



Interaction Effect in Age-Period-Cohort Analysis Vivien Goepp¹, Grégory Nuel², and Olivier Bouaziz¹ ¹MAP5, (UMR 8145), Université Paris Descartes ²LPSM, (UMR 8001), Sorbonne Université

Statistical Methods for Post Genomic Data, 31st Jan–1st Feb 2019, Barcelona





Motivating Example

The E3N Cohort Study [1]:

- Epidemiological study on the link between cancer and nutrition (EPIC).
- Population: ~ 100000 women.
- Medical data gathered every 2-3 years using questionnaires.
- Blood and saliva samples are also gathered for some participants (not used here)

Data in the Period-cohort plane



Data in the Age-cohort plane



- The event of interest is the **occurrence of breast cancer**
- These occurrences are spread over the period [1990, 2010]

Goal: estimate the incidence of breast cancer as a function of age and cohort

Right-censoring

- T_i is the age of cancer onset, U_i is the date of birth.
- We do not observe (T_i) but

 $Y_i = \min(T_i, C_i)$ and $\Delta_i = 1_{T_i = Y_i}$

where C is a censoring r.v. independent from (U, T).

• We infer the bivariate hazard rate

$$\lambda(t|u) = \lim_{dt \to 0} \frac{\mathbb{P}\left(t \le T \le t + dt | T \ge t, U = u\right)}{dt}$$

The Age-Cohort-Interaction model

• We introduce the AGE-COHORT-INTERACTION model: $\log \lambda_{j,k} = \alpha_j + \beta_k + \delta_{j,k},$ where $\delta_{\mathbf{j},\mathbf{k}}$ is the **interaction** between age and cohort. • Estimation by penalized likelihood:

Existing Models in Age-Period-Cohort Analysis

In the literature: we infer α , β , and γ , parameters of the age, cohort and period effects.

• In the AGE-COHORT model,

 $\log \lambda_{\mathbf{j},\mathbf{k}} = \alpha_{\mathbf{j}} + \beta_{\mathbf{k}}$

- -J + K 1 parameters for JK variables: regularizing
- -Strong a prior on λ .

• In the AGE-PERIOD-COHORT model,

 $\log \lambda_{\mathbf{j},\mathbf{k}} = \alpha_{\mathbf{j}} + \beta_{\mathbf{k}} + \gamma_{\mathbf{j}+\mathbf{k}-\mathbf{1}}$

- -Regularizing
- -Strong a priori on λ
- -Non identifiable

Regularization using L_0 penalization

• We enforce δ to be **piecewise constant**. Principle of the approximation:

$$\ell_n^{\text{pen}}(\theta) = \ell_n(\theta) + \underbrace{\frac{\text{pen}}{2} \sum_{j,k} v_{j,k} \left(\delta_{j+1,k} - \delta_{j,k}\right)^2 + w_{j,k} \left(\delta_{j,k+1} - \delta_{j,k}\right)^2}_{\text{regularization}}$$

Aim: enforce $\delta_{i,k} \simeq 0$ except where relevant.

Model Selection with L_0 norm

- 1. We alternate until convergence:
 - Minimize $\ell_n^{\text{pen}}(\boldsymbol{\theta})$ for fixed \mathbf{v} and \mathbf{w} .
 - Adapt \mathbf{v} and \mathbf{w} using $\boldsymbol{\theta}$.

j = 1

2. The weighted differences of η are used to **select** which the hazard is constant: over areas $w_{3,1} \left(\delta_{3,2} - \delta_{3,1} \right)^2 \simeq 0$ $v_{2,3} \left(\delta_{3,3} - \delta_{2,3}\right)^2 \simeq 1$ j = 3

- Fused L_0 regularization with the iterative Adaptive Ridge^[3] procedure.
- The estimation is iterative:

$$\begin{cases} v_{j,k} = \left(\left(\delta_{j+1,k} - \delta_{j,k} \right)^2 + \varepsilon^2 \right)^{-1} \\ w_{j,k} = \left(\left(\delta_{j,k} - \delta_{j,k-1} \right)^2 + \varepsilon^2 \right)^{-1} \end{cases}$$

Simulation results

 $\lambda_{i,k}$ (ACI model)

• 10000 data points are generated using the true hazard • We represent the **median estimate** of 500 such replications



$v_{j,k} \left(\delta_{j+1,k} - \delta_{j,k}\right)^2 \simeq \|\delta_{j+1,k} - \delta_{j,k}\|_0^2 = \begin{cases} 0 & \text{si } \delta_{j+1,k} = \delta_{j,k} \\ 1 & \text{si } s & \text{si } s \end{cases}$ Si $\delta_{j+1,k} \neq \delta_{j,k}$



Conclusion & References

Conclusion

- Joint estimation of the effects and their interaction
- More general model than APC
- Can use ensemble methods for better predictive performance

References



cohort

3. On each area : $\boldsymbol{\theta}$ is estimated by unpenalized maximum likelihood.



 $\delta_{j,k}$ (ACI model)

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Acknowledgment

This study was realized using data from the Inserm E3N cohort that has been established and is maintained with the financial support of the MGEN, the Gustave Roussy Institute and La Ligue contre le Cancer.

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