Multiblock Method for Categorical Variables

Application to the study of antibiotic resistance

S. Bougeard[1], E.M. Qannari[2] & C. Chauvin[1]

[1] *French agency for food, environmental and occupational health safety (Anses), Department of Epidemiology, Ploufragan, France*

[2] *Nantes-Atlantic National College of Veterinary Medicine, Food Science and Engineering (Oniris), Department of Chemometrics and Sensometrics, Nantes, France*

19*th* International Conference on Computational Statistics, Paris, August 22 – 27, 2010

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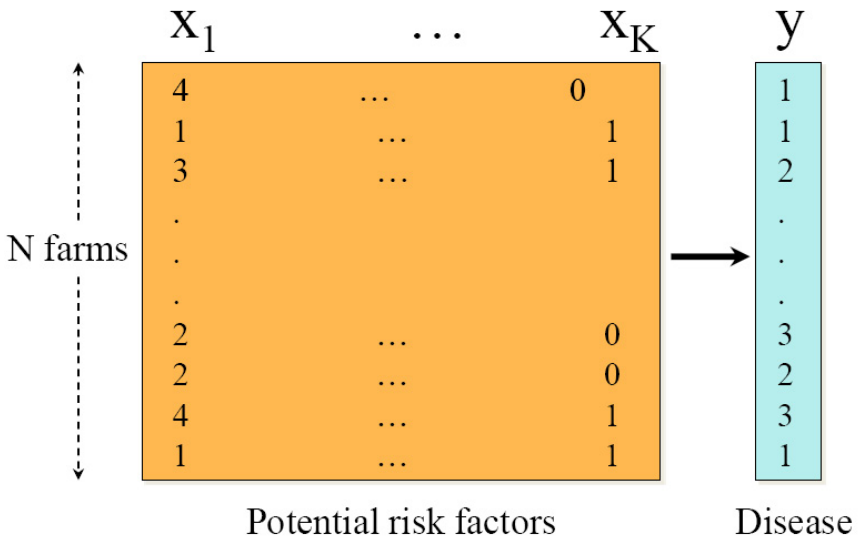
Statistical issues for epidemiological surveys



2. Expectations

- Global optimization criterion with eigensolution,
- Assessement of the risk factors,
- Factorial representation of data.

→ **Multiblock modelling** extended to categorical data.

1. Advantages & limits of usual procedures

- Generalized linear models
  - Well-adapted for categorical variables,
  - Limited number of explanatory variables,
  - Constraints when *y* consists of more than 2 categories.
- Decision trees, Random Forest
  - Small misclassification errors,
  - Variables sorted in order of magnitude,
  - No regression coefficients.
- Boosting, bagging, SVM
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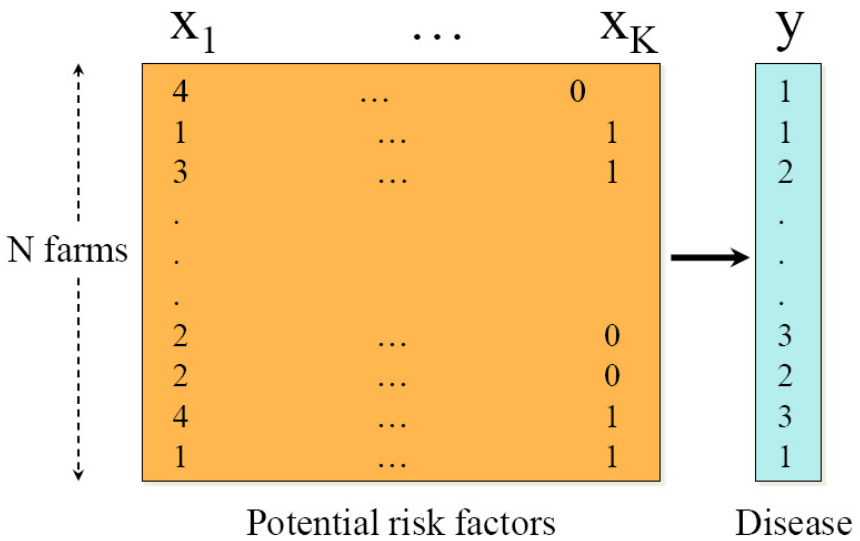

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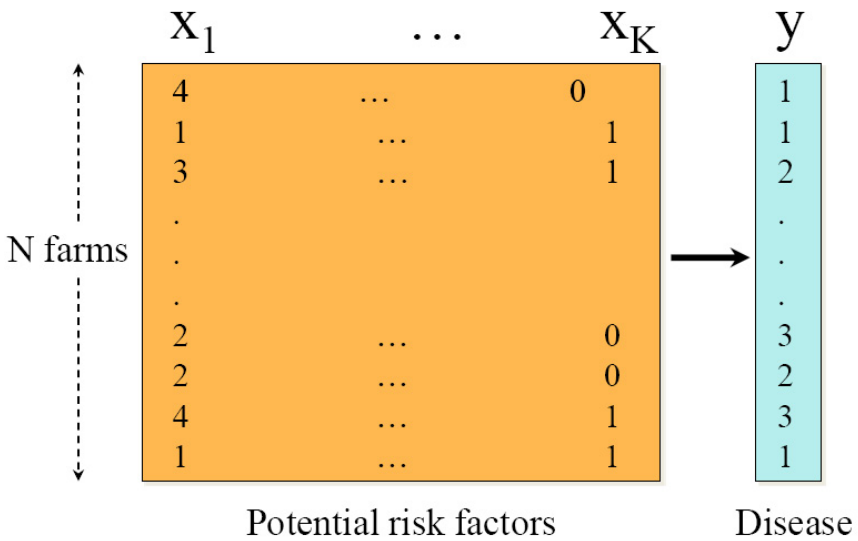

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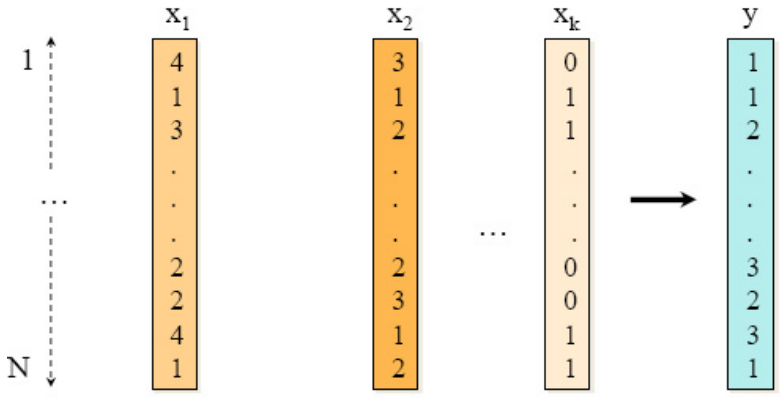

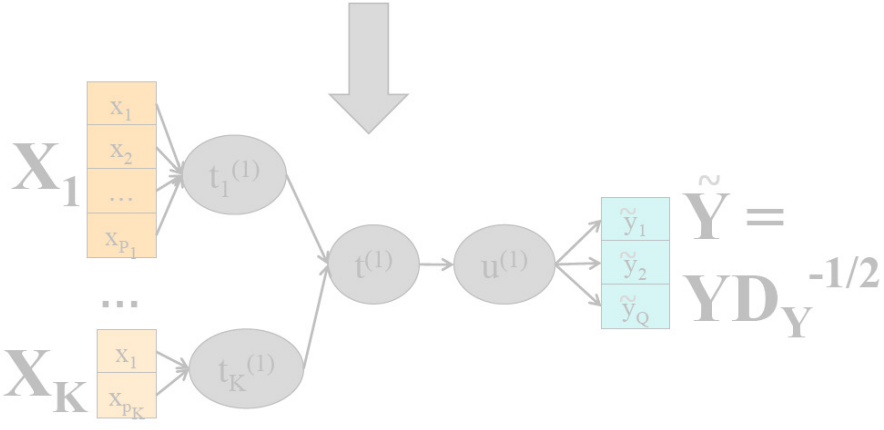

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- $\sum_k cov^2(u^{(1)}, t_k^{(1)})$, with $||t_k^{(1)}|| = ||v^{(1)}|| = 1$
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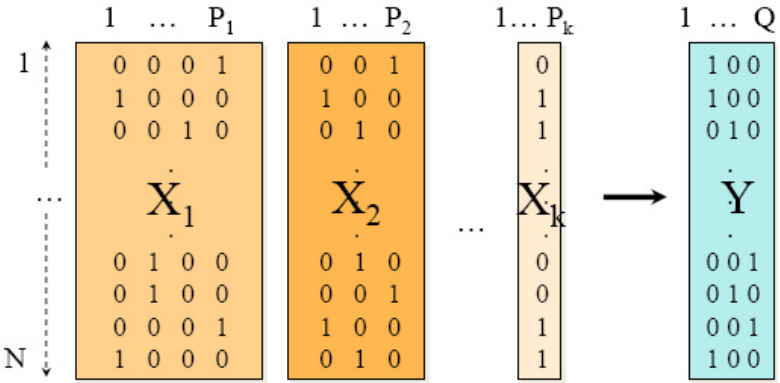

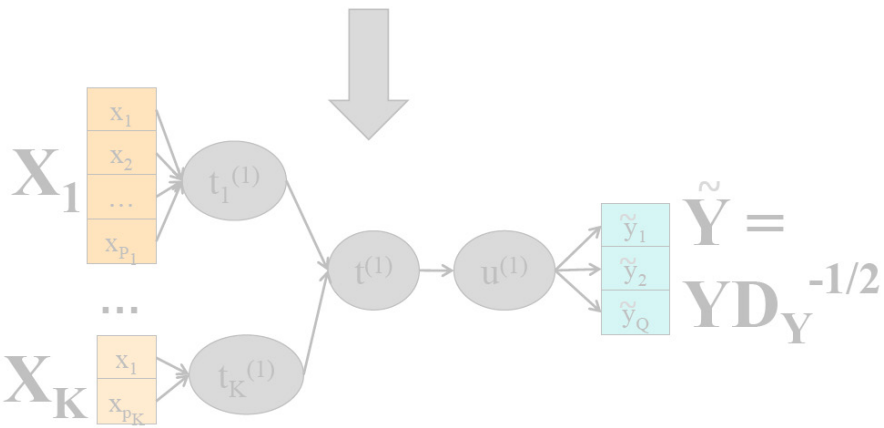

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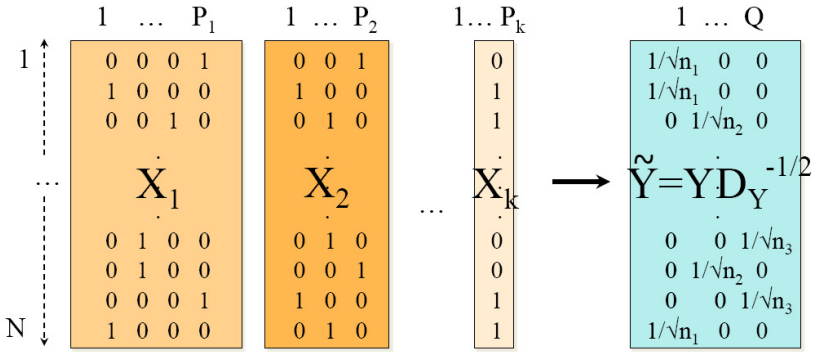

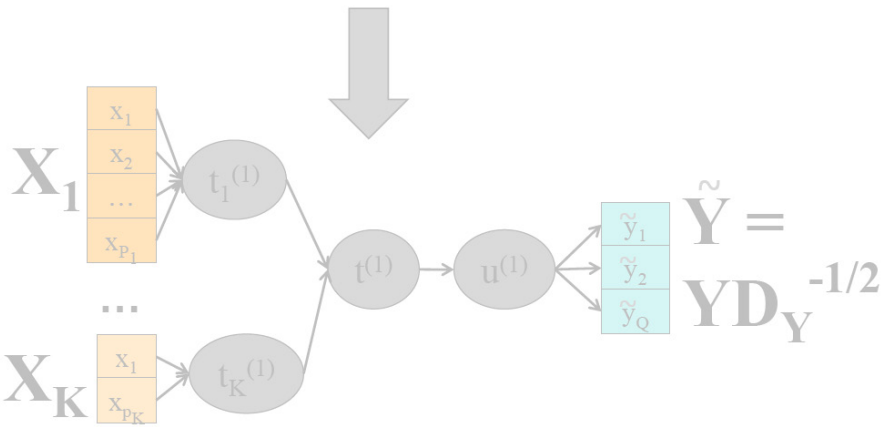

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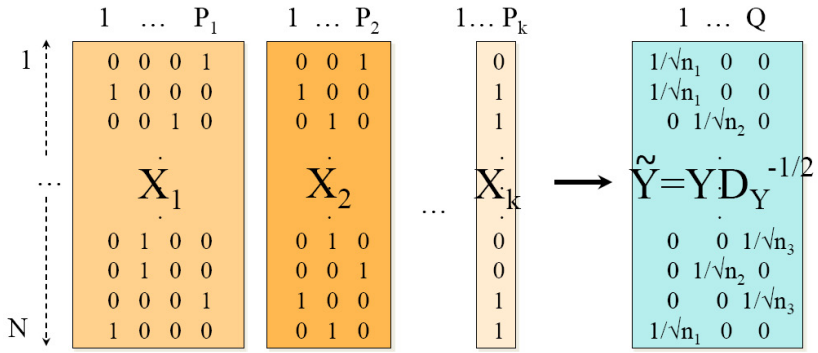

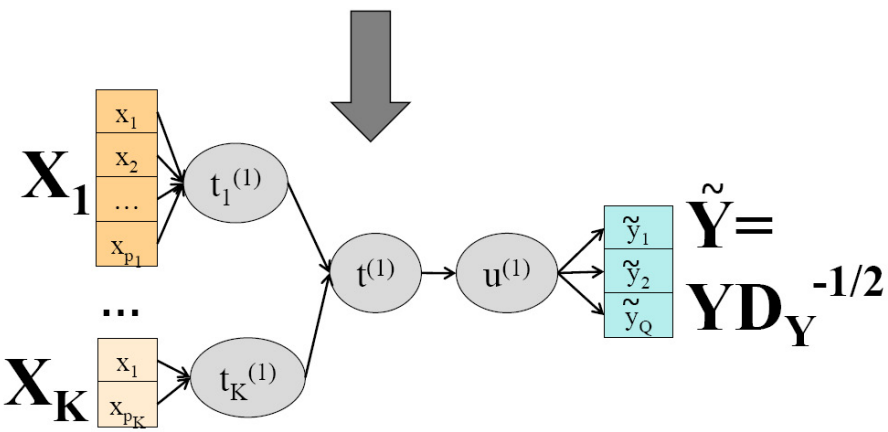

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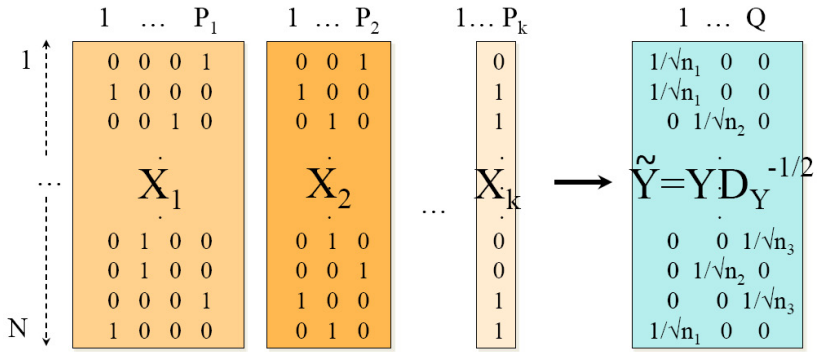

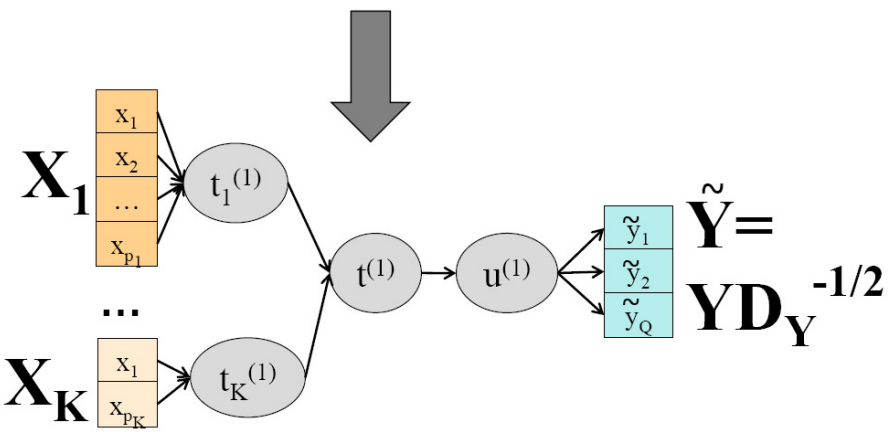

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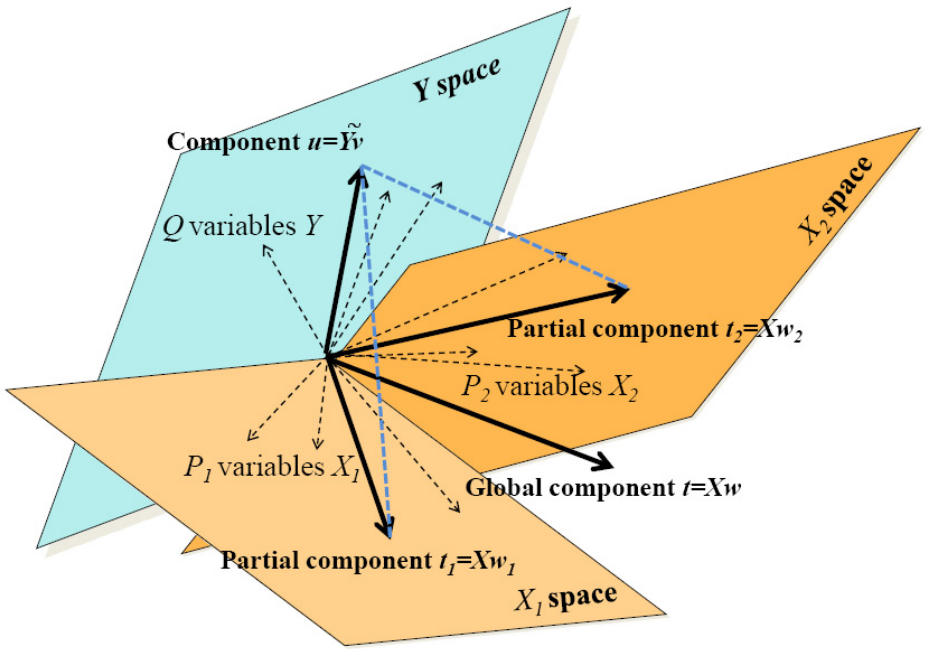

Partial components $(t_1, \ldots, t_K)$

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Synthesis with a global component t

- $t^{(1)}$ sums up all the partial codings : $t^{(1)} = \sum_k a_k^{(1)} t_k^{(1)}$ with $\sum_k a_k^{(1)^2} = 1$,
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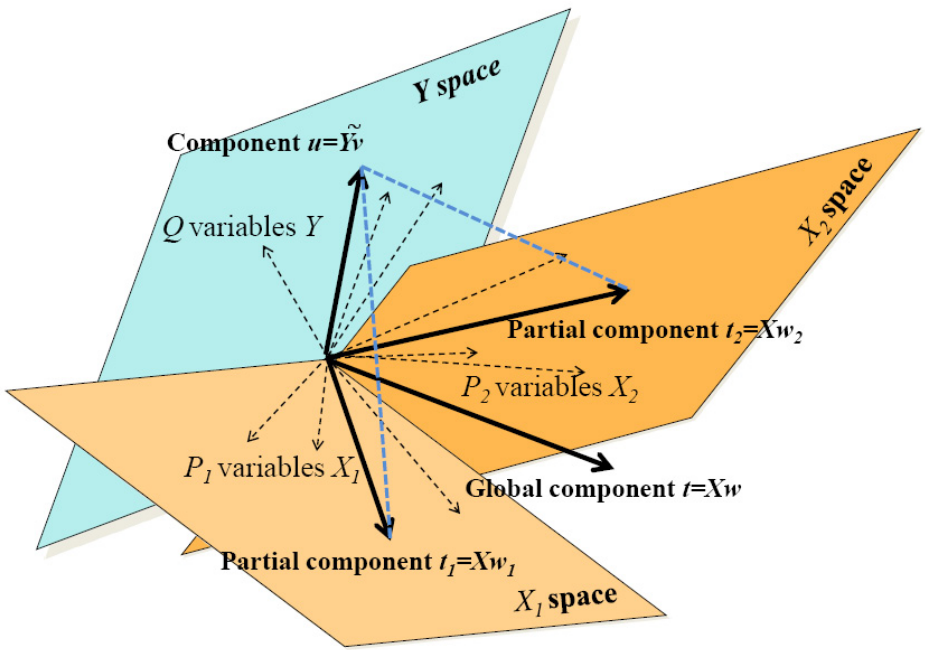

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Higher order solutions and optimal Cat-mbRA model

Higher order solutions

Aim : Orthogonalised regressions which take into account all the explanatory variables, *i.e.* orthogonal components $(t^{(1)}, \ldots, t^{(H)})$.

$\longrightarrow$ Consider the residuals of the orthogonal projections of $(X_1, \ldots, X_K)$ onto the subspaces spanned by $t^{(1)}$, $(t^{(1)}, t^{(2)})$, ...

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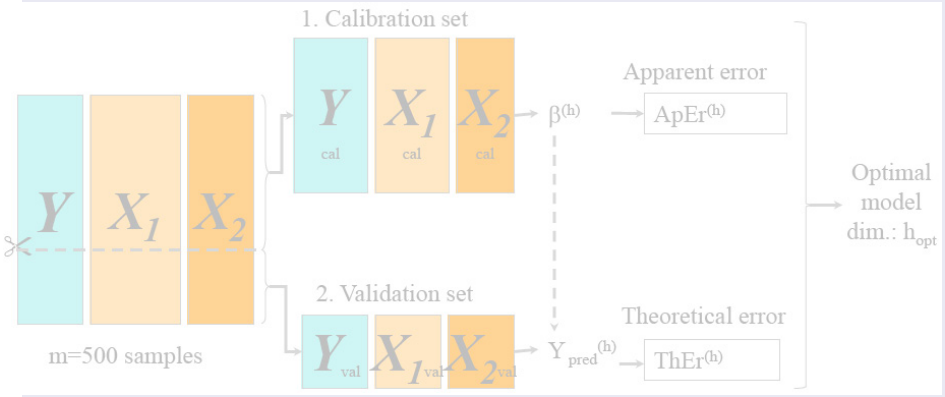

Additional information :

- Confusion matrix,
- ROC (=Receiver Operating Characteristic) curve.

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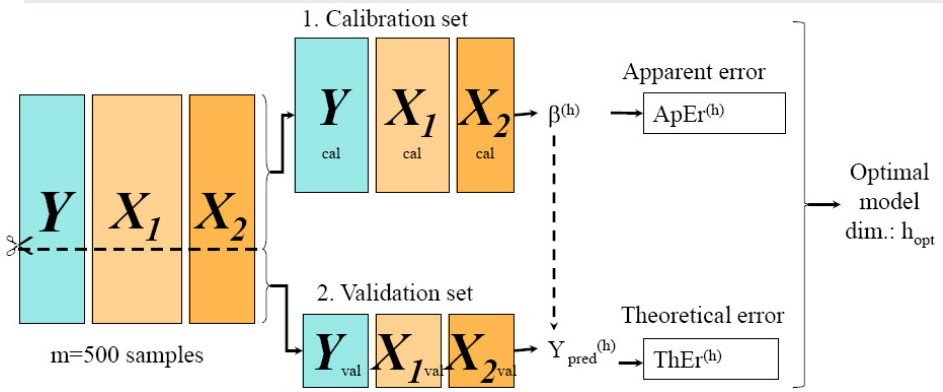

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Alternative methods for qualitative discrimination

Robust Generalized Linear Model framework

- Ridge logistic regression [Barker & Brown, 2001], principal component logistic regression [Aguilera *et al.*, 2006],
- PLS generalized regression (*e.g.* PLS logistic regression) [Marx, 1996 ; Bastien *et al.*, 2005].

Factorial analysis framework

- *Disqual* procedure [Saporta & Niang, 2006],
- Multiple non Symmetrical Correspondence Analysis [Lauro & Balbi, 1999].

Multiblock and Structural Equation Modelling framework

- Categorical extension of GCA-RT, *i.e.* MCA-RT [Kissita, 2003] and of multiblock PLS, *i.e.* MCOI-catPLS [D'Ambra et al., 2002],
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Epidemiological data

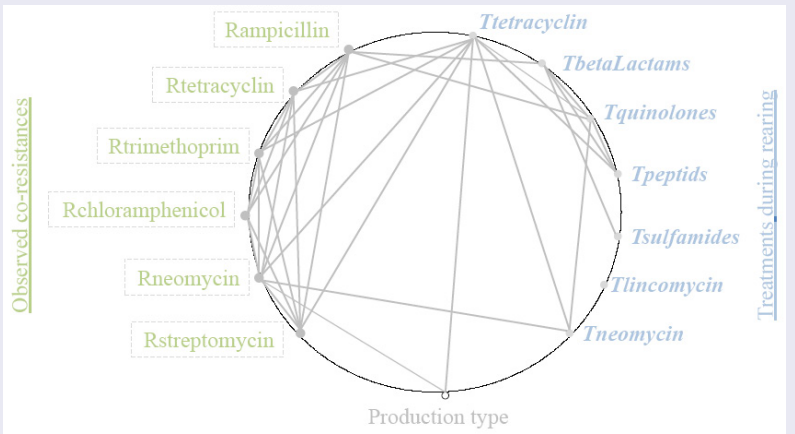
Epidemiological survey

- Part of the French antimicrobial resistance monitoring program (1999 – 2002),
- Study of the relationships between antibiotic consumption and resistance in healthy poultry.
- Screening of *E. coli* for antimicrobial resistances.

Data description

- Dependent variable : resistance to Nalidixic Acid,
- 14 explanatory variables : production type, previous antimicrobial treatments (7 var.), observed co-resistances (6 var.),
- $N = 554$ broiler chicken flocks.

Highly correlated explanatory variables



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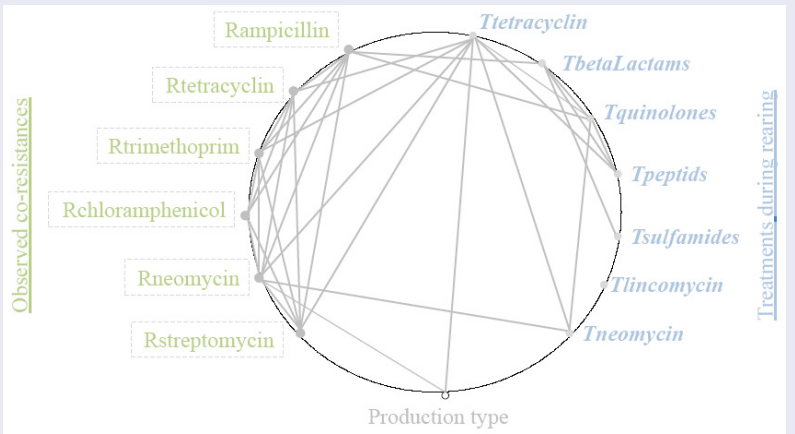

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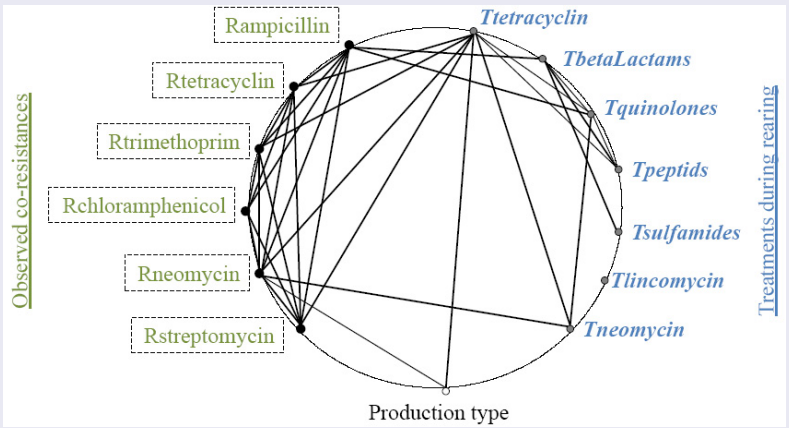
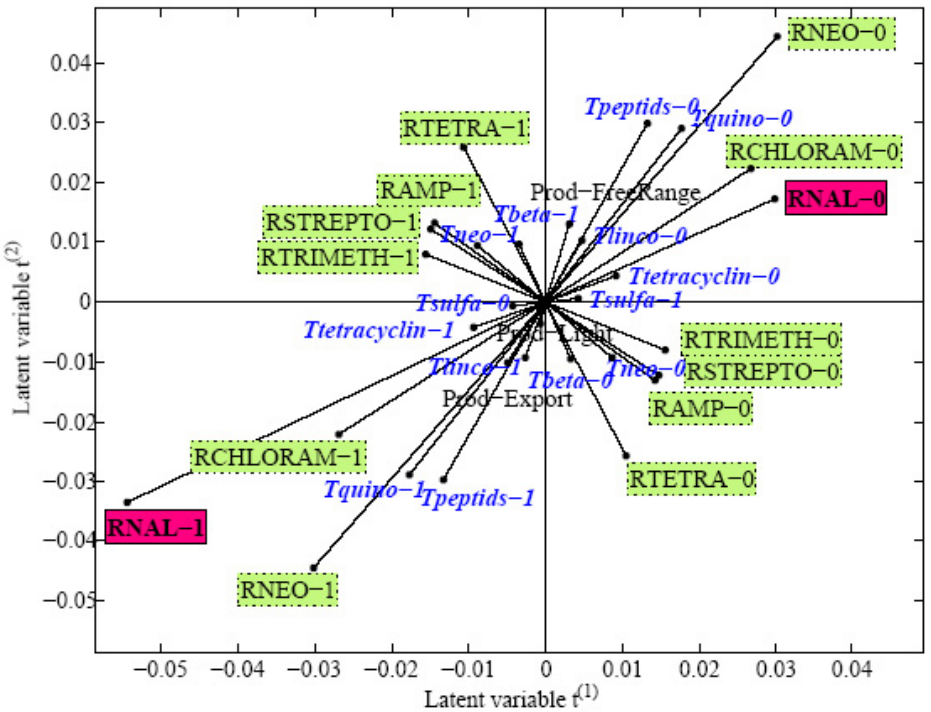


Plot of the variable loadings on the first two latent variables of cat-mbRA



- Dependent variable
- Observed co-resistances (explanatory variables),
- Previous antimicrobial treatments (explanatory variables),
- Production type (explanatory variables).

Interpretation

The resistance to Nalidixic Acid ($RNAL = 1$) is mainly associated with :

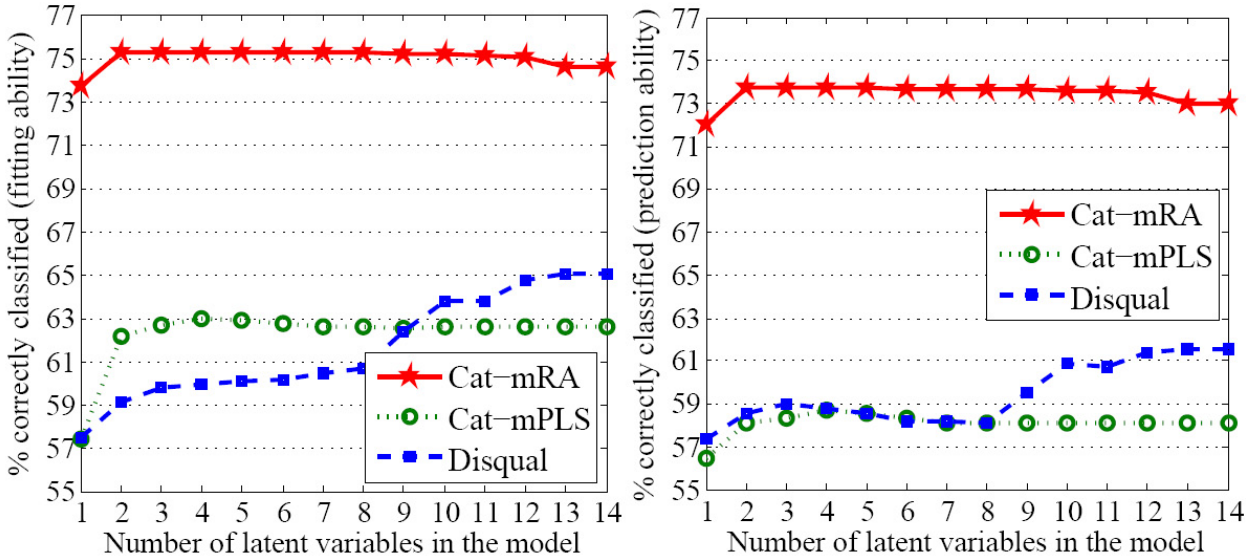
- Two other co-resistances (Chloramphenicol and Neomycin),
- Two antimicrobial treatments during rearing (Quinolones and Peptides).

Risk factors for Nalidixic Acid resistance

Results obtained from cat-mbRA with ($h_{opt} = 2$) latent variables, significant regression corfficients

Explanatory variables	**Number of cases**	**Nalidixic Acid resistance**
Treatments during rearing :		
Tetracyclin	153/554 (27.6%)	NS
Beta-lactams	75/554 (13.5%)	NS
Quinolones	93/554 (16.8%)	0.0058 [0.0015-0.0101]
Peptides	48/554 (8.7%)	NS
Sulfonamides	38/554 (6.9%)	NS
Lincomycin	33/554 (6.0%)	NS
Neomycin	26/554 (4.7%)	NS
Observed co-resistances :		
Ampicillin	278/554 (50.2%)	NS
Tetracyclin	462/554 (83.4%)	NS
Trimethoprim	284/554 (51.3%)	NS
Chloramphenicol	86/554 (15.5%)	0.0066 [0.0012-0.0119]
Neomycin	62/554 (11.2%)	0.0094 [0.0037-0.0151]
Streptomycin	297/554 (53.6%)	NS
Production :		
Export	192/554 (34.6%)	NS
Free-range	63/554 (11.4%)	NS
Light	299/554 (54.0%)	NS

Comparison with alternative methods



Additional information

- Cat-mbRA : good performance due to $Se = 96.5\%$, whereas $Sp = 17.7\%$ (fitting ab.),
- Logistic regression : surprising good performance, with $Se = 95.7\%$ and $Sp = 21.4\%$ (fitting ab.),
- Cat-mbPLS (resp. *Disqual*) : average performance with $Se = 61.2\%$ (resp. 56.4%) and $Sp = 65.2\%$ (resp. 66.2%) (fitting ab.),
- No real differences between the methods on the ROC curves.

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Conclusion

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- Extension in the field of multiblock modelling framework,
- Application to a real epidemiological survey,
- Code programs and interpretation tools developed in Matlab®.

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- Extension to the prediction of several categorical variables.

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