

# *Mixture Modelling for the Detection of Subpopulations*



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# *Problem*


Are we really sure of the hypothesis of homogeneity in a population ?

Is it possible to find heterogeneities without assumption about


-their existence ?

-their origin ?

Mixture models & Regression methods

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- 1) Detection of Heterogeneity
  - 2) Explanation of Heterogeneity

Likelihood Maximization & Gauss-Hermite Quadrature

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- 3) Estimation fixed parameters and random parameters distribution

# *Definition of the likelihood*

Likelihood formula :  $L = \prod L_i$

with  $L_i = \int_{\mathbb{R}^n} g_i(y_i, \theta, Z_i, \eta) \cdot h(\eta) \cdot d\eta$

$i$ : subject

$y_i$ : observations

$Z_i$ : covariates

$\theta$ : fixed parameters

$\eta$ : random parameters

$g_i$ : distribution of the observations

$h$  : distribution of the random effect

# *Likelihood Approximation*

Different possible methods



Taylor  
approximation  
(NONMEM)

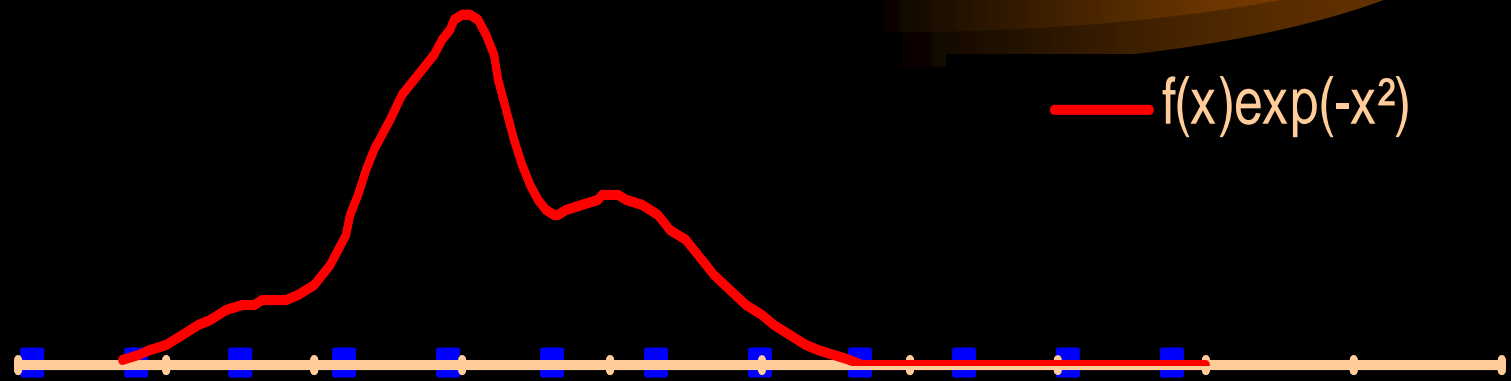


Non parametric  
approach  
NPML



Gauss-Hermite  
Quadrature

# Gauss-Hermite Quadrature



$$\int_{\mathbb{R}} f(x) \cdot e^{-x^2} dx = \sum_{k=1, \dots, r} f(x_k) \cdot A_k$$

$r$ : order of the quadrature

$A_k$ : weights of the quadrature

$x_k$ : nodes of the quadrature

# *Use of GH quadrature to approximate L*

$$L_i = \int_{\mathbb{R}^n} g_i(y_i, \theta, Z_i, \eta) \cdot h(\eta) \cdot d\eta$$

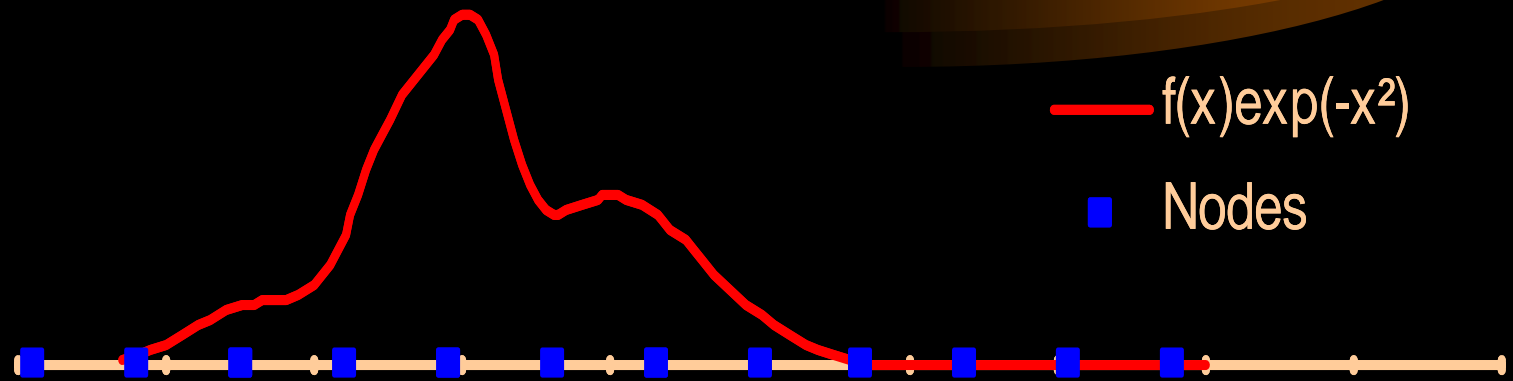


$$\int_{\mathbb{R}} f(x) \cdot e^{-x^2} dx = \sum_{k=1, \dots, r} f(x_k) \cdot A_k$$

Advantage : 

Easily identifiable to  
the likelihood function

# Use of GH quadrature to approximate $L$

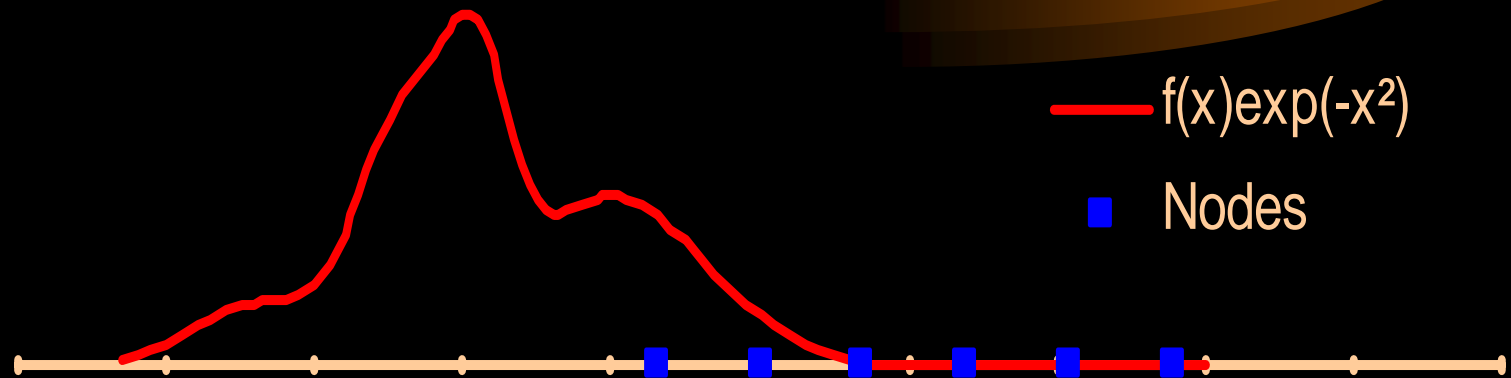


Advantage :

Quality of approximation increases with the order



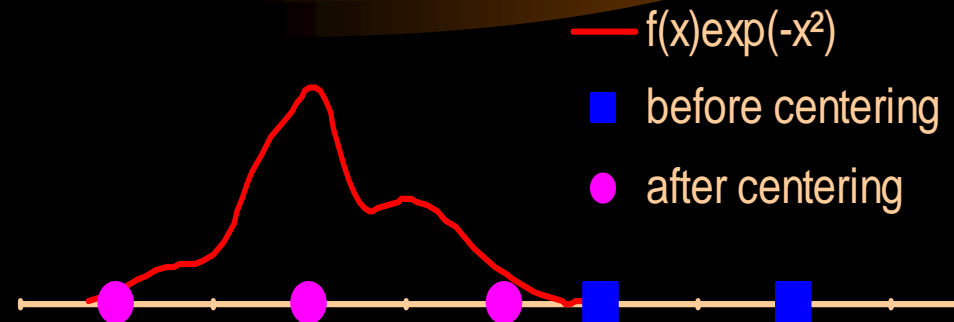
# Use of GH quadrature to approximate $L$



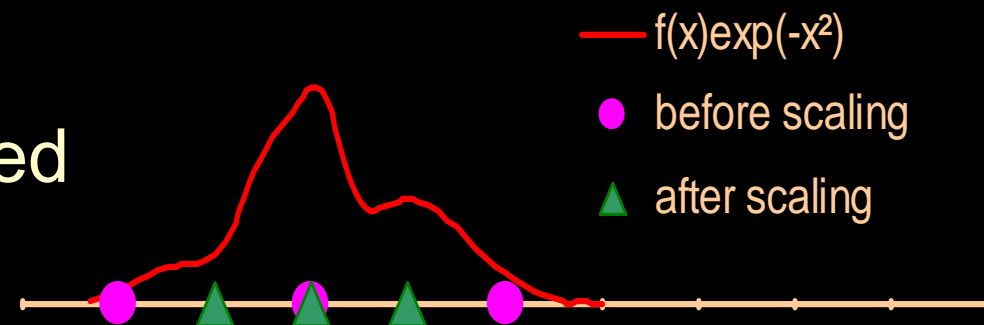
Drawback : ↪ Nodes fixed whatever the function  $f$   
(found in GH table)

# Adaptation of the Quadrature Nodes

Centering



Scaling optimized

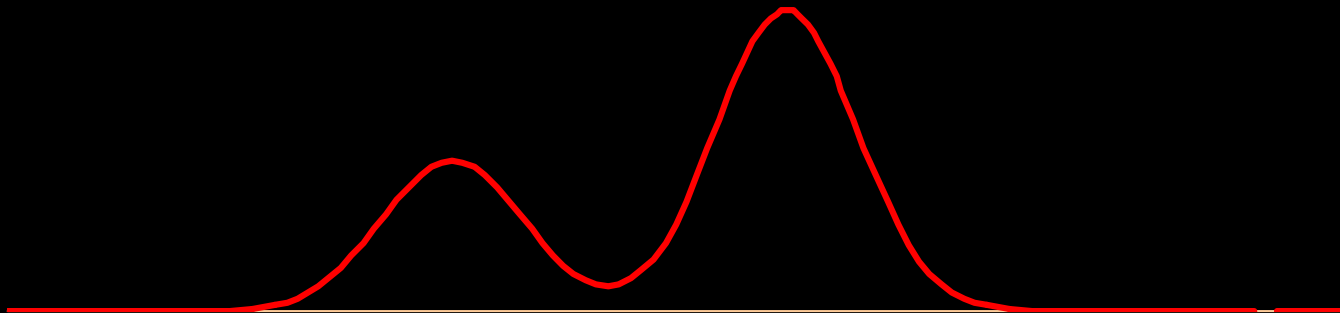


# *Detection of Heterogeneity*

## Mixture Model



Model in which the joint distribution of random effects is assumed to be a weighted sum of normal distributions



# *Test for the Number of Subpopulations*

$\Gamma_p$  : Model p components /  $\Gamma_q$  : Model q components

Kullback-Leibler test

$p < q$  , Null Hypothesis : Model with p components

$$2LR = 2 \sum_{i=1, \dots, N} \log(L_{i\Gamma_q} / L_{i\Gamma_p})$$

Asymptotic distribution of  
2LR under the null  
hypothesis



Weighted sum of  
chi2 1df

# *Attribution of patients subpopulations $G_i$*

Most Probable Subpopulation  $G_i$   
for subject  $i$



supposing  $p$  subpopulations  
and  $j=1, \dots, p$

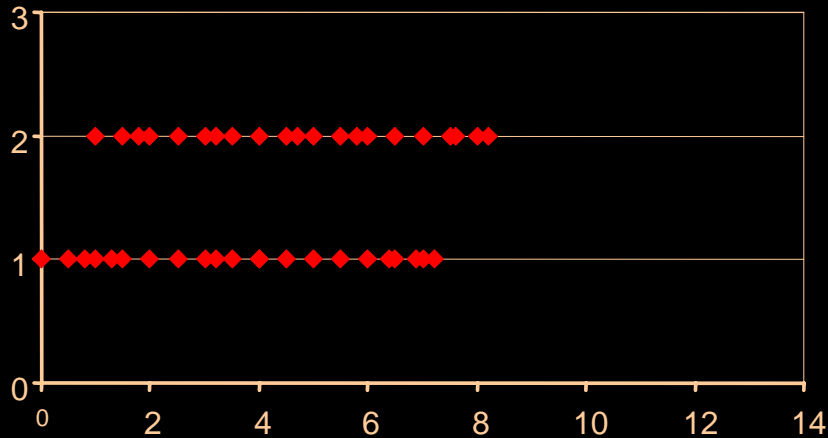
$\text{Max}_j [P(G_i=j)]$

with  $P(G_i=j) = \alpha_j L_{ij} / \sum_{k=1, \dots, p} \alpha_k L_{ik}$  and

$L_{ij}$  the likelihood associated to the  $j^{\text{th}}$  subpopulation

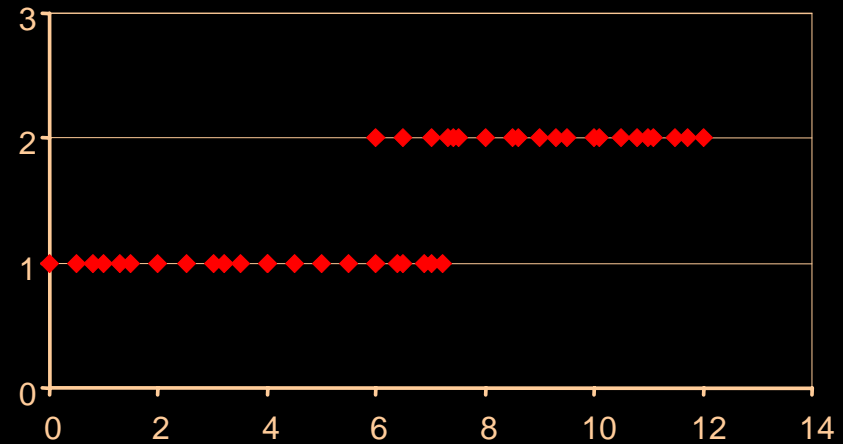
# *Relationship subpopulations-covariates*

subpopulation



covariate 1

subpopulation



covariate 2

# *Relationship covariates-parameters*

m Classes of  
Covariates significant



Non-Adapted Model

$$\text{Parameter}(Z) = \theta \cdot \exp(\eta)$$



Adapted Model

$$\text{Parameter}(Z) = [\sum_k \theta_k 1_{Z=Z_k}] \cdot \exp(\eta)$$

# *Analysis strategy*



**Global Analysis**

Same number of subpopulations on the distribution of all parameters



**Analysis parameter by parameter**

Only one parameter has many subpopulations



# *Application : S05702*

Gliclazide : antidiabetic, treatment of type II diabetes

Data : collected during the clinical development of a once a day modified release formulation

2 phase II + 2 phase III



634 patients

# *S05702 : Analysis*

AUC used to quantify the time course of effect

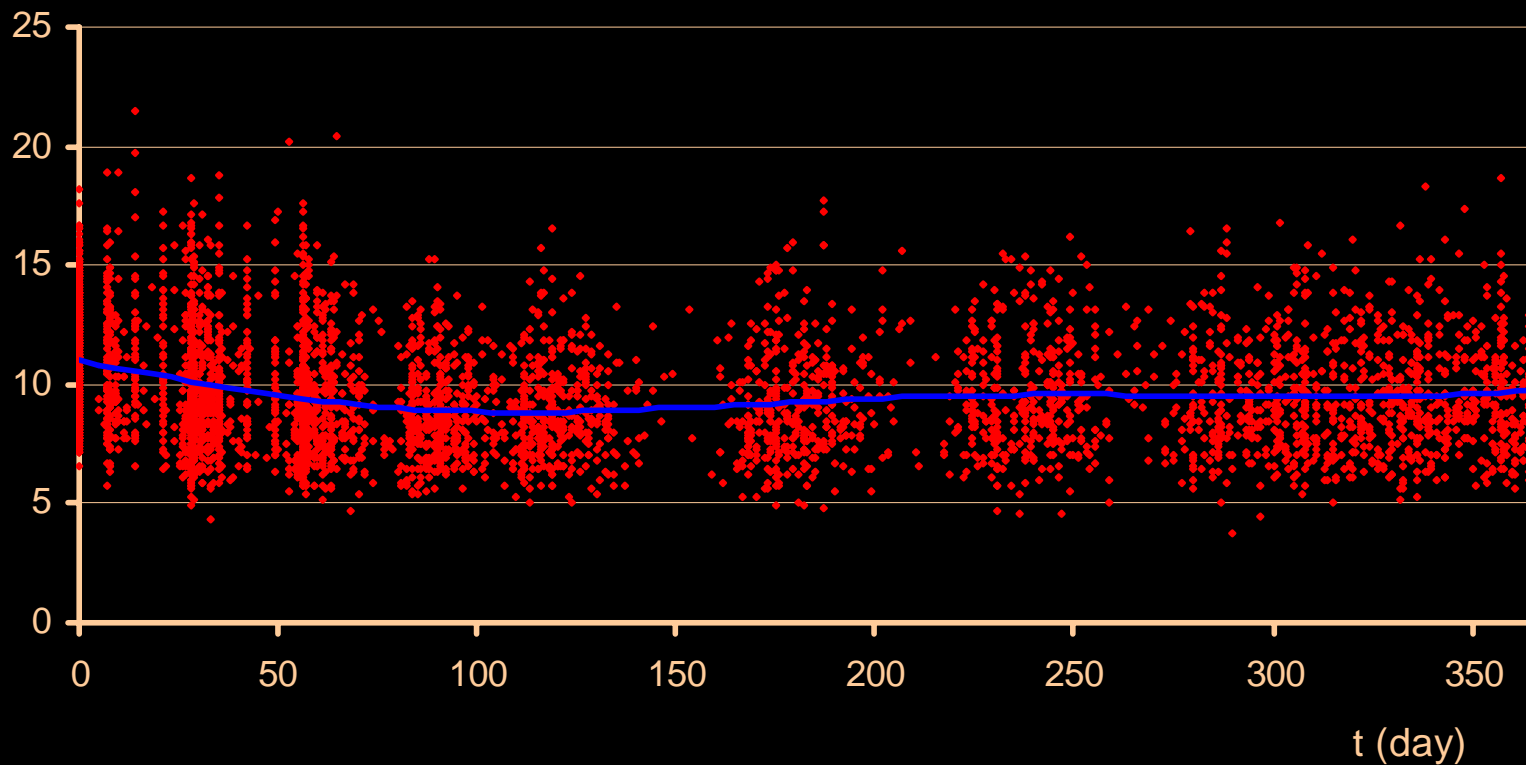
FPG (fast plasma glucose) used as biomarker

Covariates : age, sex, weight, BMI, CRCL, NBOAD, disdur,...

# *S05702 : Observed FPG*

Observed FPG

(mmol.l<sup>-1</sup>)



# *S05702 : PK/PD model*

$$\text{FPG}(t) = \text{Base} - E(t) + \text{DP}$$

with

Base : FPG baseline

DP : Disease progression (function of t)

$$E(t) = P_{\max} \cdot \text{Base} \cdot \text{AUC}_e(t) / (\text{AUC}_e(t) + \text{AUC}_{50})$$

$\text{AUC}_{50}$ : AUC associated to 50% of effect

$\text{AUC}_e(t)$ : AUC accumulated in the effect compartment

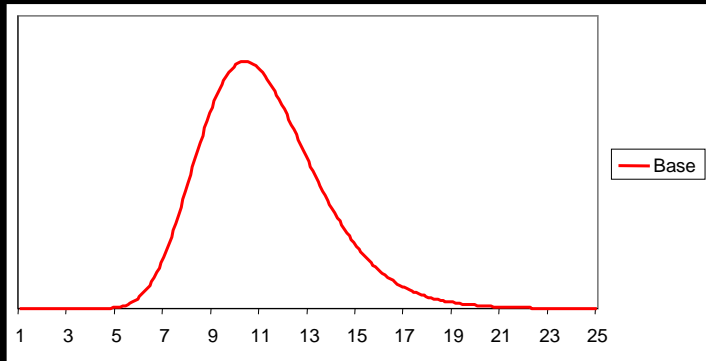
$$\text{AUC}_e(t) = \text{AUC} [1 - \exp(-k_{\text{eq}} \cdot t)]$$

$k_{\text{eq}}$ : constant of equilibration

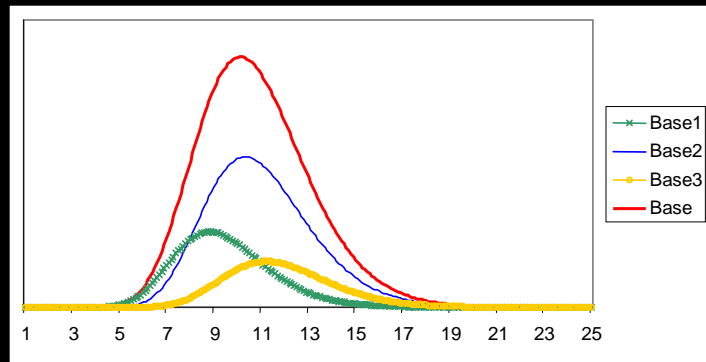
# *S05702 : GH Analysis*

- 1) Heterogeneity on Base
- 2) Global heterogeneity
- 3) Analysis parameter by parameter
- 4) Final global analysis

# *S05702 : Results on Base*

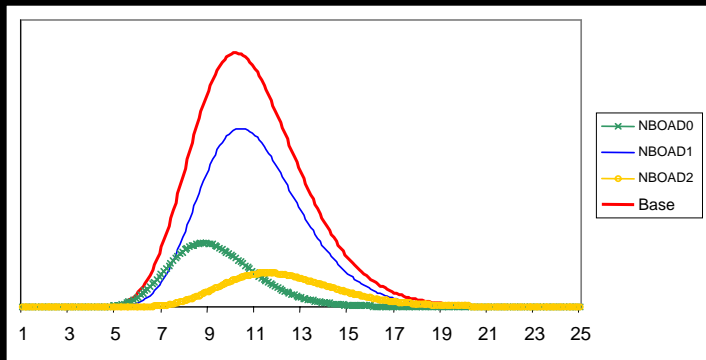


Estimation 1 subpopulation



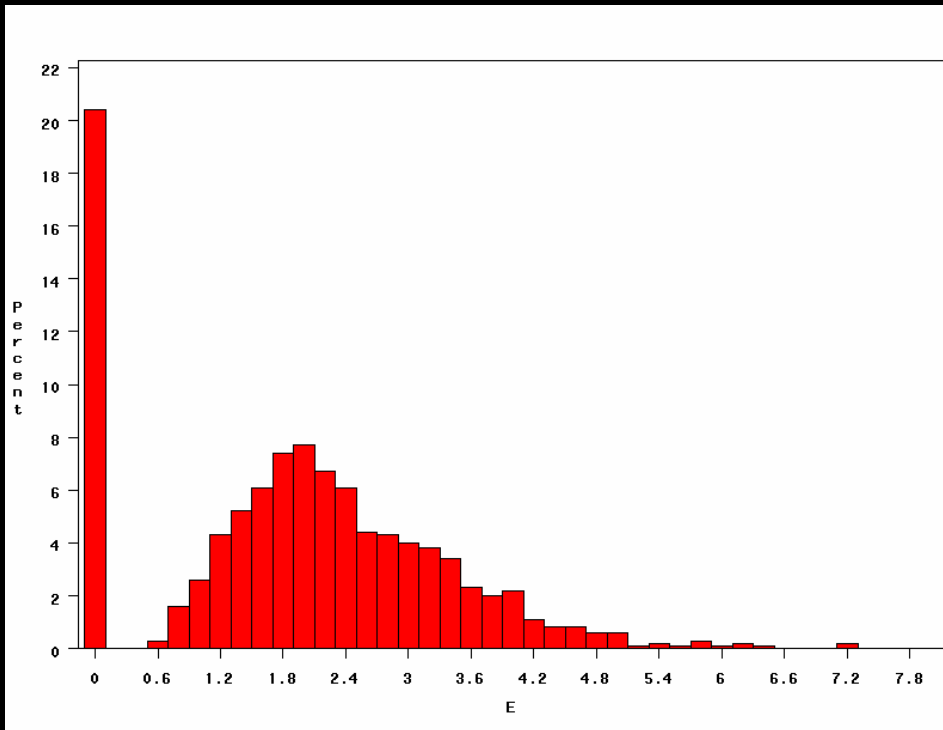
Estimation 3 subpopulations

Logistic Regression -> NBOAD



Estimation 1 subpopulation  
with the adapted model

# *S05702 : Results first global analysis*



Distribution of the effect E (mmol.l<sup>-1</sup>)

Decrease of FPG

2 subpopulations

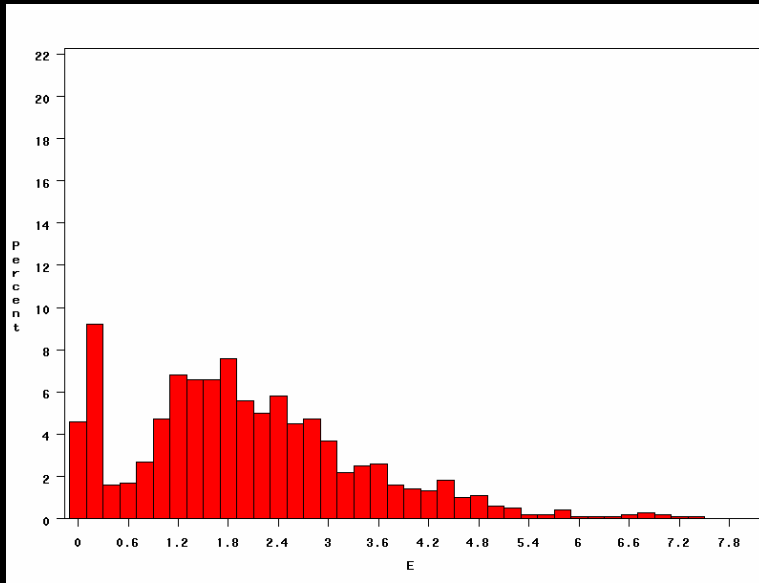
weighted with 21%/79%

One group with very bad responders

# *S05702 : Final results*

1) 2 groups on  $k_{eq}$  only partly explained using NBOAD

2) 2 groups on  $P_{max}$  explained using NBOAD



3) Final global analysis :

2 subpopulations

weighted with 15%/85%

One group with bad responders



# *S05702 : Comparison with NONMEM*

1) 3 groups of Base (mmol.l<sup>-1</sup>) related to NBOAD

	NBOAD=0	NBOAD=1	NBOAD>1
NONMEM	9.6	10.9	12.2
GH	9.2	10.8	12.9

2) Mixture model with a group of non-responders :  
E(t)=0, proportion=25%, non-responders related to  
NBOAD

3) Close estimations of parameters between the 2  
methods except for disease progression DP

$$DP_{GH}(=1.48 \text{ mmol.l}^{-1}) > DP_{NONMEM}(=0.84 \text{ mmol.l}^{-1})$$

# *Conclusion*

## Advantages

- Detection of heterogeneities with no assumption of their existence
- Possible explanation of heterogeneities
- Quality of estimation adjustable using the quadrature

## Future

- Studying different ways to adapt parameters