

# **MAINT.Data: Modeling and Analyzing Interval Data in R**

**Pedro Duarte Silva**

Faculdade de Economia e Gestão / CEGE,  
Universidade Católica Portuguesa, Porto, PORTUGAL

**Paula Brito**

Faculdade de Economia / LIAAD - INESC Porto LA  
Universidade do Porto, PORTUGAL

# Outline

- ❖ From Classical to Symbolic Data
- ❖ Parametric Modelization of Interval Data
  - Normal and Skew-Normal Models
  - Model configurations
- ❖ The MAINT.Data Package
  - The IData class and its basic methods
  - The IdtE classes and subclasses
  - The MANOVA, Ida and qda methods for Interval Data
- ❖ Conclusions and Perspectives

# From Classical to Symbolic Data

- ❖ Symbolic data → new variable types:
  - Set-valued variables : variable values are subsets of an underlying set
    - Interval variables      
    - Categorical multi-valued variables
  - Modal variables : variable values are distributions on an underlying set
    - Histogram variables

# Symbolic data array

The dataset consists of information's about patients (adults) in healthcare centers, during one semester.

Healthcare Center	Age $Y_1$	Nb. Emergency consults $Y_2$	Pulse $Y_3$	Waiting time for consultation (min) $Y_4$	Education level $Y_5$
A	[25,53]	{0,1,2}	[44,86]	([0,15[ (0), [15,30[ (0.25), [30,45[ (0.5), [45,60[ (0), $\geq 60$ (0.25) )	{9th grade, 1/2; Higher education, 1/2}
B	[33,68]	{1,4,5,10}	[54,76]	([0,15[ ( 0.25), [15,30[ (0.25), [30,45[ (0.25), [45,60[ (0.25), $\geq 60$ (0) )	{6th grade, 1/4; 9th grade, 1/4; 12th grade, 1/4; Higher education, 1/4}
C	[20,75]	{0,5,7}	[70,86]	([0,15[ (0.33), [15,30[ (0), [30,45[ (0.33), [45,60[ (0), $\geq 60$ (0.33) )	{4th grade, 1/3; 9th grade, 1/3; 12th grade 1/3}

# Interval Data

	$Y_1$	...	$Y_j$	...	$Y_p$
$\omega_1$	$[l_{11}, u_{11}]$	...	$[l_{1j}, u_{1j}]$	...	$[l_{1p}, u_{1p}]$
...	...	...	...	...	...
$\omega_i$	$[l_{i1}, u_{i1}]$	...	$[l_{ij}, u_{ij}]$	...	$[l_{ip}, u_{ip}]$
...	...	...	...	...	...
$\omega_n$	$[l_{n1}, u_{n1}]$	...	$[l_{nj}, u_{nj}]$	...	$[l_{np}, u_{np}]$

# Interval Data Representations

Original parametrisation :  $I_{ij} = [l_{ij}, u_{ij}]$

Alternative parametrisation :  $(c_{ij}, r_{ij})$

$$c_{ij} = \frac{l_{ij} + u_{ij}}{2}$$

$$r_{ij} = u_{ij} - l_{ij}$$

MAINT.Data:

Implements parametric inference methodologies



Assumes probabilistic models for interval variables

# Normal Model

Let  $R^* = \ln(R)$

Assumption:

$(C, R^*) \sim N_{2p}(\mu, \Sigma)$  with

$$\mu = \begin{bmatrix} \mu_C \\ \mu_{R^*} \end{bmatrix}$$

and  $\Sigma = \begin{bmatrix} \Sigma_{CC} & \Sigma_{CR^*} \\ \Sigma_{R^*C} & \Sigma_{R^*R^*} \end{bmatrix}$

# Skew-Normal Model

(Azzalini 1985)

Normal model - imposes a symmetrical distribution on the midpoints and a specific relation between mean, variance and skewness for the ranges

Skew-Normal - generalizes the Gaussian by introducing an additional shape parameter  $\alpha$ , while trying to preserve some of its mathematical properties

# Skew-Normal Model

p-variate density (Azzalini, Dalla Valle 1996):

$$f(\mathbf{y}) = 2\phi_p(\mathbf{x} - \boldsymbol{\xi}; \Omega) \Phi_p(\boldsymbol{\alpha}^t \boldsymbol{\omega}^{-1}(\mathbf{x} - \boldsymbol{\xi}))$$

$\boldsymbol{\xi}$  - p-dimensional vector of location parameters

$\boldsymbol{\alpha}$  - p-dimensional vector of shape parameters

$\Omega$  - symmetric positive-definite matrix

$\boldsymbol{\omega}$  - diagonal matrix formed by the square-roots of  
the diagonal elements of  $\Omega$

$\phi_p, \Phi_p$  - density and distribution function of a  
p-dimensional standard Gaussian vector

# Skew-Normal Model

log-likelihood of a p dimensional Skew-Normal :

$$l = -\frac{1}{2}n \ln |\Omega| - \frac{1}{2} \text{tr}(\Omega^{-1}V) + \sum_i \zeta_0(a^t \omega^{-1}(x_i - \xi_i)) \quad (*)$$

where  $V = \frac{1}{n} \sum_i (x_i - \xi_i)(x_i - \xi_i)^t$

and  $\zeta_0(x) = \ln(2 \Phi(x))$

# Model Configurations

Model	Characterization	$\Sigma$
1	Non-restricted	Non-restricted
2	$C_j$ not-correlated with $R_l^*$ $l \neq j$	$\Sigma_{CR^*} = \Sigma_{R^*C}$ diagonal
3	$Y_j$ 's independent	$\Sigma_{CC}, \Sigma_{CR^*} = \Sigma_{R^*C}, \Sigma_{R^*R^*}$ all diagonal
4	$C$ 's not-correlated with $R^*$ 's	$\Sigma_{CR^*} = \Sigma_{R^*C} = 0$
5	All $C$ 's and $R^*$ 's are non-correlated	$\Sigma$ diagonal

# Maximum Likelihood Estimation: Normal Model

Maximum likelihood estimator for  $\mu$

$$\hat{\mu} = \bar{X}$$

Maximum likelihood estimator for  $\Sigma$   
under Configuration 1:

$$\hat{\Sigma} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(x_i - \bar{x})^t = : \frac{1}{n} E$$

# Maximum Likelihood Estimation: Normal Model

Maximum likelihood estimator for  $\Sigma$

under configurations 3, 4 and 5:  
obtained from the non-restricted estimators → replacing by zeros the null parameters in the model for  $\Sigma$

under configuration 2:  
obtained by numerical maximization of

$$\ln L(\hat{\mu}, \Sigma) = -np \ln(2\pi) - \frac{n}{2} \ln |\Sigma| - \frac{1}{2} \text{tr} E \Sigma^{-1}$$

# Maximum Likelihood Estimation: Skew-Normal Model

under configuration 1

Log-likelihood :

$$l = -\frac{1}{2}n \ln |\Omega| - \frac{1}{2} \text{tr}(\Omega^{-1}V) + \sum_i \zeta_0 \left( \alpha^t \omega^{-1} (x_i - \xi_i) \right) (*)$$

maximized in two steps.

New parameter  $\eta = \omega^{-1} \alpha$

Then  $\hat{\Omega} = V$ .

The maximization with respect to  $\eta$  and  $\xi$  is then performed numerically.

# Maximum Likelihood Estimation: Skew-Normal Model under configurations 2-5

Given that  $\Sigma = \Omega - \omega\mu_Z\mu_Z^t$  a null covariance  $\Sigma(j,j')$   
implies that

$$\Omega(j,j') = \Omega(j,j)^{1/2} \mu_{Zj} \Omega(j',j')^{1/2} \mu_{Zj'}$$

or, equivalently  $\Sigma(j,j') = 0 \Rightarrow \Omega(j,j') = \frac{2}{\pi} \frac{\Omega_j^t \omega^{-1} \alpha \alpha^t \omega^{-1} \Omega_{j'}}{1 + \alpha^t \omega^{-1} \Omega \omega^{-1} \alpha}$

For configurations 2 - 5, this condition is imposed for the corresponding null elements of  $\Sigma$ .

It defines a system of non-linear equations on the  $\Omega(j,j')$ , which may be solved by standard numerical procedures.

# Maximum Likelihood Estimation: Skew-Normal Model under configurations 2-5

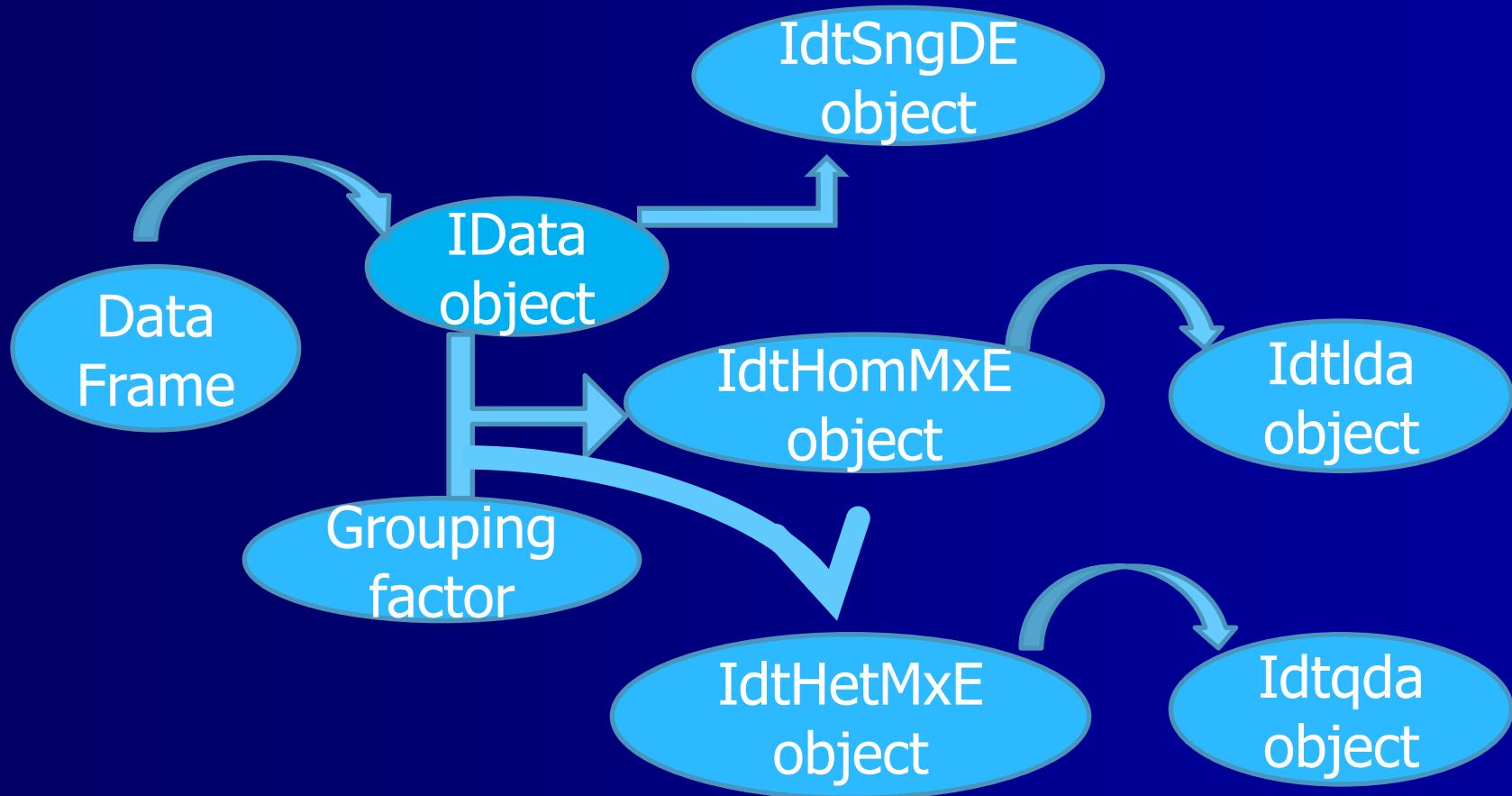
The ML estimate is then found by a Quasi-Newton optimization algorithm with:

Analytical gradients found by the chain rule and implicit function theorem

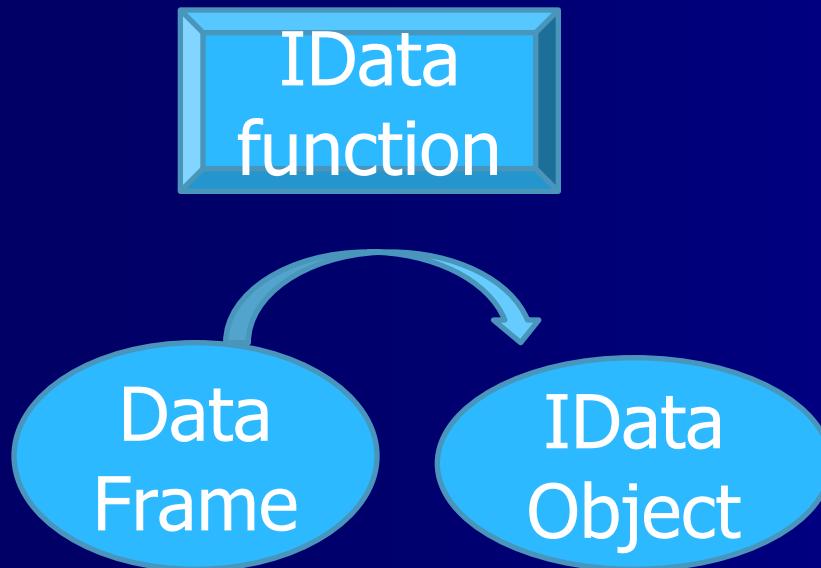
Randomly generated multiple starting points to avoid local optima

Brito, P., Duarte Silva, A. P. (2011): "Modelling Interval Data with Normal and Skew-Normal Distributions".  
Journal of Applied Statistics (in press).

# The MAINT.Data Package: Overview



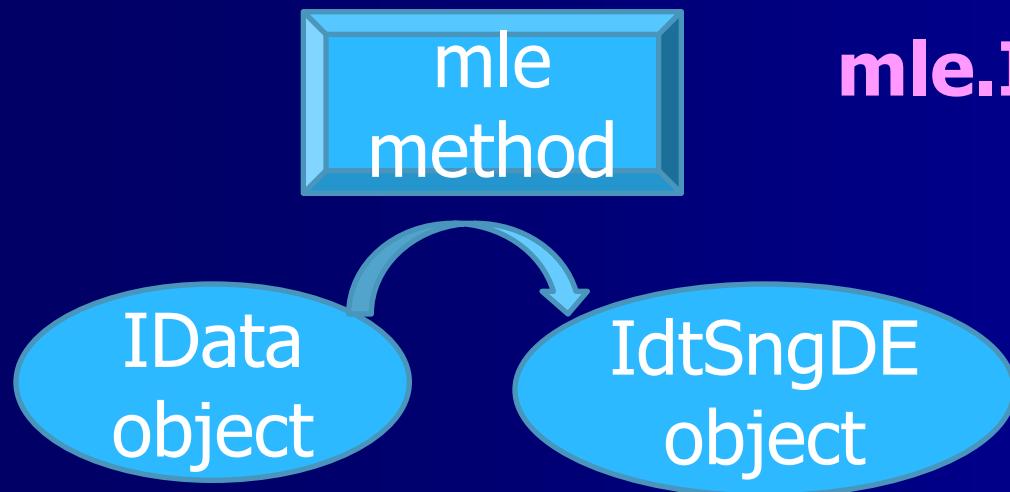
# The MAINT.Data Package: The Idata class



## **IData Methods**

- `print`
- `summary`
- `indexing`
- `assignment`
- `...`
- `mle`
- `MANOVA`

# The MAINT.Data Package: The IdtE classes I -- Single Dist.



## **mle.IData arguments**

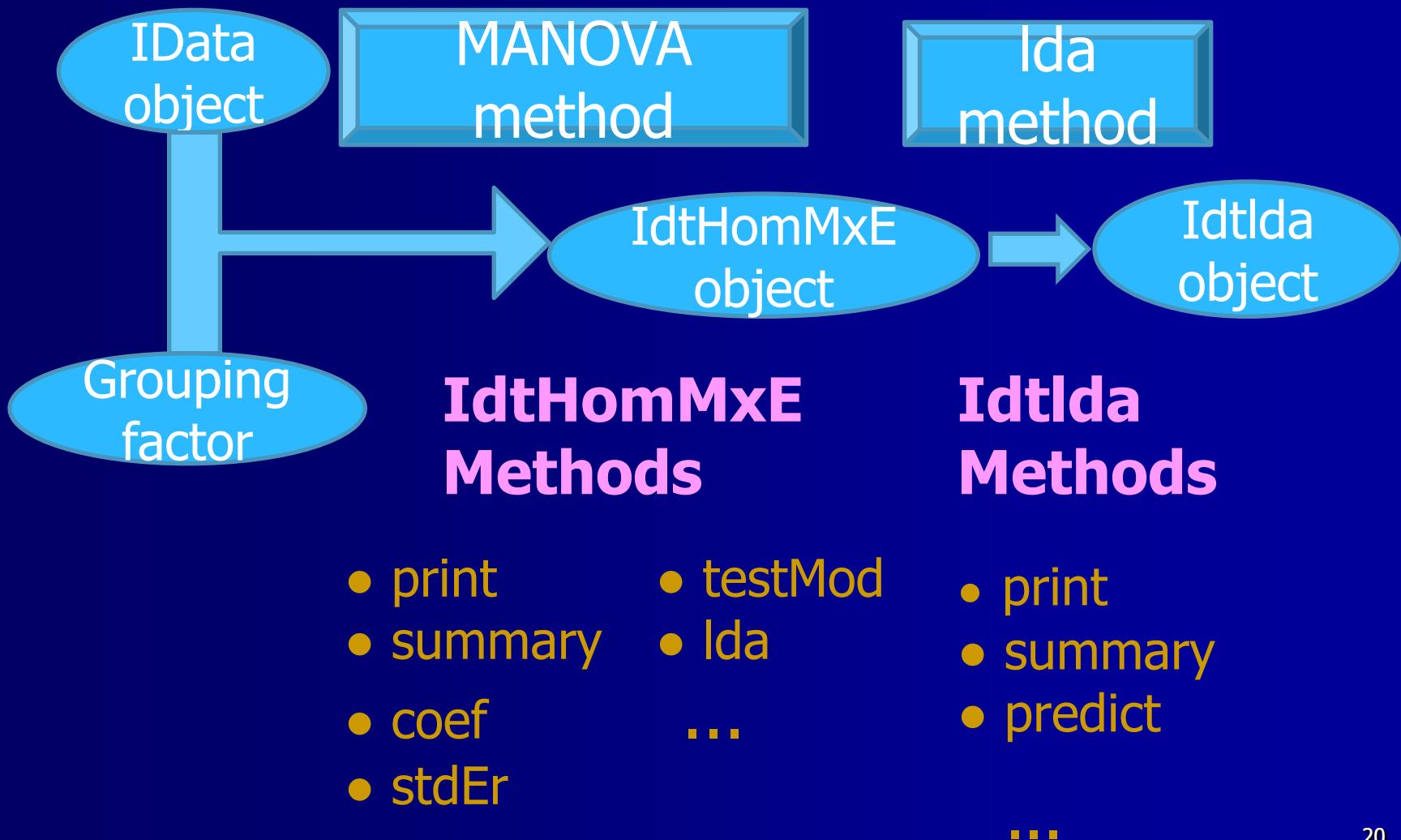
- Model
- Config
- SelCrit

## **IdtSngE Methods**

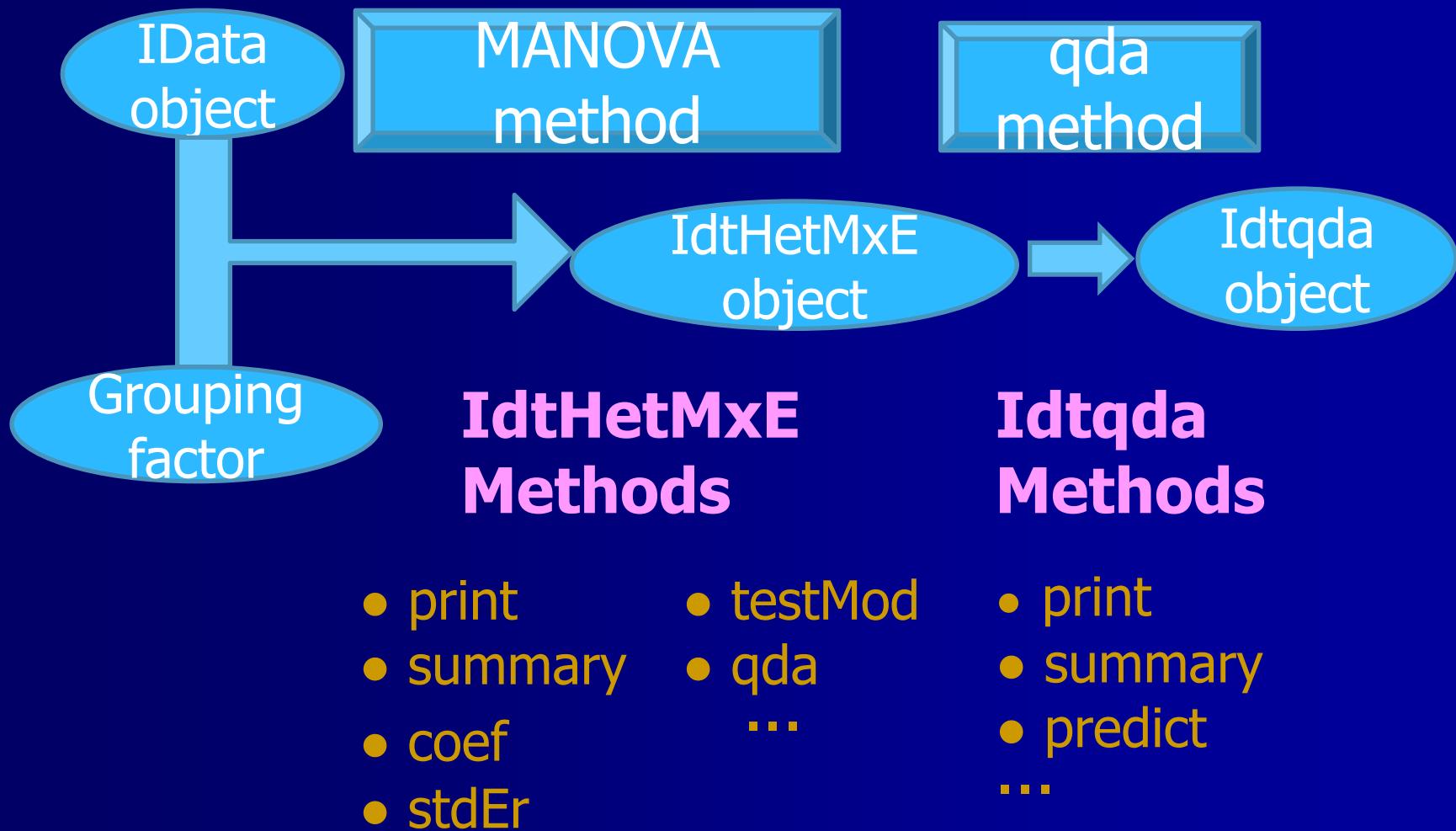
- print
- summary
- coef
- stdEr
- testMod

...

# The MAINT.Data Package: The IdtE classes II – Hom. Mixt.



# The MAINT.Data Package: The IdtE classes III – Het. Mixt.



# Creating IData Objects

```
ChinaT <- IData(ChinaTemp[1:8],  
VarNames=c("Q1","Q2", "Q3","Q4"))
```

#Display the first three observations

```
head(ChinaT,n=3)
```

	Q1	Q2	Q3	Q4
AnQing_1974	[ 0.673, 14.827]	[13.435, 28.465]	[19.821, 31.179]	[2.216, 9.984]
AnQing_1975	[ 2.319, 14.381]	[12.829, 28.471]	[23.192, 32.308]	[1.013, 10.987]
AnQing_1976	[ 0.906, 12.494]	[11.795, 28.405]	[19.680, 34.120]	[2.992, 10.308]

# # MANOVA tests

```
ManvChina <- MANOVA(ChinaT,ChinaTemp$GeoReg)  
print(ManvChina)
```

Null Model Log likelihoods:

NC1	NC2	NC3	NC4	NC5
-7336.254	-8331.416	-11564.904	-8390.351	-12648.760

Full Model Log likelihoods:

NC1	NC2	NC3	NC4	NC5
-6209.280	-6820.555	-9049.276	-6857.536	-9450.228

Full Model Akaike Information Criteria:

NC1	NC2	NC3	NC4	NC5
12586.56	13793.11	18234.55	13851.07	19012.46

Selected Model:

```
[1] "NC1"
```

Null Model log-likelihood: -7336.254

Full Model log-likelihood: -6209.28

Qui-squared statistic: 2253.949

degrees of freedom: 40

p-value: 0

# # Linear Discriminant Analysis

```
Chinalda <- lda(ManvChina)
```

```
PredRes <- predict(Chinalda,ChinaT)
```

```
#Estimate error rates by ten-fold cross-validation
```

```
CVlda <-
DACrossVal(ChinaT,ChinaTemp$GeoReg,TrainAlg=lda,
Config=BestModel(ManvChina@H1res),CVrep=1)
```

# Conclusions and Perspectives

- ❖ Probabilistic Models proposed for Interval Variables
- ❖ Normal (and Skew-Normal) distributions (different configurations) for Midpoints and Log-Ranges
- ❖ Implemented as an R package based on Maximum-Likelihood Estimation  
S4 classes and methods

# Conclusions and Perspectives

- ❖ Current version includes tools for:
  - Single distribution estimation and inference
  - ANOVA and MANOVA
  - Linear and Quadratic Discriminant Analysis
- ❖ Perspectives:
  - Extension to other multivariate methodologies (ex: Im method...)
  - Assume different distributions

# References

- Azzalini, A. (1985). A class of distributions which includes the normal ones. *Scandinavian Journal of Statistics* 12, 171-178.
- Azzalini, A. and Dalla Valle, A. (1996). The multivariate SkN-normal distribution. *Biometrika* 83(4), 715-726.
- Bock, H.-H. and Diday, E. (2000). *Analysis of Symbolic Data, Exploratory Methods for Extracting Statistical Information from Complex Data*. Springer, Heidelberg.
- Brito, P., Duarte Silva, A.P. (2011): Modelling Interval Data with Normal and Skew-Normal Distributions. *Journal of Applied Statistics* (in press).
- Diday, E. and Noirhomme-Fraiture, M. (2008). *Symbolic Data Analysis and the SODAS Software*. Wiley.