Analysis of Association on Non-Product Spaces

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JOINT WORK WITH TAMÁS RUDAS

Outline

- Motivation.
- Relational models without the overall effect.
- Properties of the MLE.
- Computation of the MLE.

Non-product sample spaces

A sample space is a proper subset of the Cartesian product of the ranges of the variables of interest (structural zeros - combinations that do not exist logically or in a particular population)

- Patterns of participation in waves of a panel study
- Lists of traffic violations
- Market basket analysis
- Congenital malformations

Data: Indicators of Features

	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5
1	1	0	1	1	1
2	1	1	1	0	1
3	1	1	1	0	0
4	1	1	0	0	0
5	1	0	1	1	1
6	1	0	0	0	0
7	0	1	1	1	0
8	0	1	0	1	0
9	0	1	1	0	1
10	0	1	1	0	1

At least one feature is present.

Independence of Malformations

• Do malformations X₁ and X₂ occur independently of each other?

	<i>X</i> ₁	
X_2	No	Yes
No	-	${f p}_{01}$
Yes	p ₁₀	\mathbf{p}_{11}

The model of independence: $\mathbf{p}_{11} = \mathbf{p}_{01}\mathbf{p}_{10}$.

A.Klimova, T.Rudas, A.Dobra (2012). Relational Models for Contingency Tables. J. Multivariate Anal., 104, 159–173.

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Observed Data

Patient	X_1	X_2
1	0	1
2	1	1
3	1	0
4	1	0
5	1	1
6	1	0
7	1	0

	X ₁	
X_2	No	Yes
No	-	47
Yes	42	13

Relational Model

The model of independence: $\mathbf{p}_{11} = \mathbf{p}_{01}\mathbf{p}_{10}$.

Generating subsets: X_1 is present; X_2 is present.

Model matrix: $\mathbf{A} = \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \end{pmatrix}$.

Log-linear representation: log $\mathbf{p} = \mathbf{A}' \boldsymbol{\beta}$, where $\boldsymbol{\beta} = exp(\boldsymbol{\theta})$.

Multiplicative representation: $p_{01} = \theta_1, p_{10} = \theta_2, p_{11} = \theta_1 \theta_2.$

Under such a model, there is no parameter that is common to every cell in the table. This is a model without the overall effect.

MLE in Curved Families

Assume that the observed distribution q is positive. The MLE p̂ exists, and it is the unique solution of the system:

 $egin{aligned} \mathbf{A}\hat{\mathbf{p}} &= oldsymbol{\gamma} \mathbf{A} \mathbf{q}, \ & & p_{01} p_{10} = p_{11}, \ & & p_{11} + p_{01} + p_{10} = 1. \end{aligned}$

- Here $\gamma = \gamma(q)$ is an adjustment factor.
- The mean-value parameters of the MLE are proportional to those of the observed distribution. (For regular exponential families, they are equal!).

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How IPF works

- Starts with a distribution $p^{(0)}$ in the model: $p_{01}^{(0)}p_{10}^{(0)} = p_{11}^{(0)}$.
- Rescales the components of **p**^(*n*) according to the values of A_i **q**, where A_i are the rows of **A**:

$$p_{ij}^{(n)} = p_{ij}^{(n-1)} \left(\frac{A_j \mathbf{q}}{A_j \mathbf{p}^{(n-1)}}\right)^{a_{ji}}$$

• The sequence $p^{(n)}$ converges to a p^* that satisfies

$$\mathbf{A}\mathbf{p}^* = \mathbf{A}\mathbf{q}, \ p_{01}^*p_{10}^* = p_{11}^*.$$

- If $p_{01}^* + p_{10}^* + p_{11}^* = 1$, then $\mathbf{p}^* = \hat{\mathbf{p}}$ is the MLE.
- Can this procedure be modified to include the adjustment factor: Ap̂ = γAq? Is it implied that p^{*}₀₁ + p^{*}₁₀ + p^{*}₁₁ = 1?

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G-IPF Algorithm (Klimova and Rudas, 2013)

- Select a value $\tilde{\gamma}$ of the adjustment factor.
- Choose a $p^{(0)}$ in the model: $p_{01}^{(0)}p_{10}^{(0)} = p_{11}^{(0)}$.
- Rescale the components of **p**⁽ⁿ⁾:

$$p_{ij}^{(n)} = p_{ij}^{(n-1)} \left(ilde{\gamma} rac{\mathcal{A}_j \mathbf{q}}{\mathcal{A}_j \mathbf{p}^{(n-1)}}
ight)^{\mathbf{a}_j}$$

- Then $\mathbf{p}^{(n)} \to \tilde{\mathbf{p}}$ that satisfies $\mathbf{A}\tilde{\mathbf{p}} = \tilde{\gamma}\mathbf{A}\mathbf{q}, \ \tilde{p}_{01}\tilde{p}_{10} = \tilde{p}_{11}.$
- If $\tilde{p}_{01} + \tilde{p}_{10} + \tilde{p}_{11} = 1$, then $\tilde{\mathbf{p}}$ is the MLE.
- Otherwise, choose a smaller or a larger $\tilde{\gamma}$ depending on whether $\tilde{p}_{01} + \tilde{p}_{10} + \tilde{p}_{11} > 1$ or $\tilde{p}_{01} + \tilde{p}_{10} + \tilde{p}_{11} < 1$.

G-IPF (Klimova and Rudas, 2013)

Iterative Scaling in Curved Exponential Families. arXiv: 1307.3282

- The algorithm converges to the MLE.
- The proof of convergence is based on Bregman divergence (generalization of Kullback-Leibler divergence).
- R-package gIPFrm.

	X1		
X_2	No	Yes	
No	-	47(44.872)	
Yes	42(39.679)	13(17.456)	

The adjustment factor = 1.039. **P**-value = 0.24.

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