

Latent variable models for time-to-event data (continuous time)

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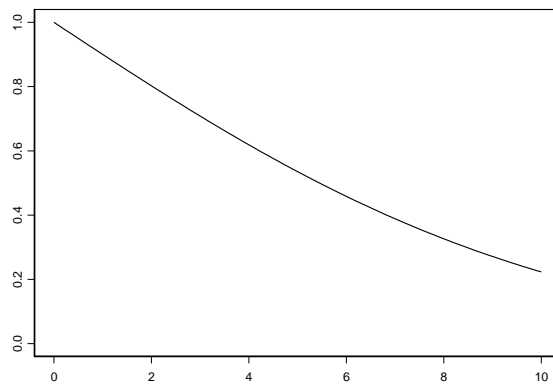
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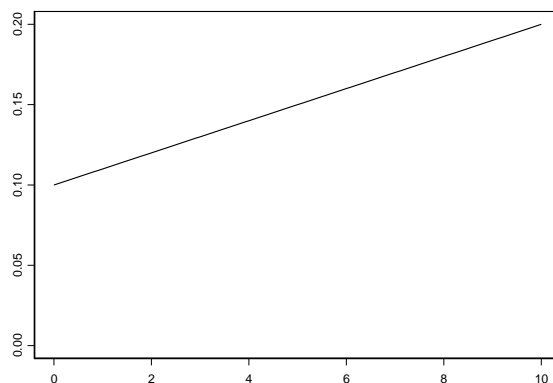
Cox's model (Cox, 1972)

T : time to event, e.g. time from onset of a disease to death

$S(t)$: probability of surviving to time t



$\lambda(t)$: intensity



$\lambda(t)$ is the continuous time counterpart to $h(t)$

Cox: proportional intensities

Combining the Growth Mixture Model and Cox's model

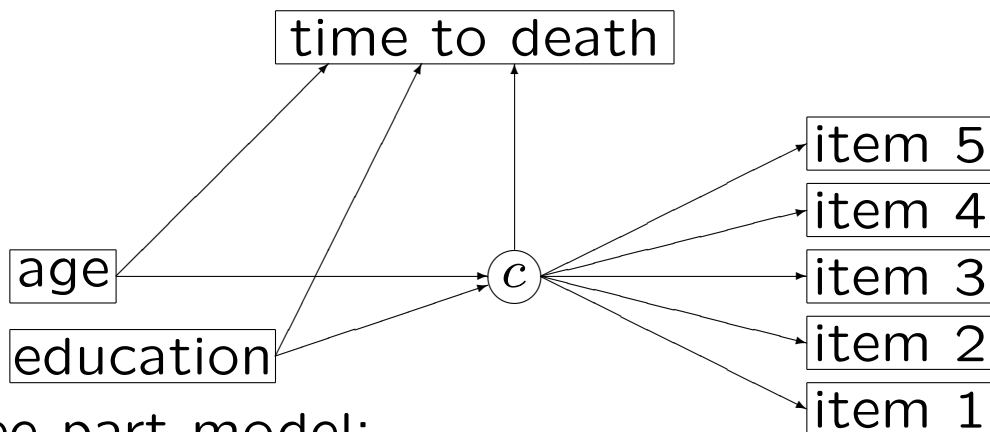
Include variables from the Growth Mixture Model as predictors in the intensity function, e.g.

1. latent continuous variables
2. latent class variables

Two examples

1. CD4 counts predicting death for people with AIDS (e.g. Tsiatis *et al*, JASA, 1995; Wulfsohn and Tsiatis, Biometrics, 1997)
2. longitudinal measurements of prostate specific antigen define latent classes that predict onset of prostate cancer (Lin *et al*, 2002*a,b* - **DRAFTS**)

Women's Health and Aging Study, Johns Hopkins, NIA



Three-part model:

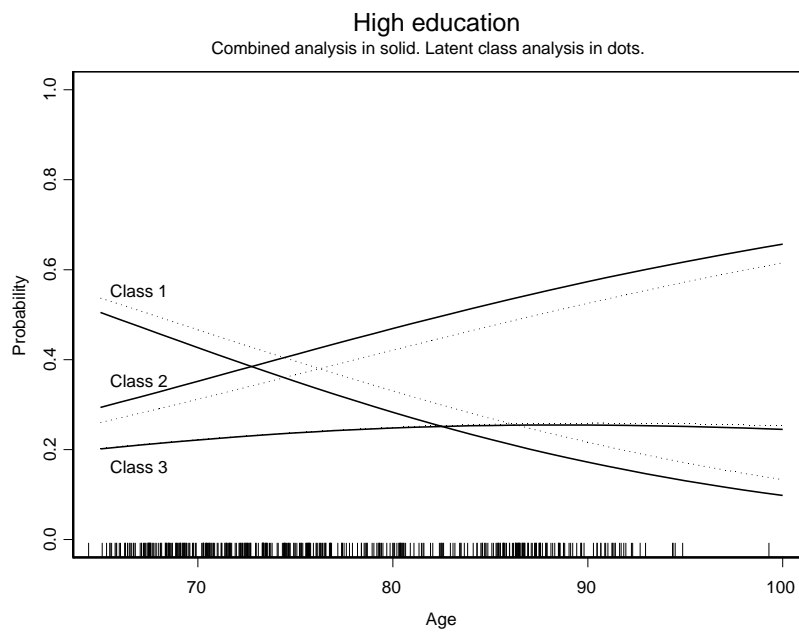
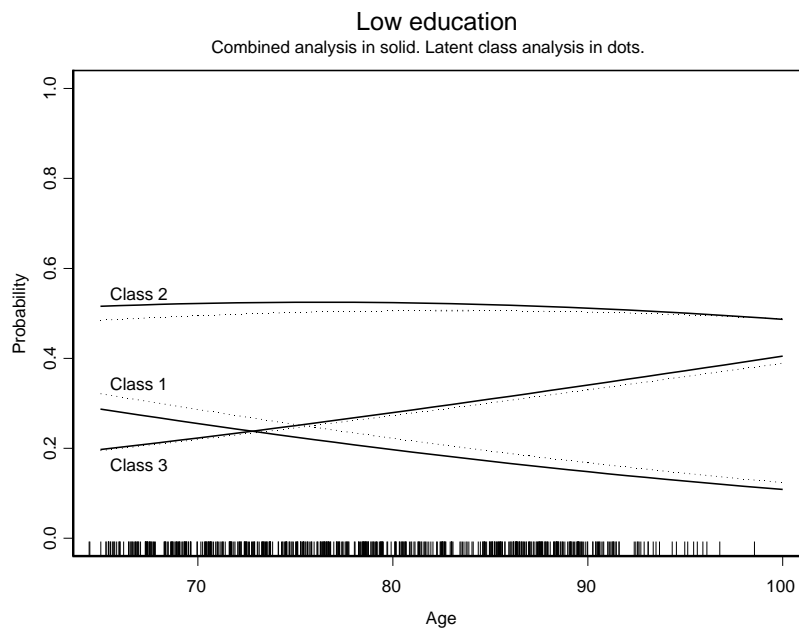
1. measuring the latent class c
2. distribution of c given covariates
3. distribution of time-to-event given covariates and latent class

Klaus Larsen (2002). Survival analysis with multiple discrete indicators of latent classes.
DRAFT

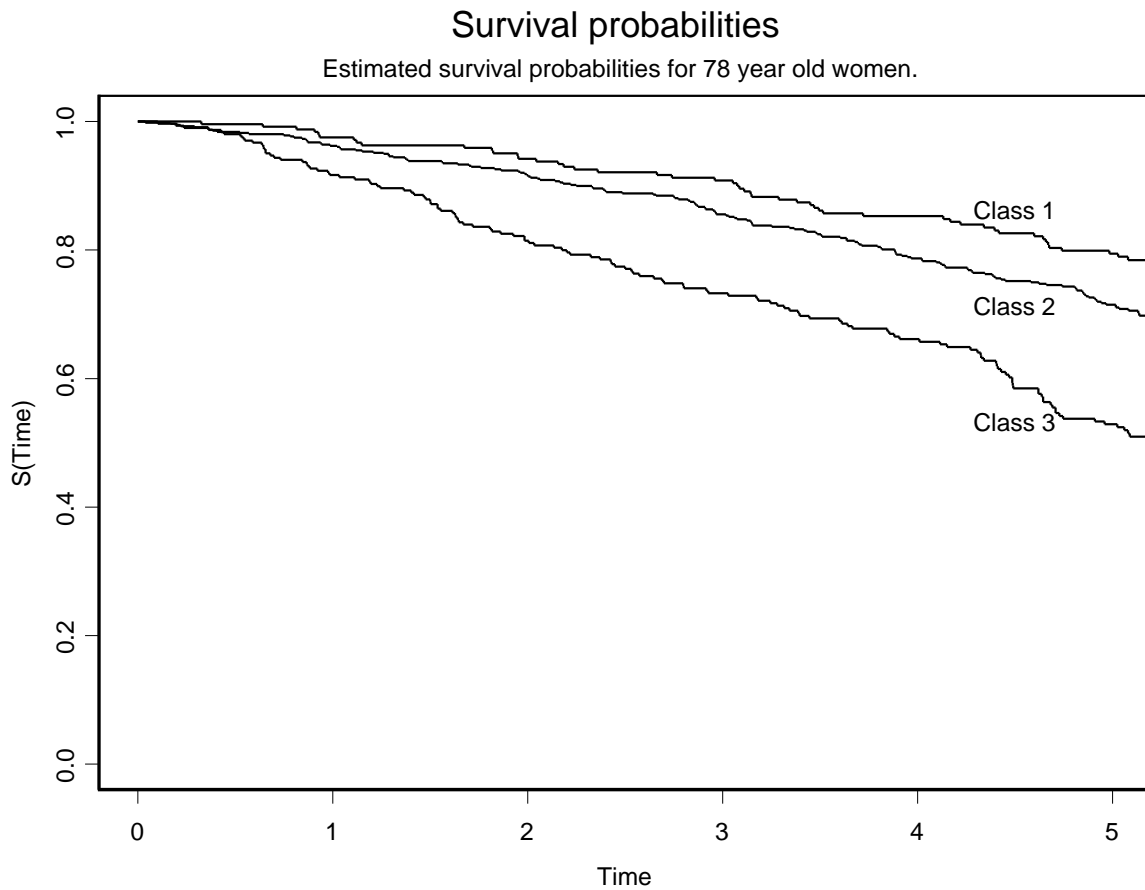
Main result: latent class analysis part

- five items measuring mobility
- three latent classes (Bandein-Roche *et al.*, 1997)
 - class 1 = good mobility
 - class 2 = moderate mobility
 - class 3 = poor mobility

Main result: latent class analysis part (cont.)

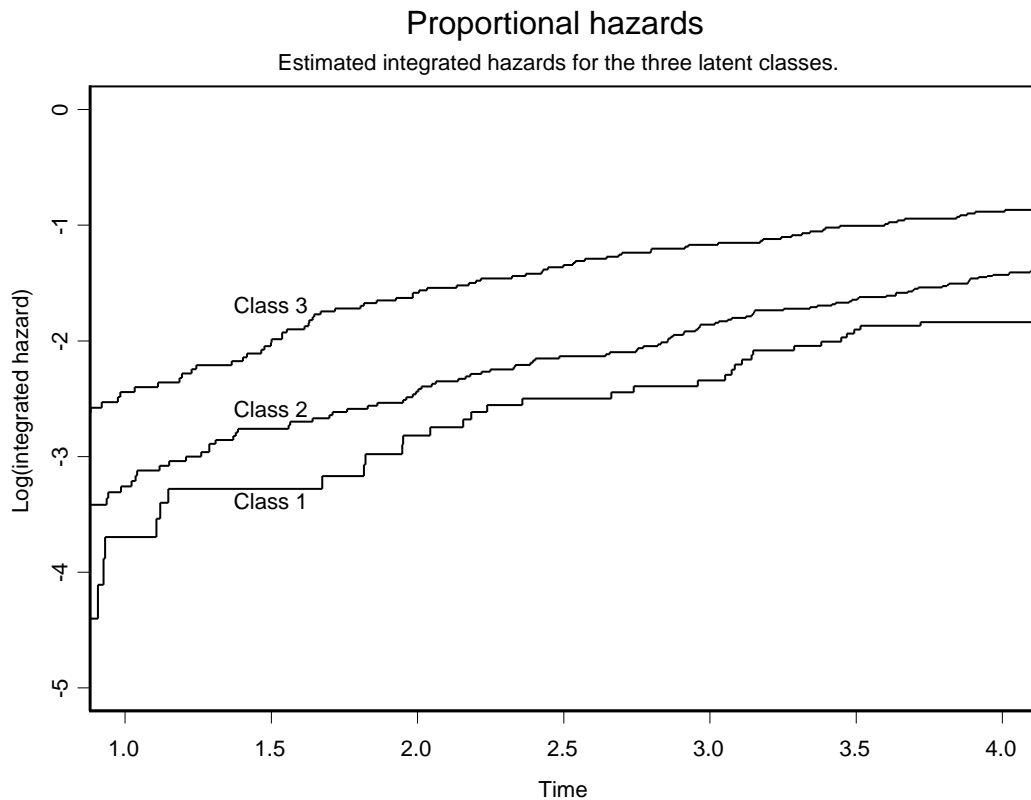


Main result: time-to-event part



Five years survival for women aged 78 years

Main result: time-to-event part (cont.)



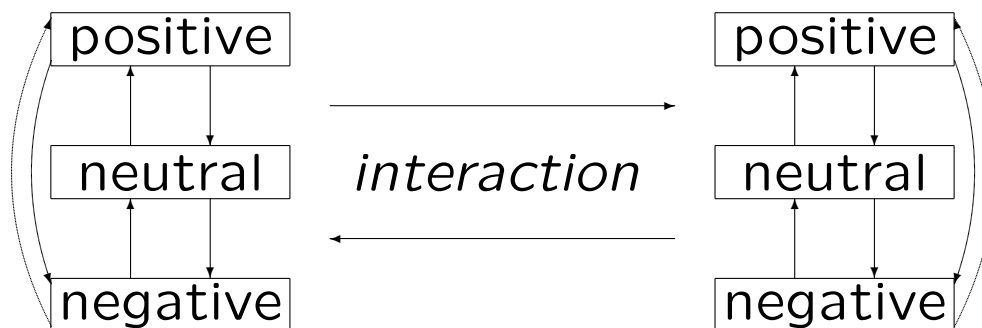
- proportional hazards assumption seems fine (curves should be parallel)
- excessive risk of approximately 195% for class 3 compared to class 1
- excessive risk of approximately 75% for class 2 compared to class 1

Modeling social processes

Thoughts generated from the presentation by Jim Snyder at the PSMG conference call, January 30th 2002

child behavior

parent behavior



- states measured each second
- several different behavior monitored

Modeling social processes (cont.)

1. **A.** Regress the child's transitions between states on the child's and the parent's history.

$$h_{\text{child}}(t) = \text{pr}(y_{\text{child}}(t) | y_{\text{child}}(t-1), y_{\text{parent}}(t-1))$$

- B.** Extend to two interacting processes by regressing both the child's and the parent's processes on their history.

$$h_{\text{child}}(t) = \text{pr}(y_{\text{child}}(t) | y_{\text{child}}(t-1), y_{\text{parent}}(t-1))$$

$$h_{\text{parent}}(t) = \text{pr}(y_{\text{parent}}(t) | y_{\text{child}}(t-1), y_{\text{parent}}(t-1))$$

2. Model $(y_{\text{child}}(t), y_{\text{parent}}(t))$ as a multi-state process.

$$h(t) =$$

$$\text{pr}(y_{\text{child}}(t), y_{\text{parent}}(t) | y_{\text{child}}(t-1), y_{\text{parent}}(t-1))$$

Challenging extensions of the latent variable models for time-to-event data for events in discrete or continuous time

- recurrent events (e.g. absence from work)
- multiple simultaneous processes (e.g. interactions between individuals)
- competing risks (e.g. death from different causes)
- multi-state models (e.g. women moving between states of mobility)
- growth mixture models (e.g. PSA and prostate cancer)