# The statistical analysis of compositional data:

Processes and regression

Prof. Dr. Juan José Egozcue Prof. Dr. Vera Pawlowsky-Glahn Ass. Prof. Dr. René Meziat

Instituto Colombiano del Petróleo Piedecuesta, Santander, Colombia March 20–23, 2007

#### **Summary**

- 1 The Normal in the simplex
- 2 Simplicial processes
- Simplicial regression

#### Normal distribution in $S^D$

Coordinates:  $X^*$  random variable in  $\mathbb{R}^{D-1}$ 

$$\mathbf{X}^* \sim \mathrm{N}(\mu^*, \mathbf{\Sigma})$$

$$f_{\mathbf{X}^*}(\mathbf{x}^*) = \frac{1}{\sqrt{2\pi(\det\Sigma)^n}} \exp\left(-\frac{1}{2}(\mathbf{x}^* - \boldsymbol{\mu}^*)'\Sigma^{-1}(\mathbf{x}^* - \boldsymbol{\mu}^*)\right)$$

Simplex: given a basis in  $S^D$  and  $\mathbf{X} = i l r^{-1}(\mathbf{X}^*)$ , then

$$\mathbf{X} \sim N_{\mathcal{S}^D}(\mu, \mathbf{\Sigma})$$

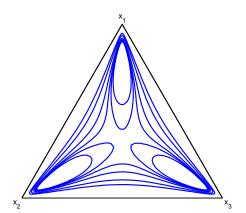
$$\mu = ilr^{-1}(\mu^*)$$

The variance is represented in both cases by  $\Sigma$ 

## Normal on the simplex (logistic-normal)

 $S^3 \subset \mathbb{R}^2$ , Lebesgue measure as reference:

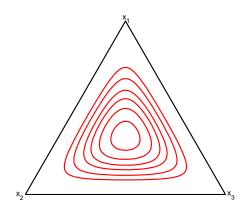
Radon-Nikodym derivative:  $f = \frac{dP}{d\lambda}$ 



## Normal on the simplex (logistic-normal)

 $S^3$  as Euclidean space, Aitchison measure as reference:

Radon-Nikodym derivative: 
$$f = \frac{dP}{d\lambda_S} = \frac{dP}{d\lambda} \cdot \frac{d\lambda}{d\lambda_S}$$



#### Representation in the ternary diagram

- Compute the elliptical contours of the Normal distribution in coordinates, by points
- Select a basis, and take ilr<sup>-1</sup> of each point in the contours
- plot the ilr<sup>-1</sup> transformed points in the ternary diagram

This procedure is equivalent to represent the density with respect to the Aitchison measure

To obtain contours with respect Lebesgue measure in the ternary diagram, the Jacobian of the ilr transformation is taken into account

#### **Exponential decay or growth**

Bacteria growth: mass of 3 species:  $x_1(t)$ ,  $x_2(t)$ ,  $x_3(t)$  Growth without interaction:

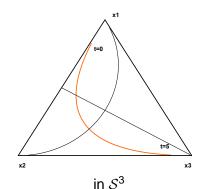
$$x_i(t) = x_i(0) \cdot \exp(\lambda_i t) , (\lambda_i > 0) , i = 1, 2, 3$$

Considered as compositional: straight-line in  $S^3$ 

$$\mathbf{x}(t) = \mathbf{x}(0) \oplus (t \odot \exp(\lambda))$$

#### **Bacteria growth**

$$\mathbf{x}(0) = [10.0, 2.0, 0.1], \ \lambda = [1, 2, 3], \ t = 0, \dots, 5$$

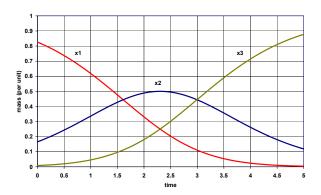


g .1 .1 .1 .2 .3 .4

coordinate representation

## **Bacteria growth**

$$\mathbf{x}(0) = [10.0, 2.0, 0.1], \ \lambda = [1, 2, 3], \ t = 0, \dots, 5$$



#### Complementary process

#### Three isotopes:

 $x_1(t)$  radioactive; decays with rate  $\lambda_1$ 

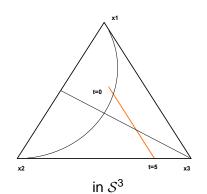
 $x_2(t)$  inert; does neither grow nor decay  $\lambda_2 = 0$ 

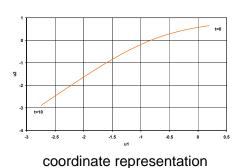
 $x_3(t)$  residual of decomposition of  $x_1$ 

$$x_1(t) = x_1(0) \cdot \exp(\lambda_1 t) , \ x_2(t) = x_2(0) , \ x_3(t) = x_3(0) + x_1(0) - x_1(t)$$

parameter	<i>X</i> <sub>1</sub>	<b>X</b> 2	<b>X</b> 3
disintegration rate	0.5	0.0	0.0
initial mass	1.0	0.4	0.5
balance 1	+1	+1	-1
balance 2	+1	-1	0

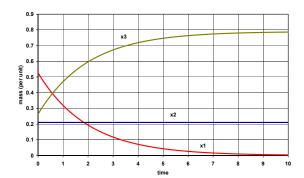
The complementary part  $x_3(t)$  makes the process non-linear





#### Radioactive disintegration

$$\mathbf{x}(0) = [10.0, 2.0, 0.1], \ \lambda = [1, 2, 3], \ t = 0, \dots, 5$$



#### **Perturbation versus mixture**

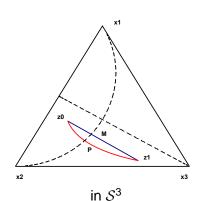
Consider a initial, final composition of a liquid, z<sub>0</sub> and z<sub>1</sub>

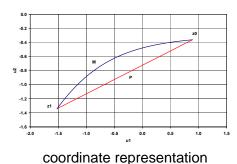
Mixing: change volume composition  $[\alpha, 1 - \alpha]$ ,  $0 \le \alpha \le 1$ 

$$\mathbf{z}(\alpha) = ((1 - \alpha) \cdot \mathbf{z}_0) + (\alpha \cdot \mathbf{z}_1)$$

Perturbing:

$$\mathbf{z}(\tau) = \mathbf{z}_0 \oplus \{\tau \odot (\mathbf{z}_1 \ominus \mathbf{z}_0)\} = ((1 - \tau) \odot \mathbf{z}_0) \oplus (\tau \odot \mathbf{z}_1)$$





#### **Regression model**

Data: for i = 1, 2, ..., ncompositional response,  $\mathbf{x}_i \in \mathcal{S}^D$ , real covariates,  $\mathbf{t}_i = [t_0, t_1, t_2, ..., t_r], t_0 = 1$ 

Statement: find compositional coefficients  $\beta_i \in \mathcal{S}^D$ , minimizing

$$SSE = \sum_{i=1}^{n} \|\hat{\mathbf{x}}(\mathbf{t}_i) \ominus \mathbf{x}_i\|_a^2,$$

$$\hat{\mathbf{x}}(\mathbf{t}) = \beta_0 \oplus (t_1 \odot \beta_1) \oplus \cdots \oplus (t_r \odot \beta_r) = \bigoplus_{i=0}^r (t_i \odot \beta_i),$$

#### Regression model in coordinates

- Select a basis in  $S^D$ , e.g. using sbp;
- Represent responses in coordinates:  $\mathbf{x}_i^* = h(\mathbf{x}_i) \in \mathbb{R}^{D-1}$ ;
- Solve D 1 ordinary regression problems in coordinates to obtain coordinates of coefficients;
- Back-transform results into S<sup>D</sup>

For k = 1, 2, ..., D, find  $\beta^*$  minimizing

$$SSE_k = \sum_{i=1}^n |\hat{X}_k^*(t_i) - X_{ik}^*|^2 , \ k = 1, 2, ..., D-1 ,$$

$$\hat{\mathbf{x}}_{k}^{*}(\mathbf{t}) = \beta_{0k}^{*} + \beta_{1k}^{*} t_{1} + \cdots + \beta_{rk}^{*} t_{r}$$

Back-transform:  $\beta_j = h^{-1}(\beta_j^*)$ 

#### Example: statement

#### Vulnerability of a dike:

- Safety level or design d (wave-height-design)
- External actions h (wave-height of a storm)
- Outputs after an action  $\theta_k$ ,  $k = 0, 1, \dots, 4$
- Vulnerability description:  $\mathbf{x}(d, h) = P[\theta_k | d, h]$

Available data (from Monte Carlo simulations):

$$\mathbf{x}(d_i, h_i) = P[\theta_k | d_i, h_i], i = 1, 2, ..., n$$

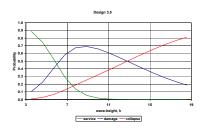
affected by errors, especially, for low probabilities.

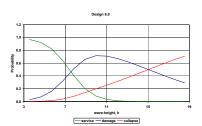
#### example: data set

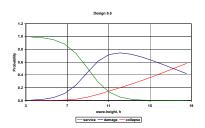
Number of data: n = 11Number of parts: D = 3

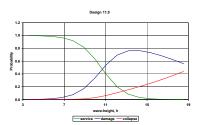
Number of covariates: r = 2

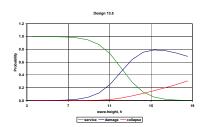
Design	Wave-height	p. service	p. damage	p.collapse
3.0	3.0	0.50	0.49	0.01
3.0	10.0	0.02	0.10	0.88
10.0	3.0	0.999	0.0009	0.0001
10.0	10.0	0.30	0.65	0.05
5.0	4.0	0.95	0.049	0.001
6.0	9.0	80.0	0.85	0.07
7.0	5.0	0.97	0.027	0.003
8.0	3.0	0.997	0.0028	0.0002
9.0	9.0	0.35	0.55	0.01

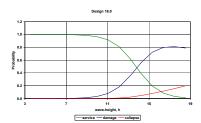


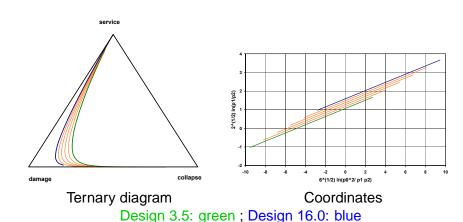












#### **Example: analysis of residuals**

#### ANOVA:

$$c_1 = \frac{1}{6} \ln \frac{p_0^2}{p_1 p_2}$$
,  $p - \text{value} = 2.69E - 05$   
 $c_2 = \frac{1}{2} \ln \frac{p_1}{p_2}$ ,  $p - \text{value} = 3.15E - 01$ 

