### Normal Distribution

Andrey Chinnov, Sebastian Honermann, Carlos Zydorek

Case Studies "Data Analytics"

## Outline

- Introduction
  - Normality as a requirement for statistical methods
  - Data Set Overview
- Transformation to Normality
- Normality Testing
  - Univariate case
  - Bivariate case
- Summary

### Normality as a requirement for statistical methods

Normality Testing

### Data Set Overview

- Glass data set from package mlbench
- sample of 214 observations
- 7 types of glass (but only 6 present in this sample)
- Variables: refractive index (RI) and 8 elements (Na, Mg, AI, Si, K, Ca, Ba, Fe)

#### Box-Cox Transformation

If data are not normally distributed, they can possibly be transformed by the parameterised power transformation

$$x^{(\lambda)} = \begin{cases} \frac{x^{\lambda} - 1}{\lambda} & \lambda \neq 0 \\ \ln(x) & \lambda = 0 \end{cases} \quad \text{for } x > 0$$

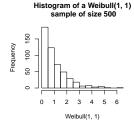
The optimal parameter  $\lambda$  for specific observations  $x_1, \ldots, x_n$  can be obtained by a maximum-likelihood estimation, maximising the log likelihood

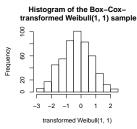
$$l(\lambda) = -\frac{n}{2} \ln \left[ \frac{1}{n} \sum_{j=1}^{n} (x_j^{(\lambda)} - \overline{x^{(\lambda)}})^2 \right] + (\lambda - 1) \sum_{j=1}^{n} \ln(x_j)$$

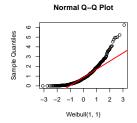
with 
$$\overline{x^{(\lambda)}} = \frac{1}{n} \sum_{j=1}^{n} x_j^{(\lambda)}$$

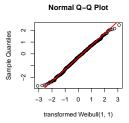


#### Box-Cox Transformation Transformation issues

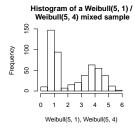


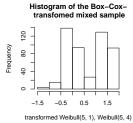


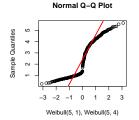


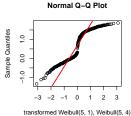


#### Box-Cox Transformation Transformation issues









#### Sample:

$$x = (x_1, x_2, \dots, x_n)$$

#### **Empirical quantiles:**

$$x_{(1)} \le x_{(2)} \le \cdots \le x_{(n)}$$

#### Theoretical quantiles:

$$q_{(i)} = \Phi^{-1}(p_{(i)}),$$

where

$$p_{(j)} = \frac{j - \frac{1}{2}}{n},$$

$$\Phi$$
 -  $N(0,1)$  c.d.f. .

Plot  $x_{(i)}$  against  $q_{(i)}$ 







Normality Testing

Theoretical Quantiles





Theoretical Quantiles



Theoretical Quantiles ĸ





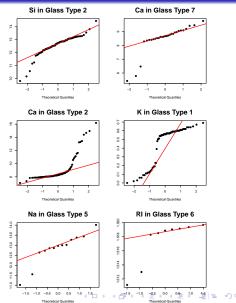




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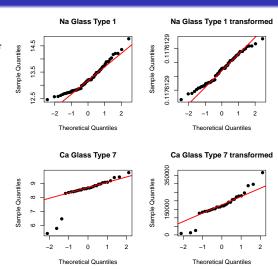
#### **QQ-Plots of the subdatasets:**

- Variables could be normally distributed within the subclasses
- For some cases there appear to be a linear relationships
- For other cases a linear relationship is questionable
- In some subdatasets a linear relationship seems plausible, however n is very small



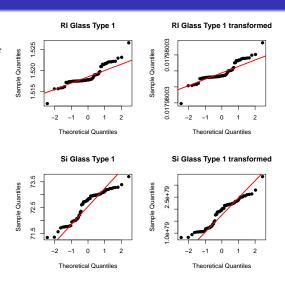
## Results of the Transformation of the Full Dataset :

- For some of the cases there seems to be a slight improvement
- For non-unimodal cases the transformation does not show significant improvements towards normality



## Results of the Transformation of the Subdatasets :

- For unimodal cases the transformation shapes the distribution closer to normality
- For non-unimodal cases the transformation does not show significant improvements towards normality



## Shapiro-Wilk Test

The test statistic  $\,W\,$  indicates the deviation of the observed quantile values from the assumed cumulative distribution function quantiles

$$W = \frac{\sum_{i=1}^{n} (a_i y_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2},$$

#### where

- $a_i$  denotes the normalised "best linear unbiased" coefficients,
- y<sub>i</sub> denotes the observations.

The critical value for W is obtained by the Monte Carlo Method  $\implies p$ -value is calculated

Important: If a variable contains only zeros the Shapiro-Wilk test is not applicable, since the term in the denominator sums up to zero.

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### Shapiro-Wilk Test

#### Testing the Full Dataset:

Null hypothesis is rejected for all variables at a 1 % significance level

#### After the Transformation:

The null hypothesis can be rejected for the four transformed variables

⇒ Possible Explanation:

Combination of different distributions in the different glass types

Γ	variable	test statistic	sig. level	critical value	p-value	rejected
Г	RI	0.87	0.01	NA	1.0766713449726e-12	yes
	Na	0.95	0.01	NA	3.4655430546966e-07	yes
	Mg	0.7	0.01	NA	< 1.0e-15	yes
	ΑI	0.94	0.01	NA	2.08315629600399e-07	yes
	Si	0.92	0.01	NA	2.17503176825416e-09	yes
	K	0.44	0.01	NA	< 1.0e-15	yes
	Ca	0.79	0.01	NA	< 1.0e-15	yes
	Ba	0.41	0.01	NA	< 1.0e-15	yes
	Fe	0.65	0.01	NA	< 1.0e-15	yes

Test results of the Shapiro-Wilk test on the whole data sample

variable	test statistic	sig. level	critical value	p-value	rejected
RI	NA	NA	NA	NA	NA
Na	0.95	0.01	NA	8.75605777309153e-07	yes
Mg	NA	NA	NA	NA	NA
Αl	0.97	0.01	NA	0.000244326513056066	yes
Si	0.93	0.01	NA	1.58998125691823e-08	yes
K	NA	NA	NA	NA	NA
Ca	0.89	0.01	NA	1.13880689831982e-11	yes
Ba	NA	NA	NA	NA	NA
Fe	NA	NA	NA	NA	NA

Test results of the Shapiro-Wilk test on the whole transformed data sample

## Shapiro-Wilk Test

Testing the Subdatasets Example - Glass Type 1:

Null hypothesis is rejected for all variables at a 1 % significance level

variable	test statistic	sig. level	critical value	p-value	rejected
RI	0.88	0.01	NA	6.36192013015468e-06	yes
Na	0.95	0.01	NA	0.00459078607995831	yes
Mg	0.82	0.01	NA	8.02702432879544e-08	yes
ΑĬ	0.9	0.01	NA	5.42971629496434e-05	yes
Si	0.91	0.01	NA	0.000117060780025464	yes
K	0.77	0.01	NA	3.14049093233846e-09	yes
Ca	0.93	0.01	NA	0.00103561283726753	yes

Normality Testing

Test results of the Shapiro-Wilk test on type 1 glass

#### After the Transformation:

The null hypothesis cannot be rejected for 3 of the transformed variables

→ Appearently the transformation was successful

variable	test statistic	sig. level	critical value	p-value	rejected
RI	0.89	0.01	NA	1.62433657125306e-05	yes
Na	0.98	0.01	NA	0.353792914291578	no
Mg	0.83	0.01	NA	1.40023833110547e-07	yes
Αl	0.96	0.01	NA	0.0459207068393172	no
Si	0.94	0.01	NA	0.00269629206710463	yes
K	NA	NA	NA	NA	NA
Ca	0.97	0.01	NA	0.148237775100495	no

Test results of the Shapiro-Wilk test on the transformed type 1 glass

### Graphical Methods for Normality Testing Shapiro-Wilk Test

Normality Testing

# Pearson's Chi-Squared Test Theoretical foundations

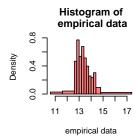
- Divide observations  $X_1, \ldots, X_N$  into pairwise disjoint classes  $C_1, \ldots, C_K$
- Common requirement: minimum class size of 5
- Compare observed class frequencies to expected theoretical class frequencies for a certain distribution

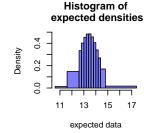
test statistic: 
$$\chi^2 = \sum_{k=1}^K \frac{(O_k - E_k)^2}{E_k}$$

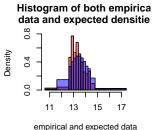
• The test statistic is approximately  $\chi^2$ -distributed with K-1 degrees of freedom (minus one degree of freedom per estimated parameter)

## Pearson's Chi-Squared Test

Theoretical foundations







#### Pearson's Chi-Squared Test Theoretical foundations

 Test under the null hypothesis that the sample is drawn from a population with unknown distribution  $\mathbb{P}$  which is equal to the assumed distribution  $\mathbb{P}_0$ :

$$H_0$$
:  $\mathbb{P} = \mathbb{P}_0$ ,  $H_1$ :  $\mathbb{P} \neq \mathbb{P}_0$ .

Normality Testing

#### Decision rule

$$\delta = \left\{ \begin{array}{ll} 1 & \text{if } \chi^2 > F^{-1}(1-\alpha) \\ 0 & \text{otherwise} \end{array} \right. \quad \text{with } F = \chi^2_{K-1-p}$$

(significance level  $\alpha$ , number of estimated parameters p)

## Pearson's Chi-Squared Test

Test results for the whole sample

variable	test statistic	sig. level	critical value	p-value	rejected
RI	64.95	0.01	13.28	2.64011035255862e-13	yes
Na	36.99	0.01	13.28	1.80797974702607e-07	yes
Mg	158.3	0.01	11.34	< 1.0e- $15$	yes
Al	27.2	0.01	9.21	1.24084046404516e-06	yes
Si	38.85	0.01	13.28	7.4876188027595e-08	yes
K	95.97	0.01	NA	NA	NA
Ca	131.13	0.01	13.28	< 1.0e-15	yes
Ba	31.37	0.01	NA	NA	NA
Fe	70.96	0.01	13.28	1.4210854715202e-14	yes

### Pearson's Chi-Squared Test Test results for type 1 glass

variable	test statistic	sig. level	critical value	p-value	rejected
RI	28.01	0.01	9.21	8.26265138420545e-07	yes
Na	3.25	0.01	13.28	0.51688441877949	no
Mg	18.81	0.01	6.63	1.44068580684165e-05	yes
Al	23.55	0.01	11.34	3.10284613768141e-05	yes
Si	23.68	0.01	13.28	9.26014020323773e-05	yes
K	114.86	0.01	11.34	< 1.0e-15	yes
Ca	22.58	0.01	15.09	0.000405198755082603	yes
Fe	18.65	0.01	9.21	8.91413549507503e-05	yes

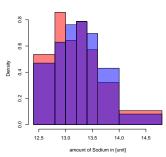
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Al	23.55	0.01	11.34	3.10284613768141e-05	yes
Si	23.68	0.01	13.28	9.26014020323773e-05	yes
K	114.86	0.01	11.34	< 1.0e-15	yes
Ca	22.58	0.01	15.09	0.000405198755082603	yes
Fe	18.65	0.01	9.21	8.91413549507503e-05	yes

# Pearson's Chi-Squared Test Test results for sodium of type 1 glass

class	frequencies			
(interval)	observed	expected		
]12.4, 12.8]	15	13.15		
]12.8, 13]	12	8.81		
]13, 13.2]	9	10.68		
]13.2, 13.4]	11	11.04		
]13.4, 13.6]	8	9.74		
]13.6, 14]	9	12.06		
]14, 14.8]	6	4.52		

#### Histogram of observed and expected densities



### Pearson's Chi-Squared Test Test results for transformed type 1 glass

variable	test statistic	sig. level	critical value	p-value	rejected
RI	27.81	0.01	6.63	1.33864150764218e-07	yes
Na	1.59	0.01	13.28	0.810360513797024	no
Mg	17.87	0.01	NA	NA	NA
Al	6.41	0.01	11.34	0.093110657016404	no
Si	16.87	0.01	13.28	0.00205136639513992	yes
K	NA	0.01	NA	NA	NA
Ca	3.35	0.01	11.34	0.341234021909645	no
Fe	NA	0.01	NA	NA	NA

Let  $x = (x_1, x_2, \dots, x_n)$  be a sample of unknown distribution  $\mathbb{P}$ .

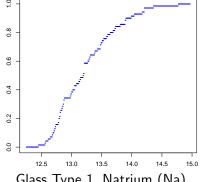
Normality Testing

#### Definition

Introduction

$$F_n(x) = \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{\{x_i \le x\}}(x)$$
  
- empirical c. d. f. , where

$$\mathbb{1}_{\{x_i \le x\}}(x) = \begin{cases} 1 & \text{if } x_i \le x \\ 0 & \text{otherwise.} \end{cases}$$



Glass Type 1, Natrium (Na)

Let  $x = (x_1, x_2, \dots, x_n)$  be a sample of unknown distribution  $\mathbb{P}$ .

Normality Testing

#### **Definition**

Introduction

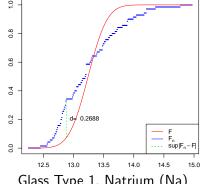
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F(x) - theoretical normal c. d. f. with

$$\bar{x} = \frac{1}{n} \sum x_i, \quad \sigma_x^2 = \frac{1}{n} (x_i - \bar{x})^2$$



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Normality Testing

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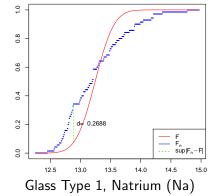
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$$d = \sup_{x \in \mathbb{R}} |F_n(x) - F(x)|$$

distance between them





Let  $x=(x_1,x_2,\ldots,x_n)$  be a sample of unknown distribution  $\mathbb{P}$ . Theoretical c. d. f. F defines a distribution  $\mathbb{P}_0$ .

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:  $\mathbb{P} = \mathbb{P}_0$ ,  $H_1$ :  $\mathbb{P} \neq \mathbb{P}_0$ .

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KS test statistics:

$$D_n = \sqrt{n} \cdot \sup_{x \in \mathbb{R}} |F_n(x) - F(x)|.$$

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Properties of  $D_n$  in case  $H_0$  is TRUE:

• Distribution of  $\hat{D}_n := (D_1, D_2, \dots, D_n)$  does not depend on F

Normality Testing

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- Distribution of  $\hat{D}_n := (D_1, D_2, \dots, D_n)$  does not depend on F
  - ⇒ tabulated

 $\bullet \ \forall t>0$ :

$$P(D_n \le t) \xrightarrow[n \to \infty]{} H(t) = 1 - 2\sum_{i=1}^{\infty} (-1)^{i-1} \exp^{-2i^2t^2}$$

The KS test uses the decision rule

$$\delta = \left\{ \begin{array}{ll} H_0 & : & D_n \le c \\ H_1 & : & D_n > c \end{array} \right.,$$

where c - critical value

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$$\implies c \approx H_{1-\alpha}$$

The KS test uses the decision rule for a given significance level lpha

$$\delta = \begin{cases} H_0 : D_n \le H_{1-\alpha} \\ H_1 : D_n > H_{1-\alpha} \end{cases}, \quad H(t) = 1 - 2\sum_{i=1}^{\infty} (-1)^{i-1} \exp^{-2i^2 t^2}$$

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The KS test uses the decision rule for a given significance level  $\alpha$ 

Normality Testing

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### **Example:**

13.5 Glass Type 1, Natrium (Na)

13.0

14.0

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12.5

The KS test uses the decision rule for a given significance level  $\alpha$ 

Normality Testing

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### **Example:**

• 
$$n = 70$$

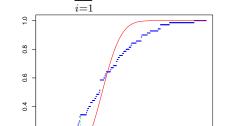
$$i=1$$
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### **Example:**

- n = 70
- $D_n = \sqrt{n} \sup |F_n F| =$ 2.2493



13.5 Glass Type 1, Natrium (Na)

13.0

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14.0

12.5

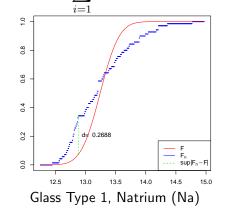
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Normality Testing

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### **Example:**

- n = 70
- $D_n = \sqrt{n} \sup |F_n F| =$ 2.2493
- $\alpha = 0.01$  $\implies c = H_{1-\alpha} = 1.6276$



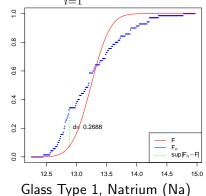
The KS test uses the decision rule for a given significance level  $\alpha$ 

Normality Testing

$$\delta = \begin{cases} H_0 : D_n \le H_{1-\alpha} \\ H_1 : D_n > H_{1-\alpha} \end{cases}, \quad H(t) = 1 - 2\sum_{i=1}^{\infty} (-1)^{i-1} \exp^{-2i^2t^2}$$

### **Example:**

- n = 70
- $D_n = \sqrt{n} \sup |F_n F| =$ 2.2493
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- $D_n > c \implies H_0$  rejected



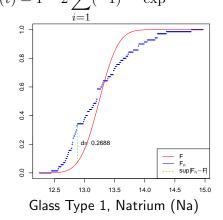
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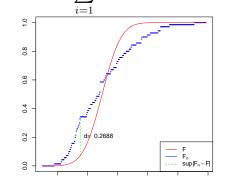
Case Studies "Data Analytics"

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- data not normally



13.0

14.0

12.5

Normality Testing

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## Quantitative Methods for Normality Testing Improved Kolmogorov-Smirnov Test

KS test is improved by solving the following optimization problem

$$KS(\mu, \sigma) = \sup_{x \in \mathbb{R}} |F_n(x) - F(x, \mu, \sigma)| \to \min.$$

R code used:

KS test is improved by solving the following optimization problem

$$KS(\mu, \sigma) = \sup_{x \in \mathbb{R}} |F_n(x) - F(x, \mu, \sigma)| \to \min.$$

R code used:

c(mean(dat), var(dat))

[1] 13.2422857 0.2493019

#optim is a predifined R function in stats package
#defalut method of optimization is Nelder and Mead
result = optim(c(mean(dat), var(dat)), KS)
result\$par

[1] 13.1769501 0.4682486

result\$value

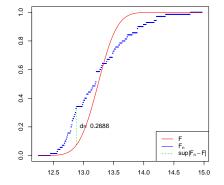
[1] 0.07870673

KS test is improved by solving the following optimization problem

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Normality Testing

- Initial vector of parameters  $\mu = 13.2423, \quad \sigma^2 = 0.2493$
- Optimized vector of parameters  $\hat{\mu} = 13.1770, \quad \hat{\sigma}^2 = 0.4682$

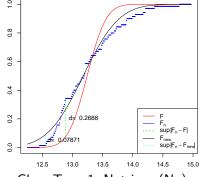


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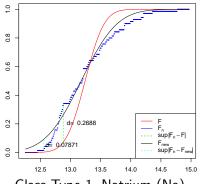
Glass Type 1, Natrium (Na)

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- $D_n = \sqrt{n} \sup |F_n F_{new}| =$ 0.6585



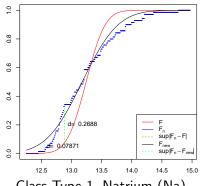
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- $D_n = \sqrt{n} \sup |F_n F_{new}| =$ 0.6585
- c = 1.6276



Glass Type 1, Natrium (Na)

KS test is improved by solving the following optimization problem

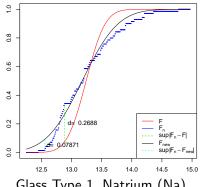
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Introduction

•  $D_n < c \implies H_0$  accepted



Glass Type 1, Natrium (Na)

KS test is improved by solving the following optimization problem

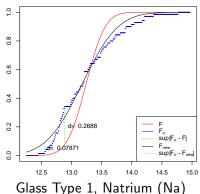
$$KS(\mu, \sigma) = \sup_{x \in \mathbb{R}} |F_n(x) - F(x, \mu, \sigma)| \to \min.$$

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Introduction

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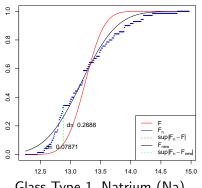
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Introduction

- $D_n < c \implies H_0$  accepted
- $\bullet \implies \mathbb{P} = \mathbb{P}_0$
- ⇒ data normally distributed!



Glass Type 1, Natrium (Na)

variable	test statistic	sig. level	critical value	p-value	rejected
RI	1.34	0.01	1.63	0.0561963016778131	no
Na	0.87	0.01	1.63	0.43825271603342	no
Mg	2.94	0.01	1.63	6.18457917100912e-08	yes
ΑI	0.84	0.01	1.63	0.474757887353829	no
Si	0.96	0.01	1.63	0.314710019077325	no
K	2.14	0.01	1.63	0.000212776619708754	yes
Ca	1.33	0.01	1.63	0.057710602872685	no
Ba	2.60	0.01	1.63	2.75476085742632e-06	yes
Fe	4.68	0.01	1.63	< 1.0e-15	yes

Results of Improved KS test on the whole data set:

variable	test statistic	sig. level	critical value	p-value	rejected
RI	1.34	0.01	1.63	0.0561963016778131	no
Na	0.87	0.01	1.63	0.43825271603342	no
Mg	2.94	0.01	1.63	6.18457917100912e-08	yes
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• 5 variables are normaly distributed (RI,Na,AI,Si,Ca)

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- 4 variables are not (Mg,K,Ba,Fe)

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Fe	4.68	0.01	1.63	< 1.0e-15	yes

- 5 variables are normaly distributed (RI,Na,AI,Si,Ca)
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- The best statistics test value for Al
- The worst statistic test value for Fe

## Quantitative Methods for Normality Testing

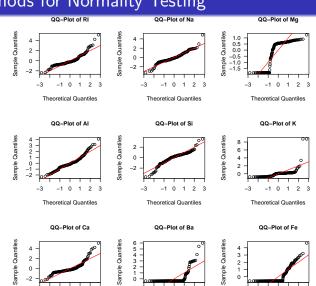
#### Test Results:

variable	rejected
RI	no
Na	no
Mg	yes
ΑI	no
Si	no
K	yes
Ca	no
Ba	yes
Fe	yes

## Quantitative Methods for Normality Testing

### Test Results:

rejected
no
no
yes
no
no
yes
no
yes
yes



0

Theoretical Quantiles...

Theoretical Quantiles

-1 0 1 2 3
Theoretical Quantiles

## Plot of multivariate normal distribution

## Theoretical foundations

 Contour lines of the plot of a multivariate normal distribution are shaped elliptically

Normality Testing

• Ellipsoids are centered at  $\mu: \{x: (x-\mu)' \Sigma^{-1}(x-\mu) = c^2\}$  with some constant c.

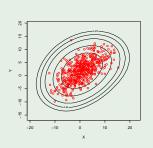
#### Example

Introduction

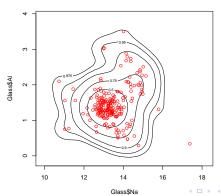
Multivariate normal distribution with sample size 500 and parameters

$$\mu = \begin{pmatrix} 1 \\ 2 \end{pmatrix}$$

$$\Sigma = \begin{bmatrix} 27 & 15 \\ 15 & 18 \end{bmatrix}$$



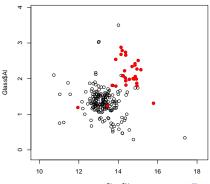
- Concerning the complete sample, the p-values for the variables Na and Al are highest among all used test methods.
- Plot data points and determine contour lines.



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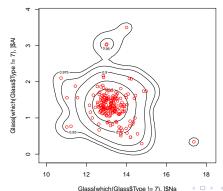
# Plot of multivariate normal distribution Application

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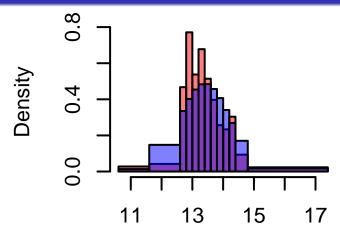
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## Summary

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## Pearson's Chi-Squared Test

Theoretical foundations



empirical and expected data

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