Modeling the cumulative incidence function of clustered competing risk data

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Clustered competing risk data

Key terms:

- Clustered: groups with a dependence structure (e.g. families);
- Causes competing by *something*.

Something?

- **Failure** of an industrial or electronic component;
- **Occurence** or **cure** of a disease or some biological process;
- **Progress** of a patient clinic state.

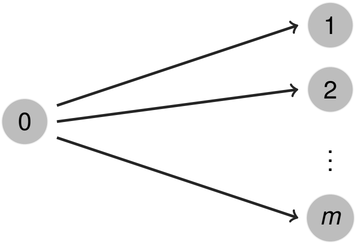
Independent of the application, always the same framework

Cluster	ID	Cause 1	Cause 2	Censorship	Time	Feature
1	1	Yes	No	No	10	A
1	2	No	No	Yes	8	A
2	1	No	No	Yes	7	B
2	2	No	Yes	No	5	A

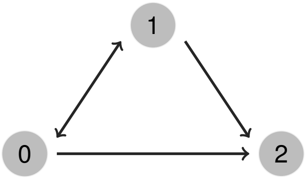
Data designs

Failure time process

Competing risk process



Multistate process



Data designs

Failure time process

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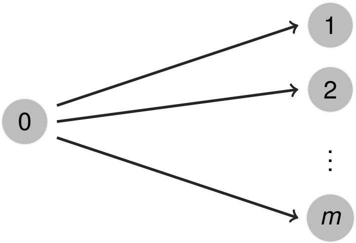
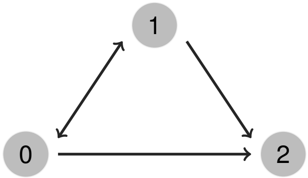


Multistate process



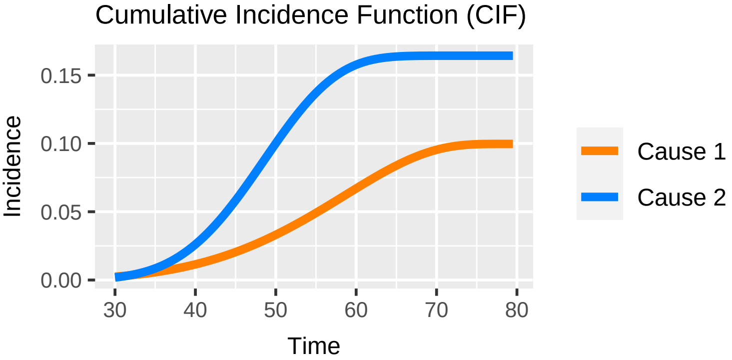
Modeling framework

We have to choose which scale we model the **survival experience.**
Usually, is the

hazard (failure rate) scale : $\lambda(t \mid \text{features}) = \lambda_0(t) \times c(\text{features})$.

In the competing risk setting . . .

a more attractive possibility is to work on the probability scale, focusing on the cause-specific



i.e.

$$\text{CIF} = \mathbb{P}[\text{ failure time} \leqslant t,\ \text{a given cause} \mid \text{features }]$$

Main focus application: cancer incidence in twins

Clustered competing risks data
↳ Clusters? Families
↳Family studies
↳ Twins data

Family studies $\Rightarrow$ within-family dependence

That may reflect

- Disease **heritability**;
- The impact of shared **environmental effects**;
  - **Parental effects**:

Our contribution: a hierarchical approach

Thinking on two competing causes

... for the outcome y_{ijt} of a subject i, family j, in the time t, we have

$$y_{ijt} \mid \underbrace{\{u_{1j}, u_{2j}, \eta_{1j}, \eta_{2j}\}}_{\text{latent effects}} \sim \text{Multinomial}(p_{1ijt}, p_{2ijt}, p_{3ijt})$$

$$\begin{bmatrix} u_{1j} \\ u_{2j} \\ \eta_{1j} \\ \eta_{2j} \end{bmatrix} \sim \begin{array}{c}\text{Multivariate}\\ \text{Normal}\end{array} \left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2_{u_1} & \sigma_{u_1,u_2} & \sigma_{u_1,\eta_1} & \sigma_{u_1,\eta_2} \\ & \sigma^2_{u_2} & \sigma_{u_2,\eta_1} & \sigma_{u_2,\eta_2} \\ & & \sigma^2_{\eta_1} & \sigma_{\eta_1,\eta_2} \\ & & & \sigma^2_{\eta_2} \end{bmatrix} \right)$$

$$\begin{aligned} p_{kijt} &= \frac{\partial \text{CIF}}{\partial t} \\ &= \frac{\partial}{\partial t} \underbrace{\pi_k(X, u_1, u_2 \mid \beta)}_{\substack{\text{cluster-specific} \\ \text{risk level}}} \underbrace{\Phi[w_k g(t) - X^\top \gamma_k - \eta_k]}_{\substack{\text{cluster-specific} \\ \text{failure time trajectory}}}, \end{aligned}$$

$k = 1, 2.$

Contributions & challenges

- A clear and simpler modeling structure;
- **There is no free lunch**
  Computational challenges overcame via an
  efficient implementation and estimation routines;
- The data is very simple,
  we just know the outcome (**yes** or **no**);
- We have to be able to build the CIF curves;
- And accommodate the within-family dependence properly,
  that can happen in different manners;
- ...

Thank you

Joint work with

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