

# Competing risks, when and how to incorporate them in the analysis

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October 12, 2023



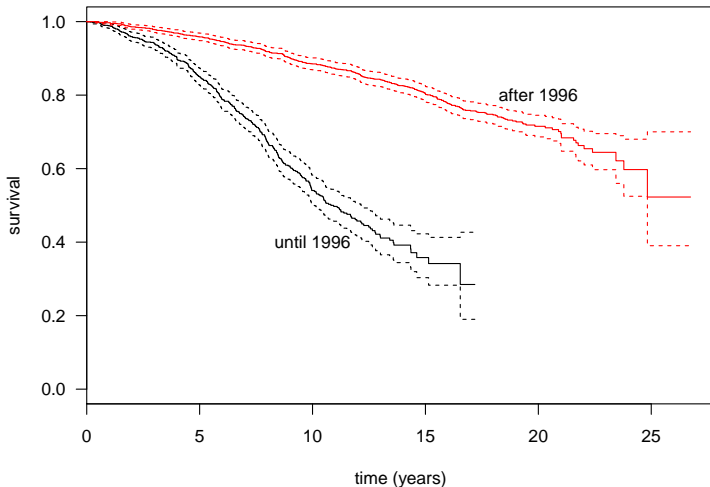
## Where I work

- Head of biostatistics group at OUCRU (Oxford University Clinical Research Unit) with units in Vietnam, Nepal and Indonesia
- Established in 1991 in Ho Chi Minh City, connected to Hospital for Tropical Diseases, founded in 1862
- Research institute on **infectious diseases**
  - Malaria: <10/3000 deaths per year in Vietnam/Indonesia
  - Tuberculosis: 17,000/100,000 deaths per year in Vietnam/Indonesia
  - Dengue: <50/500 deaths in Vietnam/Indonesia
  - Tetanus, Diphteria, Measles, Hand Foot Mouth Disease, ...
  - Drug resistant infections: >40,000/>100,000 deaths per year in Vietnam/Indonesia





## Example: death after HIV infection, powerful therapy since 1996



Problem: right censored data  $\longrightarrow$  rate/hazard

## Rate and Risk

$T$  time to event (e.g. death)

- **Risk:**  $P(T \leq t)$  (or survival  $P(T > t)$ )
- **Rate** (hazard, incidence):

$$\lambda(t_i) = P(T = t_i | T \geq t_i)$$

*discrete*

$$\lambda(t) = \lim_{\Delta t \downarrow 0} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t}$$

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$$P(T > t) = \prod_{t_i \leq t} \{1 - \lambda(t_i)\}$$

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- Hazard basis for
  - Kaplan-Meier

# Kaplan-Meier

year	0-1	1-2	2-3	3-4	4-5	5-6	6-7	Total
death	1	2	6	11	9	11	2	60
censor	5	9	6	6	9	12	4	86



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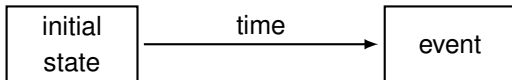
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- Hazard basis for

- Kaplan-Meier
- Cox model  $\lambda(t) = \lambda_0(t) \exp\{\beta_1 X_1 + \dots + \beta_p X_p\}$

## Beyond classical survival analysis

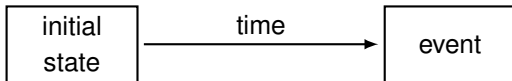
- Classical: transition between two states, one event type.  
“We all die, but not all at the same age”



- Life and **death** are richer than that
  1. Multiple causes of death. Competing risks:  
Event-type outcomes that are mutually exclusive  
“we all die, but not all at the same age and from the same cause”

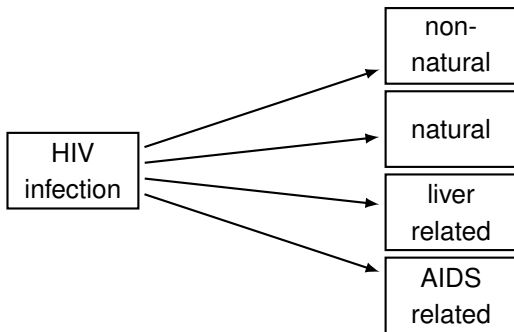
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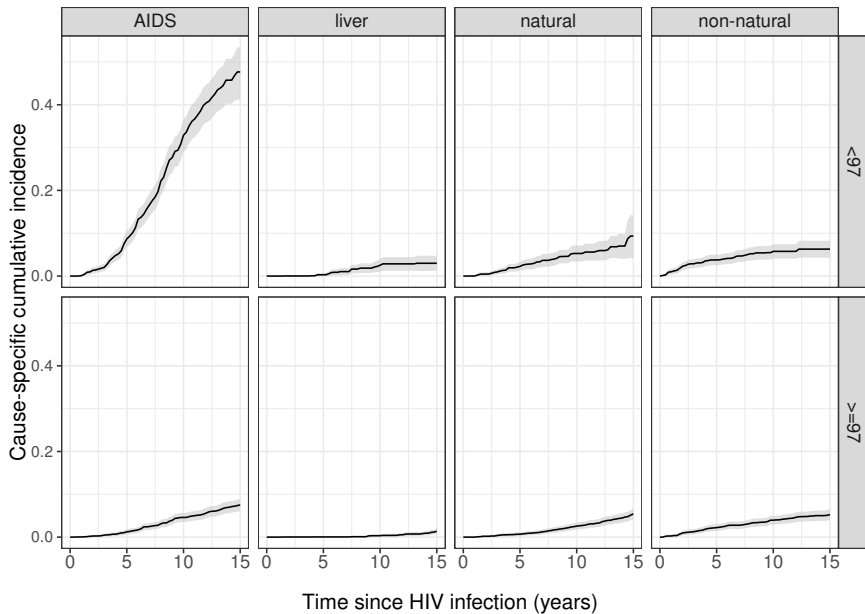
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**Event-type outcomes that are mutually exclusive**  
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## I: Causes of death (COD) after HIV infection



- Has the spectrum in causes of death changed after the introduction of cART (combination anti-retroviral therapy)

## Cause-specific mortality by calendar period





## Role of competing risks

- All event types of interest
  - Impact of cART on causes of death
  - Effect of dexamethasone on death and recovery after SARS-CoV-2 infection (binary outcome, complimentary levels)

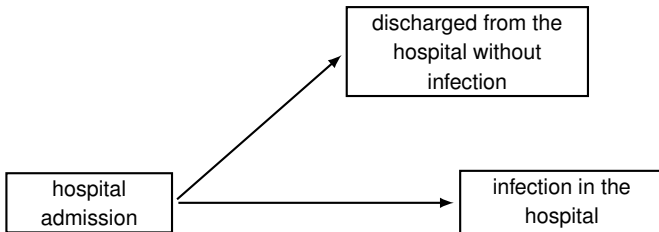
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- One event type of interest, other event prevents it from occurring
  - **Intervention (transplantation/treatment) competing risk for natural disease course**
  - Discharge competing risk for hospital-acquired infection
  - Death competing risk of non-fatal event (e.g. disease onset)

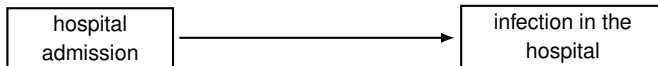
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## II: Time to staphylococcus infection during hospital stay



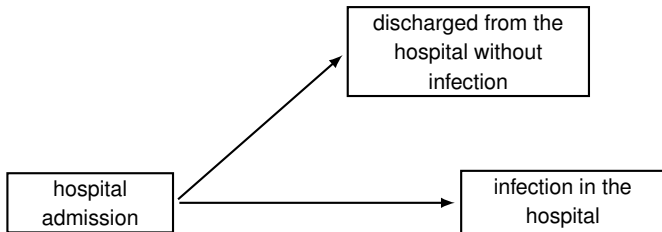
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- Etiology (biological question): infection risk in hospital. What would happen if everyone stayed in hospital?
  - **marginal distribution/net risk**



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- Etiology (biological question): infection risk in hospital. What would happen **if** everyone stayed in hospital?
  - marginal distribution/net risk
- Predict (clinical question): burden due to infection **while** in hospital; discharge prevents event to occur
  - cause-specific cumulative incidence /subdistribution/crude risk



## Estimation, no censored data

week	0-1	1-2	2-3	3-4	4-5	5-6	6-7	> 7
infection	1	2	6	11	9	11	2	18
cumulative	1	3	9	20	29	40	42	60
discharge	5	9	6	6	9	12	4	35
cumulative	5	14	20	26	35	47	51	86



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- **Subdistribution**. Estimated as frequency of events:

$$\hat{P}(\text{infection} \leq 6 \text{ weeks}) = 40 / 146$$

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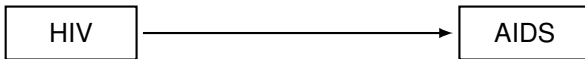
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- **Marginal distribution.** Discharged individuals treated and interpreted as censored; assumes independent censoring



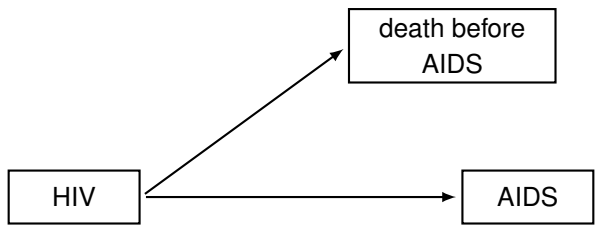


### III: Time from HIV infection to AIDS



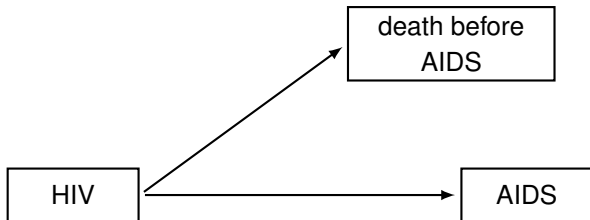
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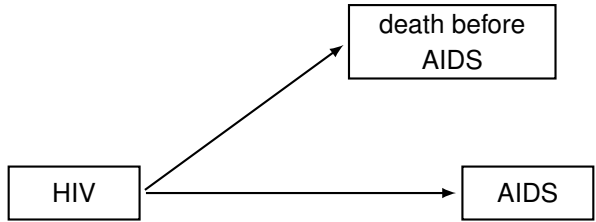


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**Interest in etiology and marginal distribution**



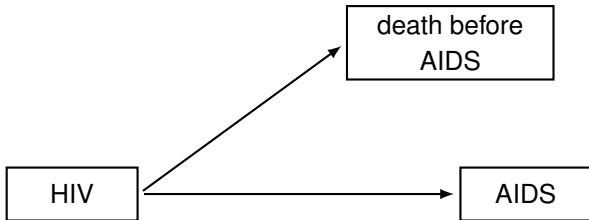


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Interest in etiology and marginal distribution
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**Assumption: deaths equal AIDS risk**

## Explanation: dependent censoring

- Extra information on cause of death before AIDS

	IDU	MSM
Reason of death	Number	
HIV related infections	3	0
overdose/suicide	6	0
violence/accident	2	0
liver cirrhosis	2	0
cancer	0	1
heart attack	0	1
unknown	4	3

- Some causes of pre-AIDS death in IDU related to AIDS progression. Censoring close to AIDS, hence estimate for IDU too optimistic

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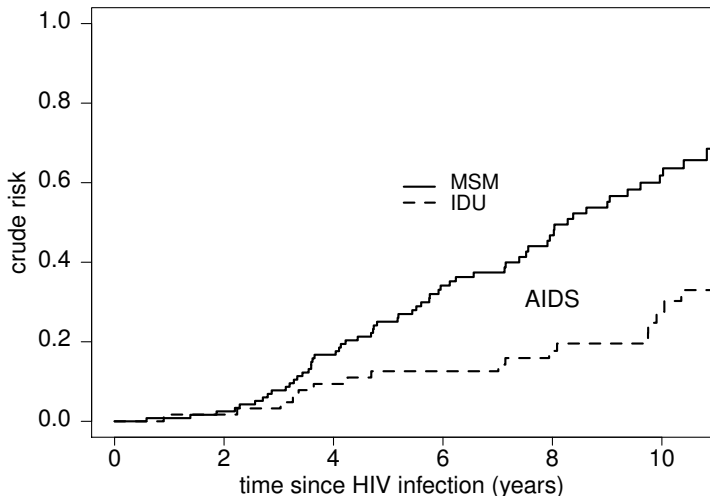
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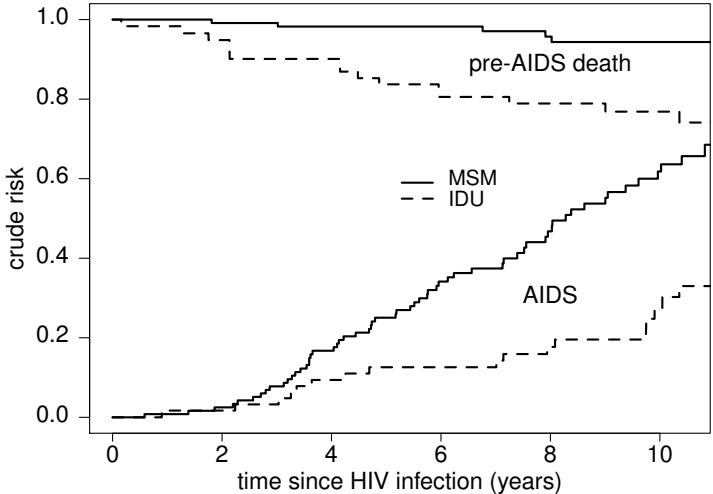
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- **What if:** ii) deaths would never have developed AIDS

## ii) AIDS-specific cumulative incidence



AIDS-specific cumulative incidence (pre-AIDS death prevents AIDS)

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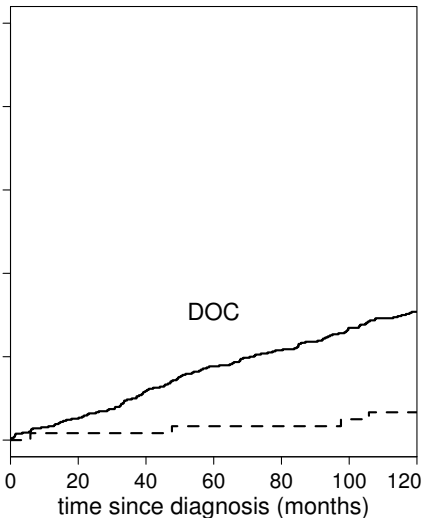
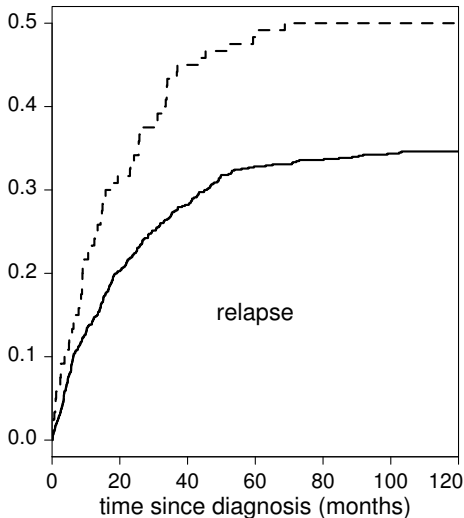


AIDS-specific cumulative incidence (pre-AIDS death prevents AIDS)

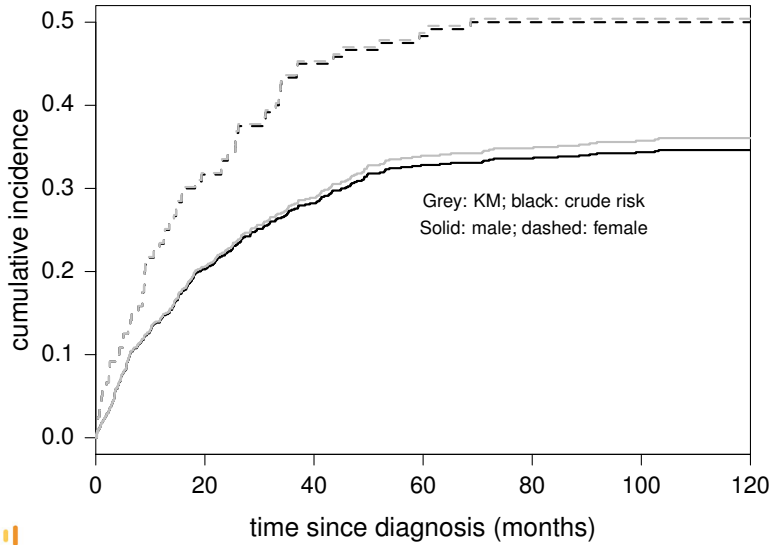




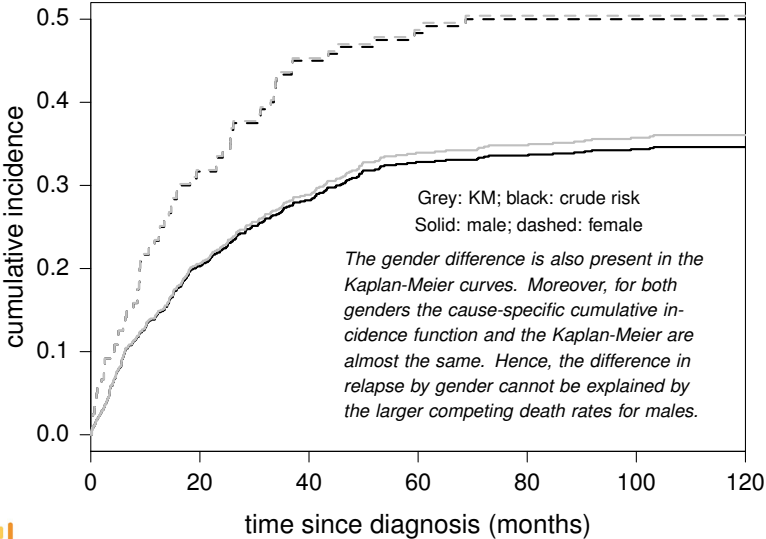
## IV: Bladder cancer; relapse, death other causes (DOC) competing



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## Competing risks versus marginal analysis

- Is setting without competing risk realistic or completely hypothetical? Can occurrence of competing risk be prevented?
  - Biological event: disease onset, death from “natural” cause
  - Human intervention: start of treatment, discharge, death from suicide
- Can the marginal distribution be estimated? Do those with the competing risk have the same event risk as the ones that remain event free? Is censoring due to competing risks independent?
- Examples:
  - Hospital infection and discharge
  - AIDS and pre-AIDS death
  - Relapse and DOC





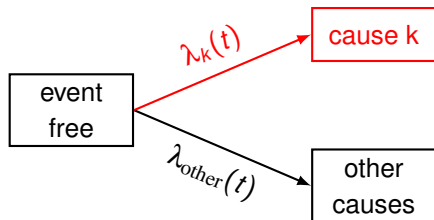
## Setup and notation

- Competing risks: type  $E \in \{1, \dots, K\}$
- $T \sim F$  time to event (of any type);  $F(t) = P(T \leq t)$
- Overall hazard  $h$ :  $P(T > t) = \exp\{-\int_0^t h(s) ds\}$
- Notation:  $\bar{F}(t) = 1 - F(t) = P(T > t)$





## The multi-state approach: cause-specific hazard

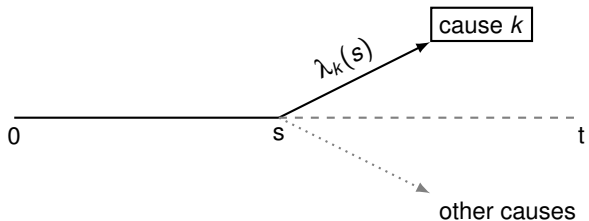


- Transition rate to cause k. For continuous distribution:

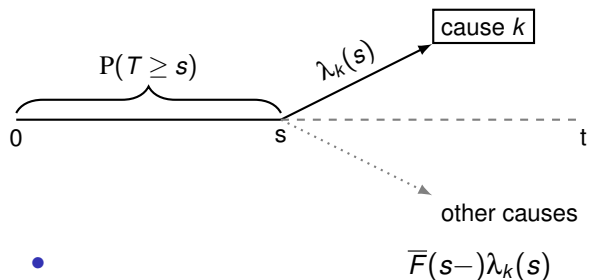
$$\lambda_k(t) = \lim_{\Delta t \downarrow 0} \frac{P(t \leq T < t + \Delta t, E = k \mid T \geq t)}{\Delta t}$$



## From hazard to cumulative scale $P(T \leq t, E = k)$

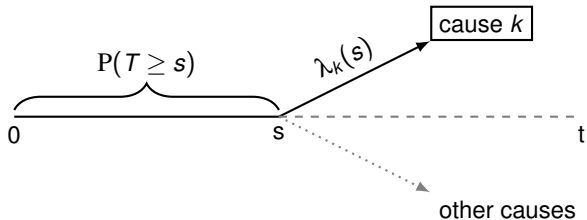


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- $F_k(t) = P(T \leq t, E = k) = \int_0^t \bar{F}(s-) \lambda_k(s) ds$
- Depends on all cause-specific hazards via overall “survival”

$$\bar{F}(s) = \exp\left\{-\int_0^s h(u)du\right\} = \exp\left\{-\sum_{e=1}^K \int_0^s \lambda_e(u)du\right\}$$

- $\implies \lambda_k$  does not uniquely specify  $P(T \leq t, E = k)$



## The subdistribution approach

## Setup and notation

- Competing risks: type  $E \in \{1, \dots, K\}$
- cause-specific cumulative incidence :  $F_k(t) = \text{P}(T \leq t, E = k)$
- Subdistribution random variable  $T_k \sim F_k$ :  

$$T_k = T \times I\{E = k\} + \infty \times I\{E \neq k\}$$

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 $T_k = T \times I\{E = k\} + \infty \times I\{E \neq k\}$
- $P(T_k \leq t) = P(T \leq t, E = k), \quad \bar{F}_k(t) = 1 - F_k(t) = P(T_k > t)$





















# Rates and risks in competing risks setting

	hazard		cumulative	
competing risks	marginal	$\lambda^m$	net risk	$F^m(t)$
	cause-specific subdistribution	$\lambda_k$ $h_k$	marginal survival function marginal cumulative incidence no corresponding quantity crude risk cause-specific cumulative incidence	$F_k(t)$
combined	overall	$h$	overall risk overall survival function overall cumulative incidence	$F(t)$



## Observed data

- $\{(x_1, \mathbf{e}_1 \delta_1), \dots, (x_N, \mathbf{e}_N \delta_N)\}$
- $x_j = \min\{t_j, c_j\}, \delta_j = \{t_j \leq c_j\}, \mathbf{e}_j \in \{1, \dots, K\}$
  - $t_{(j)}$  ordered unique event times of any type

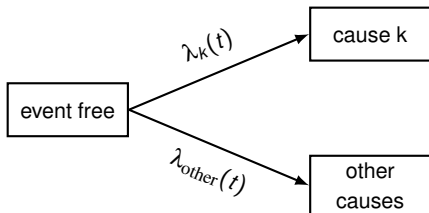
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- $t_{(i)}$  ordered unique event times of any type
- $r(t_{(i)})$  number observed at risk
  
- $d_k(t_{(i)})$  number of events at  $t_{(i)}$  of type  $k$



## Cause-specific hazard



- Individuals with a competing event are no longer at risk  $\implies$  leave the risk set

$$\hat{\lambda}_k(t_{(i)}) = \frac{d_k(t_{(i)})}{r(t_{(i)})}.$$

- Standard rate estimation.** Same estimator as marginal hazard, but different interpretation, unless censoring due to competing risks is non-informative

## Aalen-Johansen estimator of $F_k$

- Plug-in estimator based on  $F_k(t) = \int_0^t \mathbb{P}\{T \geq s\} \lambda_k(s) ds$ :

$$\hat{F}_k^{\text{AJ}}(t) = \sum_{i:t(i) \leq t} \hat{F}^{\text{PL}}(t(i)-) \times \hat{\lambda}_k(t(i)) \text{ with}$$

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$$\widehat{F}^{PL}(t(i)-) = \prod_{j:t(j) < t(i)} \left( 1 - \frac{d(t(j))}{r(t(j))} \right) \text{ Kaplan-Meier}$$

## Observed data

$$\{(x_1, e_1 \delta_1), \dots, (x_N, e_N \delta_N)\}$$

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- $d_k(t_{(i)})$  number of events at  $t_{(i)}$  of type  $k$
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- Single event type: equal to Kaplan-Meier
- Competing risks: same hazard estimate as for marginal distribution, but cumulative quantity different







## IV: Answer

- The Kaplan-Meier tries to compare the marginal distribution of time to relapse for males and females. Only valid if DOC is noninformative for relapse.
- Aalen-Johansen and Kaplan-Meier estimates almost equal because there is little mortality due to other causes, at least during the first 40 months.
- If we combine both event times, the curves for males and females will become similar. Would estimate marginal hazard if every person that died would have progressed on the next day.

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- If we combine both event times, the curves for males and females will become similar. Would estimate marginal hazard if every person that died would have progressed on the next day.
- All we can conclude is that females have a higher relapse-specific cumulative incidence than males. And females have a lower DOC-specific incidence than males.



## The subdistribution approach

- Subdistribution hazard ( $T_k = T \times I\{E = k\} + \infty \times I\{E \neq k\}$ ):

$$\begin{aligned}
 h_k(t) &= \lim_{\Delta t \downarrow 0} \frac{1}{\Delta t} \times \text{P}\{t \leq T_k < t + \Delta t \mid T_k \geq t\} \\
 &= \lim_{\Delta t \downarrow 0} \frac{\frac{1}{\Delta t} \text{P}\{t \leq T < t + \Delta t, E = k\}}{\text{P}\{T \geq t \text{ or } (T < t, E \neq k)\}}
 \end{aligned}$$

- Denominator: event free or with earlier competing event
- Interpretation controversial
  - Not a rate in epidemiological sense, unless we can assume that those with the competing event were immune for the event of interest (cure model)
- One-to-one relation with crude risk

$$\bar{F}_k(t) = \prod_{t_j \leq t} \left\{ 1 - h_k(t_j) \right\} \quad \text{or} \quad \bar{F}_k(t) = \exp \left\{ - \int_0^t h_k(u) du \right\}$$

## Observed data

$$\{(x_1, e_1 \delta_1), \dots, (x_N, e_N \delta_N)\}$$

- $x_i = \min\{t_i, c_i\}$ ,  $\delta_i = \{t_i \leq c_i\}$ ,  $e_i \in \{1, \dots, K\}$
- $t_{(i)}$  ordered unique event times of any type
- $r(t_{(i)})$  number observed at risk
- $r^*(t_{(i)})$  number in risk set (for subdistribution hazard)
- $d_k(t_{(i)})$  number of events at  $t_{(i)}$  of type  $k$
- $d(t_{(i)})$  total number of events at  $t_{(i)}$



## Subdistribution $\hat{F}_k$ : product-limit estimator

$$\hat{F}_k^{\text{PL}}(t) = \prod_{i:t_{(j)} \leq t} \left\{ 1 - \hat{h}_k(t_{(j)}) \right\}$$

with

$$\hat{h}_k(t_{(j)}) = \frac{d_k(t_{(j)})}{r^*(t_{(j)})}$$

**No censoring:** individuals with competing event remain in risk set forever. Small change in data, standard software

## Estimation, no censored data

week	0-1	1-2	2-3	3-4	4-5	5-6	6-7	> 7
infection	1	2	6	11	9	11	2	18
cumulative	1	3	9	20	29	40	42	60
discharge	5	9	6	6	9	12	4	35
cumulative	5	14	20	26	35	47	51	86

- **Subdistribution.** Estimated as frequency of events:

$$\hat{P}(\text{infection} \leq 6 \text{ weeks}) = 40/146$$

$$\hat{P}(\text{discharge} \leq 6 \text{ weeks}) = 47/146$$

Individuals with competing event remain in denominator,  
competing event ignored in estimation

## Subdistribution $\widehat{F}_k$ : product-limit estimator

$$\widehat{F}_k^{\text{PL}}(t) = \prod_{i:t_{(j)} \leq t} \left\{ 1 - \widehat{h}_k(t_{(j)}) \right\}$$

with

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**No censoring:** individuals with competing event remain in risk set forever. Small change in data, standard software

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**No censoring:** individuals with competing event remain in risk set forever. Small change in data, standard software

**Administrative censoring:** individuals with competing event leave risk set at their date of censoring. Small change in data, standard software

**General censoring:** Estimate time-to-censoring distribution, then

- multiply impute censoring times for those with competing event
- **reweight** them by probability to remain uncensored

## Right Censored Data

$$\hat{h}_k(t_{(i)}) = \frac{d_k(t_{(i)})}{r^*(t_{(i)})}$$

Contribution  $\omega_l(t_{(i)})$  of individual  $l$  to the risk set  $r^*(t_{(i)})$  is:

- censored or event of type  $k$  before  $t_{(i)}$ : 0

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- competing event at  $t_{(j)}$  before  $t_{(i)}$ :

estimate of  $P\{C \geq t_{(i)} | C \geq t_{(j)}\}$  :



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Contribution  $\omega_l(t_{(i)})$  of individual  $l$  to the risk set  $r^*(t_{(i)})$  is:

- censored or event of type  $k$  before  $t_{(i)}$ : 0
- still at risk at  $t_{(i)}$ : 1
- competing event at  $t_{(j)}$  before  $t_{(i)}$ :

estimate of  $P\{C \geq t_{(i)} | C \geq t_{(j)}\} : \hat{\Gamma}(t_{(i)}-) / \hat{\Gamma}(t_{(j)}-)$

- $\hat{\Gamma}$ : reverse role of event time  $T_i$  and censoring  $C_i$ :

$$\hat{\Gamma}(t) = \prod_{j:c_{(j)} \leq t} \left\{ 1 - \frac{m_j}{r(c_{(j)})} \right\}$$



## Estimation, no censored data

week	0-1	1-2	2-3	3-4	4-5	5-6	6-7	> 7
infection	1	2	6	11	9	11	2	18
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Individuals with competing event remain in denominator,  
competing event ignored in estimation

## Subdistribution $\widehat{F}_k$ : ECDF estimator

- Without censoring

$$\widehat{F}_k^{\text{EC}}(t) = \frac{\#\{t_i \leq t\}}{N} = \sum_{t_{(j)} \leq t} \frac{d_k(t_{(j)})}{N}.$$

- Right censored data

$$\widehat{F}_k^{\text{EC}}(t) = \frac{1}{N} \sum_{t_{(j)} \leq t} \frac{d_k(t_{(j)})}{\widehat{\Gamma}(t_{(j)}-)}$$

### Equivalence

If  $\widehat{\bar{\Gamma}}$  based on the PL-form, then we have

$$\widehat{F}_k^{AJ} \equiv \widehat{F}_k^{PL} \equiv \widehat{F}_k^{EC}$$

(Geskus 2011, Biometrics)

$$\widehat{F}_k^{AJ}(t) = \sum_{i:t_{(i)} \leq t} \widehat{F}_k^{PL}(t_{(i)} -) \times \widehat{\lambda}_k(t_{(i)})$$

$$\widehat{F}_k^{PL}(t) = \prod_{i:t_{(i)} \leq t} \left\{ 1 - \widehat{h}_k(t_{(i)}) \right\}$$

$$\widehat{F}_k^{EC}(t) = \frac{1}{N} \sum_{t_{(j)} \leq t} \frac{d_k(t_{(j)})}{\widehat{\bar{\Gamma}}(t_{(j)} -)}$$

## Estimators in competing risks setting

hazard	estimate	estimate cumulative incidence
marginal	$\left\{ \widehat{\lambda}(t) = d_k(t)/r(t) \right\}$	$\left\{ \widehat{F}_k^{m,PL}(t) = \prod_{t_{(j)} \leq t} \left[ 1 - \widehat{\lambda}(t_{(j)}) \right] \right\}$
cause-specific	$\widehat{\lambda}_k(t) = d_k(t)/r(t)$	$\widehat{F}_k^{AJ}(t) = \sum_{t_{(j)} \leq t} \widehat{F}^{PL}(t_{(j)}-) \widehat{\lambda}_k(t_{(j)})$
subdistribution	$\widehat{h}_k(t) = d_k(t)/r^*(t)$	$\widehat{F}_k^{PL}(t) = \prod_{t_{(j)} \leq t} \left[ 1 - \widehat{h}_k(t_{(j)}) \right]$  $\widehat{F}_k^{EC}(t) = \frac{1}{N} \sum_{t_{(j)} \leq t} \frac{d_k(t_{(j)})}{\widehat{\Gamma}(t_{(j)}-)}$
overall	$\widehat{h}(t) = d(t)/r(t)$	$\widehat{F}^{PL}(t) = \prod_{t_{(j)} \leq t} \left[ 1 - \widehat{h}(t_{(j)}) \right]$



# Outline

Competing Risks; When

**Competing Risks; How**

- Main Quantities
- Nonparametric Estimation
- Regression**

**Which Approach to Choose?**

- Marginal versus competing risks
- Which competing risks approach to choose?



## Subdistribution hazard

- Proportional subdistribution hazards (Fine and Gray model)

$$h_k(t | \mathbf{Z}_i) = h_{k,0}(t) \exp(\beta_k^\top \mathbf{Z}_i).$$

- Estimation: those with competing event remain in risk set, with weight reflecting probability to remain uncensored
  - SE completely standard
- Simulation study (Geskus 2011, Biometrics): sandwich estimator as suggested by Fine and Gray performed worse
- Standard software with time-varying individual weights
  - Interpretation difficult, but direct relation with cause-specific cumulative incidence

## Cause-specific cumulative incidence

- (Proportional odds) logistic regression

$$\text{logit}[P(T_k \leq t \mid \mathbf{Z}_i)] = \log[\pi_{k,0}(t)] + \beta_k^\top \mathbf{Z}_i$$

translates to the cause-specific cumulative incidence as

$$P(T_k \leq t \mid \mathbf{Z}_i) = \frac{\pi_{k,0}(t) \exp(\beta_k^\top \mathbf{Z}_i)}{1 + \pi_{k,0}(t) \exp(\beta_k^\top \mathbf{Z}_i)}.$$

- Estimation: estimating equations, with weights reflecting probability to remain uncensored
  - Scheike *et al.* (2008): event weighted as in  $\hat{F}_k^{EC}$
  - Eriksson *et al.* (2015): weights as in  $\hat{h}_k$
  - Blanche *et al.* (2023): individuals weighted as in  $\hat{F}_k^{EC}$
- SE based on sandwich estimator











## Competing risks

- Competing risk is a separate event
  - Individuals censored by competing event don't have to be represented by the ones that remain at risk.  
Other censoring (administrative/loss to follow-up) must be independent







## Marginal or competing risks?

- Example I: spectrum in COD  
**Competing risks**; marginal analysis completely hypothetical
- Example II: staphylococcus infection in hospital
  - **Marginal**: what if everyone would stay in hospital
  - **Competing risks**: how many infections are observed in hospital
- Example III: difference in natural history between IDU en MSM  
**Marginal** analysis, but difficult to perform
- Example IV: bladder cancer relapse and DOC  
**Marginal interpretation, but does it make sense?**  
 Can we eliminate DOC? Is their mechanism completely separate from mechanism leading to relapse?



## Cause-specific hazard, subdistribution hazard or crude risk?


- Cause-specific may often be closer to causal effects, but any hazard is problematic as causal estimand
- Cumulative scale combination of etiology and effect on other event types.  
“In the end we all die, but cause of death may be different”  
“Impact” instead of “effect”
- Cumulative estimate final aim for prediction, but each may serve as basis for model
- Subdistribution hazard directly relates to cumulative scale  
Regression: impact on cumulative scale via parameters
- Some suggest to quantify both hazards

# Published by CRC Press, 2015

Chapman & Hall/CRC Biostatistics Series

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 **CRC Press**  
Taylor & Francis Group  
A CHAPMAN & HALL BOOK





