds <- as.matrix(dist(Z, method="euclidean"))
ds <- as.dist(ds)
round(ds, 3)
# 마할라노비스 거리
library(biotools)
dm<-D2.dist(X, S)
round(sqrt(dm), 3)

# 시티블릭 거리
dc <- as.matrix(dist(X, method="manhattan"))
dc <- as.dist(dc)
round(dc, 3)
```

Euclidean distance

$$x_1 - x_2 = (65 - 65, 85 - 80, 85 - 90)^t = (0, 5, -5)^t$$

```
1 2 3 4 5 6 7 8 9
2 7.071  
3 66.895 66.521
4 6.164 9.899 66.880
5 61.262 60.934 6.164 61.033
6 10.344 7.550 72.746 10.247 67.007
7 61.303 61.303 10.630 60.465 6.403 66.940
8 4.690 9.055 65.704 2.000 59.908 10.817 59.498
9 78.568 78.186 11.747 78.403 17.378 84.321 19.261 77.272
10 77.201 78.549 22.694 77.730 26.019 85.059 27.604 76.381 22.113
```

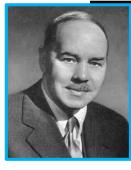
$$d_{12} = [(x_1 - x_2)^t (x_1 - x_2)]^{1/2}$$

$$= [(0, 5, -5)(0, 5, -5)^t]^{1/2}$$

$$= [0^2 + 5^2 + (-5)^2]^{1/2} = 7.071$$

Univariate Distributions vs. Multivariate Distributions

| Univariate | Multivariate |
|------------------|---------------------------|
| Normal dist. | Multivariate normal dist. |
| Chi-square dist. | Wishart dist. |
| t-dist. | Hotelling's T^2 dist. |
| F-dist. | Wilks' ∧ dist. |



Harold Hotelling(September 29, 1895 – December 26, 1973) was an American mathematical statistician and an influential economic theorist, Hotelling's T-squared distribution in statistics. He also developed and named the principal component analysis method widely used.

John Wishart (28 November 1898 – 14 July 1956) was a Scottish mathematician and agricultural statistician. worked successively at University College London with Karl Pearson, at Rothamsted Experimental Station with Ronald Fisher. He first formulated the Wishart distribution in his honour, in 1928.



• Univariate normal distribution : $X \sim N(\mu, \sigma^2)$

$$f(x) = \frac{1}{\sqrt{2\pi} \sigma} \exp\left\{-\frac{1}{2} \left(\frac{x-\mu}{\sigma}\right)^2\right\}, \quad -\infty < x < \infty$$



Samuel Stanley Wilks (June 17, 1906 – March 7, 1964) was an American mathematician and academic who played an important role in the development of mathematical statistics. He provided Wilks' Theorem in the theory of likelihood ratio tests, where he showed the distribution of log likelihood ratios is asymptotically χ 2.

• Multivariate Normal Distribution: $N_p(\mu, \Sigma)$

$$f(\mathbf{x}) = \frac{1}{(\sqrt{2\pi})^p |\Sigma|^{1/2}} \exp\left\{-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^t \Sigma^{-1} (\mathbf{x} - \boldsymbol{\mu})\right\}$$

Likelihood function: $L(\mu, \Sigma) = \prod_{i=1}^{n} f(x_i)$

$$= \frac{1}{(\sqrt{2\pi})^{np}|\Sigma|^{n/2}} exp(-\frac{1}{2}\sum_{i=1}^{n}(\mathbf{x_{i}}-\boldsymbol{\mu})^{'}\Sigma^{-1}(\mathbf{x_{i}}-\boldsymbol{\mu}))$$

 \clubsuit Bivariate Normal Distribution: $N_2(\mu, \Sigma)$

$$\begin{split} f(x_1, \ x_2) &= \frac{1}{2\pi \sqrt{\sigma_{11}\sigma_{22}(1-\rho_{12}^2)}} \\ &\times \exp\biggl\{-\frac{1}{2(1-\rho_{12}^2)} \biggl[\biggl(\frac{x_1-\mu_1}{\sqrt{\sigma_{11}}}\biggr)^2 + \biggl(\frac{x_2-\mu_2}{\sqrt{\sigma_{22}}}\biggr)^2 - 2\rho_{12} \biggl(\frac{x_1-\mu_1}{\sqrt{\sigma_{11}}}\biggr) \biggl(\frac{x_2-\mu_2}{\sqrt{\sigma_{22}}}\biggr) \biggr] \biggr\} \end{split}$$

• Deriving $N_2(\mu, \Sigma)$ from $N_p(\mu, \Sigma)$

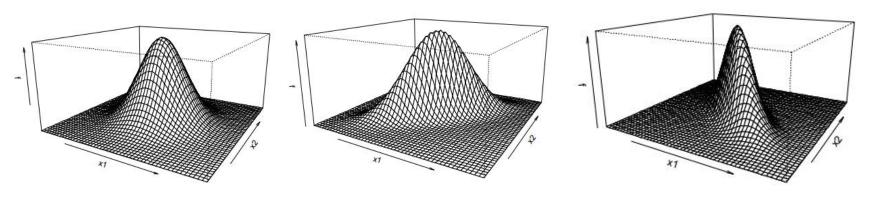
$$\begin{aligned} \mathbf{x} &= (x_1,\, x_2)^{'} \sim N_2(\boldsymbol{\mu},\, \boldsymbol{\varSigma}) \\ \mathbf{with} \quad \boldsymbol{\mu} &= \quad (\mu_{1,}\, \mu_2)^{'} \text{ and } \quad \boldsymbol{\varSigma} &= \begin{bmatrix} \sigma_{11}\, \sigma_{12} \\ \sigma_{21}\, \sigma_{22} \end{bmatrix}. \end{aligned}$$

$$\rho_{12} = \frac{\sigma_{12}}{\sqrt{\sigma_{11}} \, \sqrt{\sigma_{22}}}$$
 : correlation coefficient

$$\begin{split} |\varSigma\>| &= \sigma_{11}\sigma_{22} - \sigma_{12}\sigma_{21} = \sigma_{11}\sigma_{22} \left(1 - \rho_{12}^2\right) \\ \varSigma^{-1} &= \frac{1}{|\varSigma\>|} \begin{bmatrix} \sigma_{22} - \sigma_{21} \\ -\sigma_{12} & \sigma_{11} \end{bmatrix} \\ &= \frac{1}{\sigma_{11}\sigma_{22} \left(1 - \rho_{12}^2\right)} \begin{bmatrix} \sigma_{22} & -\rho_{12}\sqrt{\sigma_{11}}\sqrt{\sigma_{22}} \\ -\rho_{12}\sqrt{\sigma_{11}}\sqrt{\sigma_{22}} & \sigma_{11} \end{bmatrix} \\ (x - \mu)^t \varSigma^{-1} (x - \mu) &= [x_1 - \mu_1, \ x_2 - \mu_2] \ \frac{1}{\sigma_{11}\sigma_{22} \left(1 - \rho_{12}^2\right)} \\ &\times \begin{bmatrix} \sigma_{22} & -\rho_{12}\sqrt{\sigma_{11}}\sqrt{\sigma_{22}} \\ -\rho_{12}\sqrt{\sigma_{11}}\sqrt{\sigma_{22}} & \sigma_{11} \end{bmatrix} \begin{bmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \end{bmatrix} \\ &= \frac{1}{1 - \rho_{12}^2} \left[\left(\frac{x_1 - \mu_1}{\sqrt{\sigma_{11}}}\right)^2 + \left(\frac{x_2 - \mu_2}{\sqrt{\sigma_{22}}}\right)^2 - 2\rho_{12} \left(\frac{x_1 - \mu_1}{\sqrt{\sigma_{11}}}\right) \left(\frac{x_2 - \mu_2}{\sqrt{\sigma_{22}}}\right) \right] \end{split}$$

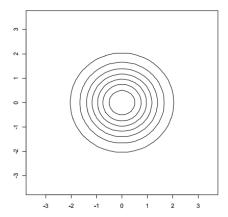
Bivariate normal distribution

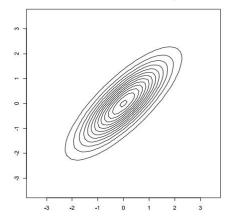
$$\mu = (0.0, 0.0)^t$$

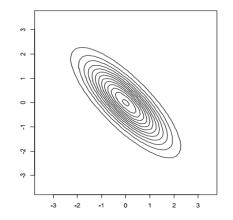


(a)
$$\sigma_{11} = \sigma_{22} = 1$$
, $\rho_{12} = 0.0$ (b) $\sigma_{11} = \sigma_{22} = 1$, $\rho_{12} = 0.8$ (c) $\sigma_{11} = \sigma_{22} = 1$, $\rho_{12} = -0.8$

Contour of normal distribution $\{m{x}: m{x}^t m{\Sigma}^{-1} m{x} = c^2\}$: Ellipsoid







(a)
$$\sigma_{11} = \sigma_{22} = 1$$
, $\rho_{12} = 0.0$ (b) $\sigma_{11} = \sigma_{22} = 1$, $\rho_{12} = 0.8$ (c) $\sigma_{11} = \sigma_{22} = 1$, $\rho_{12} = -0.8$

c)
$$\sigma_{11} = \sigma_{22} = 1$$
, $\rho_{12} = -0.8$

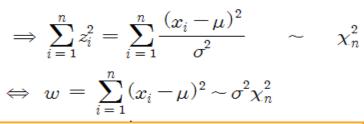
1.7 Wishart W-dist and Hotelling's T^2 -dist

Chi-square dist. and Wishart dist.

Karl Pearson(27 March 1857 - 27 April 1936): English mathematician and biostatistician



$$-p=1$$
, $x_1,...,x_n \sim {}^{iid} N(\mu, \sigma^2) \Rightarrow z_i = \frac{x_i - \mu}{\sigma}$, $i=1,...,n$, $\sim {}^{iid} N(0, 1)$.



Using
$$\bar{x}$$
 instead of $\mu \implies w = \sum_{i=1}^n (x_i - \bar{x})^2 = (n-1)s^2 \sim \sigma^2 \chi_{n-1}^2$

Wishart distribution in the multivariate case

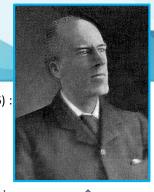
Friedrich Robert Helmert (July 31, 1843 - June 15, 1917): German geodesist

Let
$$\mathbf{x}_1 = (x_{11}, ..., x_{1p})^{'}, ..., \mathbf{x}_i = (x_{i1}, ..., x_{ip})^{'}, ..., \mathbf{x}_n = (x_{n1}, ..., x_{np})^{'} \sim N_p(\mathbf{\mu}, \Sigma)$$

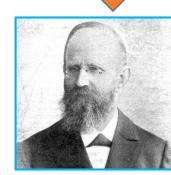
$$W = \sum_{i=1}^{n} (\boldsymbol{x}_{i} - \boldsymbol{\mu})(\boldsymbol{x}_{i} - \boldsymbol{\mu})' \sim W_{p}(n, \Sigma)$$
: Wishart distribution with \boldsymbol{n} df

Using
$$\overset{-}{m{x}}$$
 instead of $m{\mu}$ \implies

Using
$$\overline{\boldsymbol{x}}$$
 instead of $\boldsymbol{\mu} \implies W = \sum_{i=1}^{n} (\boldsymbol{x}_{i} - \overline{\boldsymbol{x}}) (\boldsymbol{x}_{i} - \overline{\boldsymbol{x}})' = (n-1)S = V \sim W_{p}(n-1, \Sigma)$







1.7 Wishart W-dist and Hotelling's T^2 -dist

• t-dist. and T^2 -dist.

William Sealy Gosset (13 June 1876 – 16 October 1937) was an English statistician. He published under the pen name **Student**, and developed the **Student**'s t-distribution. Guinness prohibited its employees from publishing any papers regardless of the contained information.

h d

t-distribution in the univariate case

$$\overline{x} = \frac{1}{n} \sum_{i=1}^{n} x_i, \ s^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \overline{x})^2 \longrightarrow t = \frac{\overline{x} - \mu}{s / \sqrt{n}} \sim t_{(n-1)}$$

$$t^2 = \frac{(\overline{x} - \mu)^2}{(s / \sqrt{n})^2} = n(\overline{x} - \mu)(s^2)^{-1}(\overline{x} - \mu)$$

• T^2 -distribution in the multivariate case

$$T^{2} = n(\overline{x} - \mu)'S^{-1}(\overline{x} - \mu) \sim T_{p}^{2}(n-1) = \frac{(n-1)p}{n-p}F_{p, n-p}$$

Note:
$$p = 1 : F_{1, m} = T_1^2(m)$$

$$t \sim t(m) \implies t^2 \sim F_{1,m} \sim T_1^2(m)$$

1.8 Testing multivariate normality

Steps for chi-squire plot

Prasanta Chandra Mahalanobis (29 June 1893 – 28 June 1972): an Indian scientist and applied statistician

Mahalanobis distance:
$$m_i^2 = (x_i - \overline{x})^t S^{-1}(x_i - \overline{x}), i = 1, ..., n$$



[Step 1] Order the Mahalanobis distances from smallest to largest as

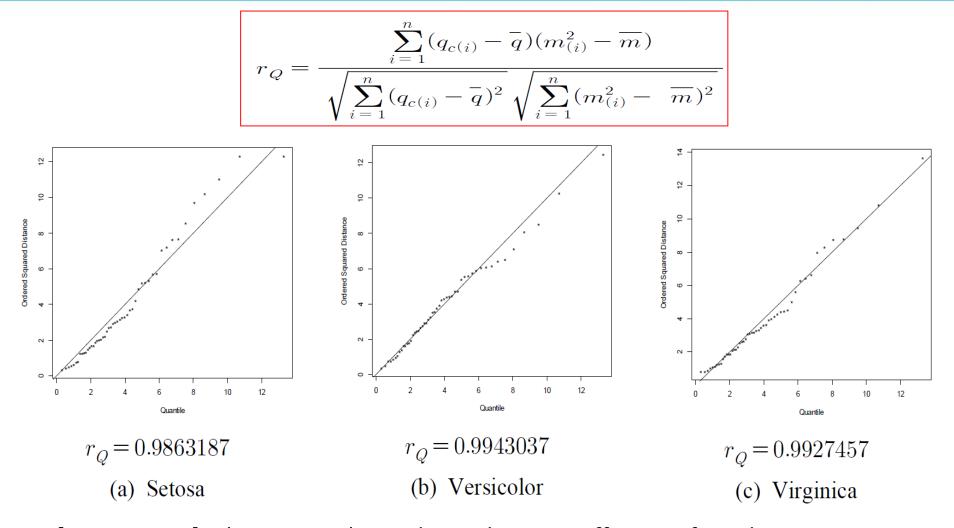
$$m_{(1)}^2 \leq m_{(2)}^2 \leq \cdots \leq m_{(n)}^2$$

[Step 2] Calculate the $100\left(i-\frac{1}{2}\right)/n$, i=1,...,n percentile $q_{c(i)}$ of chi-square distribution with p d.f.

[Step 3] Plot the pairs
$$(q_{c(i)}, m_{(i)}^2), i = 1, ..., n$$

[Step 4] Check the straightness of plot.

[Example 1.8.1] Normality test: Chi-square Plot



[Figure 1.8.1] Chi-square plot and correlation coefficient of iris data

[Example 1.8.2] Normality test: Multivaiate Skewness & Kurtosis



Kantilal Vardichand Mardia (born 1935): Indian statistician specializing in multivariate analysis and statistical shape analysis

$$m_{rs} = (\boldsymbol{x}_r - \overline{\boldsymbol{x}})^t S^{-1} (\boldsymbol{x}_s - \overline{\boldsymbol{x}}), \quad r, \quad s = 1, \dots, n$$

$$b_{1p} = \frac{1}{n^2} \sum_{r=1}^n \sum_{s=1}^n m_{rs}^3 \approx \frac{6}{n} \chi_{(p(p+1)(p+2)/6)}^2$$

$$b_{2p} = \frac{1}{n} \sum_{r=1}^n m_{rs}^2 \approx N \left(p(p+2), \frac{8p(p+2)}{n} \right)$$

$$n < 20 \quad b_{1p} = \frac{1}{n^2} \sum_{r=1}^n \sum_{s=1}^n m_{rs}^3 \sim \frac{6}{nk} \chi_{(p(p+1)(p+2)/6)}^2$$

| Mardia's Multivariate Normality Test | Mardia's Multivariate Normality Test | Mardia's Multivariate Normality Test |
|---------------------------------------|--|--|
| data : setosa | data : versicolor | data : virginica |
| g1p : 3.079721 | g1p : 3.022201 | g1p : 3.152472 |
| chi.skew : 25.66434 | chi.skew : 25.18501 | chi.skew : 26.2706 |
| p.value.skew : 0.1771859 | p.value.skew : 0.1944445 | p.value.skew : 0.1570597 |
| g2p : 26.53766 | g2p : 22.87938 | g2p : 24.29906 |
| z.kurtosis : 1.294992 | z.kurtosis : -0.5718664 | z.kurtosis : 0.1526142 |
| p.value.kurt : 0.1953229 | p.value.kurt : 0.5674125 | p.value.kurt : 0.8787025 |
| chi.small.skew: 27.85973 | chi.small.skew: 27.33939 | chi.small.skew : 28.51784 |
| p.value.small: 0.1127617 | p.value.small: 0.1259826 | p.value.small : 0.09769648 |
| Result : Data are multivariate normal | . Result : Data are multivariate normal. | Result : Data are multivariate normal. |

[Figure 1.8.2] MVN of iris data ← [R-code 1.8.2](iris-MVNtest.R)

k = (p+1)(p+1)(p+3)/(p(p+1)(p+1)-6)

1.9 R for EDA: Practice Time

R-code:

| EDA | |
|-------------------------------|--|
| summary() | Descriptive Statistics |
| cov(), cor() | Covariance, Correlation Matrices |
| plot() boxplot() stem() | Multiple Scatter Plot Multiple Box-and-Whisker Plot Stem-and-Leaf Plot |
| star() parcoordlabel() | Stars Plot Parallel Coordinate Plot, library(gclus) |
| mardiaTest() mvn() | Skewness & Kurtosis Tests, library(MVN) qqplot=TRUE mvnTest="mardia" multivariatePlot="qq" |

1.9 R for EDA: Practice Time

[R-code 1.8.1] iris-chisqplot.R

```
data(iris)
     setosa = iris[1:50, 1:4] # Iris data only for setosa
    #versicolor = iris[51:100, 1:4] # Iris data only for versicolor
    #virginica = iris[101:150, 1:4] # Iris data only for virginica
# Chi-squre Plot for Checking MVN
     x=setosa
     n=dim(x)[[1]]
     p=dim(x)[[2]]
     S = cov(x)
     xbar=colMeans(x)
     m=mahalanobis(x, xbar, S)
     m = sort(m)
     id=seq(1, n)
      pt = (id - 0.5)/n
     q=qchisq(pt, p)
      plot(q, m, pch="*", xlab="Quantile", ylab="Ordered Squared Distance")
     abline(0, 1)
# Correlation Coefficient Test for Normailty
     rq = cor(cbind(q, m))[1,2]
     rq
```

1.9 R for EDA: Practice Time

[R-code 1.8.2] iris-MVNtest.R

```
library("MVN")
iris
# MVN tests based on the Skewness and Kurtosis Statistics
par(mfrow=c(1, 3))
setosa=iris[1:50, 1:4] # Iris data only for setosa and four variables
versicolor=iris[51:100, 1:4] # Iris data only for versicolor and four variables
virginica=iris[101:150, 1:4] # Iris data only for virginica and four variables
result_setosa=mardiaTest(setosa, qqplot=TRUE)
result versicolor=mardiaTest(versicolor, ggplot=TRUE)
result_virginica=mardiaTest(virginica, qqplot=TRUE)
result setosa
                    mvn(setosa, mvnTest="mardia", multivariatePlot="qq")
result versicolor
result_virginica
```