

# Traditional (biostatistical) approaches to event-time prediction

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NationScale Fall Meeting: September 10th, 2021

# Research questions of interest

Time until a certain event of interest takes place

- ▶ What is the probability that the event does (not) take place in the next  $X$  years?
- ▶ Are there differences in event timing between groups?
- ▶ How do certain personal, behavioral or other characteristics affect when the event takes place in an individuals' life?

## Time-to-event analysis: basic quantities

- ▶  $T$  = time of the event, random variable with density function  $f(t)$
- ▶  $C$  = censoring time
- ▶ Survival = probability of surviving up to time  $t$ , a “risk”:  
 $S(t) = P(T > t)$
- ▶ Hazard = instantaneous probability of event at time  $t$  given one has not experienced the event before, a “rate”:  
 $\lambda(t) = P(T \in (t, t + \Delta t) \mid T \leq t)$
- ▶ Hazard has a direct relation to the survival:  $\lambda(t) = \frac{f(t)}{S(t)}$

# Time-to-event analysis: the proportional hazards model

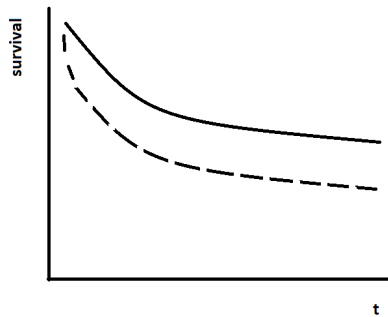
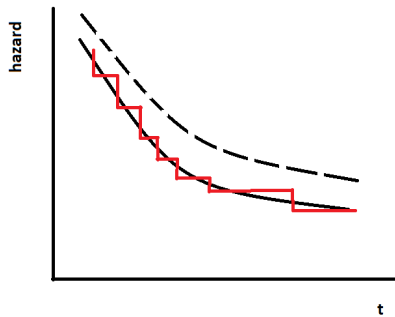
$$\lambda_i(t) = \lambda_0(t) \exp(\mathbf{s}_i(t)' \boldsymbol{\gamma})$$

- ▶  $\lambda_i(t)$  = hazard at time  $t$  for individual  $i$
- ▶  $\lambda_0(t)$  = baseline hazard at time  $t$
- ▶  $\mathbf{s}_i(t)$  = vector of covariates at time  $t$  for individual  $i$
- ▶  $\boldsymbol{\gamma}$  = vector of coefficients

$\exp(\boldsymbol{\gamma})$ , interpretation as a relative risk

Can be written as a poisson model for (piecewise constant) hazard rates. Convenient for ML methods (see e.g. Bender, Rügemer, Scheipl, & Bischl (2020)).

# Visualization



# Modelling issues/challenges

## 1. Censoring

- ▶ Hazard can be computed for right censored data (uses individuals at risk).
- ▶ Maybe less of a problem in register data, but immigration/emigration.
- ▶ Under right censoring, using a logistic regression model results in biased estimates.
- ▶ Dependent, left, interval censoring

## 2. Competing risks

- ▶ An event that either hinders the observation of the event of interest or modifies the chance that the event occurs.
- ▶ Dying twice.
- ▶ No one-to-one relation between hazard and survival of a single event (Andersen, Geskus, Witte, & Putter (2012)).

# Modelling issues/challenges (cont.)

3. Recurrent events
  - ▶ Repeated observations of the same event, e.g. doctor visits, birth of children, change of job (Amorim & Cai (2015))
4. Time varying covariates
5. Time varying effects ( $\gamma_t$ )
6. Random effects, frailty (Balan & Putter (2020))
7. Endogeneity of covariates
  - ▶ Bias if association between covariate and event is bidirectional.
  - ▶ Solution: joint models (economics: simultaneous equations, simultaneous hazard), with multiple outcomes (Rizopoulos (2012))
8. Causality
9. Including lots and lots of covariates and (non-linear) associations for many individuals over a long time period





# Time-to-event analysis: basic quantities (with equations)

- ▶  $T$  time of the event, r.v. with density function  $f(t)$
- ▶  $C$  censoring time
- ▶ Probability that event has occurred by time  $t$ , c.d.f.:
$$P(T \leq t) = \int_0^t f(t)dt$$
- ▶ Survival = probability of surviving up to time  $t$ :
$$S(t) = P(T > t) = 1 - F(t) = \int_t^\infty f(t)dt = \exp(-\int_0^t \lambda(t)dt)$$
- ▶ Hazard = instantaneous probability of event at time  $t$  given one has not experienced the event before:
$$\lambda(t) = P(T \in (t, t + \Delta t) \mid T \leq t) = \frac{f(t)}{S(t)} = -\frac{d}{dt} \log S(t)$$
- ▶ Cumulative hazard,  $\Lambda(t) = \int_0^t \lambda(t)dt$

## References

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