Saddle Point Science

# Introduction to SaddlePoint Mosaics

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London, UK www.saddlepointscience.com

## Survival analysis for `complex' cohorts

Aimed at survival data where latent or disease heterogeneity and informative censoring arising from competing risks might be present

Multi-risk latent class modelling

Each class obeys the proportional hazards assumption (for each risk) All risks modelled simultaneously for more efficient extraction of information from cohort data

Each model is defined by the following quantities:

- Number of latent classes (L)
- Personalised hazard rate complexity (M) Model configuration
- Complexity of base hazard rates (K)

• Latent class weightings

- Frailty parameters
- Association parameters
- Base hazard rate parameters \_\_\_\_\_

Risk-specific marginal hazard rates and survival functions, "decontaminated" of the effects of informative censoring

Model parameters

Bayesian regression and model selection Avoid over-fitting and unnecessary model complexity

Cohort stratification Retrospective class assignment Provides additional insight into a cohort

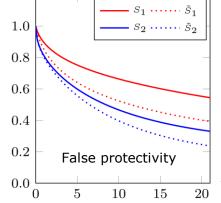


A latent class model for competing risks

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Survival data analysis becomes complex when the proportional hazards assumption is violated at population level or when cruch bazard rates are no longer estimators of marginal ones. We develop a Bayesian survival analysis method to deal with these situations, on the basis of assuming that the complexities are induced by latent colort or disease heterogeneity that is not captured by covariates and that proportional hazards hold at the level of individuals. This leads to a description from which risk-specific marginal hazard rates and survival functions are fully accessible, 'decontaminated' of the effects of informative censoring, and which includes Cox, random effects and latent class models as special cases. Simulated data confirm that our approach can map a cohort's substructure and remove heterogeneity induced informative censoring effects. Application to data from the Uppsal Longitudinal Study of Adult Men cohort leads to plausible alternative explanations for previous counter-intuitive informeds with breast cancer. The importance of managing cardiovascular disease as a comorbidity in women diagnosed with breast cancer is suggested on application to data from the Swedish Apolipoprotein Mortality Risk. Study, Copyright 0: 2017 Jahn Wiley & Sons, Lid.

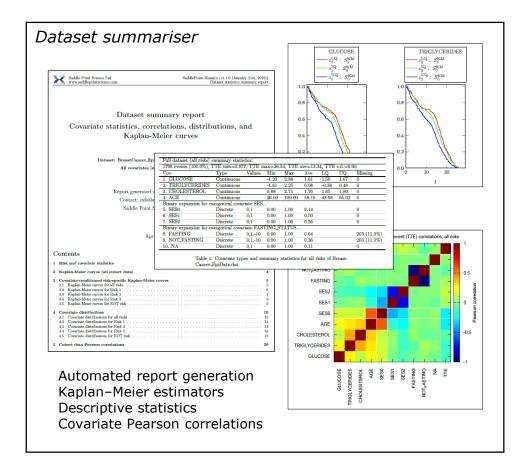
Keywords: survival analysis; heterogeneity; informative censoring; competing risks



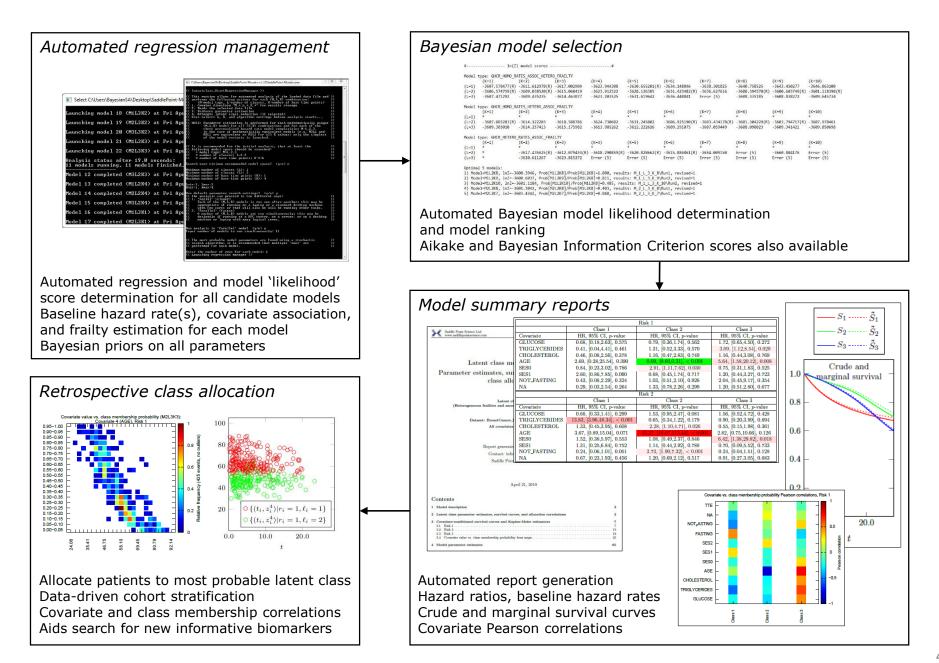
### Multi-risk latent class analysis / Dataset management

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3	660704	1.722766598	-0.223143551	1.8562979	9 86	SESO	NOT FASTING	0.106776	
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5	736276	1.667706821	-0.356674944	1.87180217			FASTING	0.123203	2
6	254518	1.85629799	0.405465108	1.97408102		SESO	FASTING	0.142368	
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Automated categorical covariate expansion with user selection of baseline Missing data regression variable generation Automated metadata generation



## Multi-risk latent class analysis / Regression management

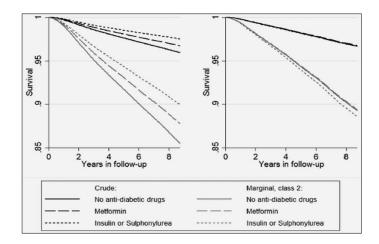


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#### Some application examples

Prostate cancer: Heterogeneity and competing risks effects found

Haggstrom et al., "Heterogeneity in risk of prostate cancer: A Swedish population-based cohort study of competing risks and Type 2 diabetes mellitus", IJC, 2018



Colorectal cancer: Re-analysis of COIN trail (NEJM, 2011)

PR Barber et al., under review, 2019

Diabetic retinopathy: Heterogeneity in disease severity found for patients with Type 1 diabetes mellitus

Larsen et al., under review, 2019

