Chris Jackson (Population Health): current interests

Current work

Survival and multistate modelling methods

Applications in multiple areas

Chronic disease prevention

Methods in microsimulation models

Also Value of Information, uncertainty quantification, design...

Survival (time-to-event) and multi-state models

Motivated by two contexts

- times to severe events (hospital admission, ICU, death...) in respiratory infections
- health economic decision models combining trial, disease registry and population data

and two challenges

(a) extrapolation over time

(b) scalability to bigger problems

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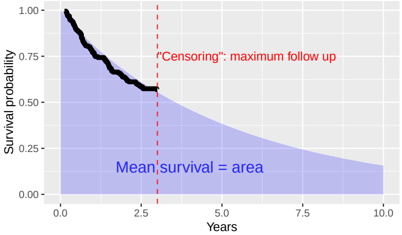
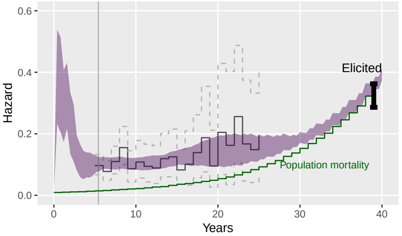
Extrapolation - long-term estimation





Estimating long-term, expected survival based on

- individual shorter term survival data (e.g. from a clinical trial)
- aggregated longer term data from a broader population (e.g. registry, national data),
- expert judgements

Paper finished on a flexible (spline) Bayesian survival model framework and software

https://arxiv.org/abs/2306.03957

https://chjackson.github.io/survextrap/

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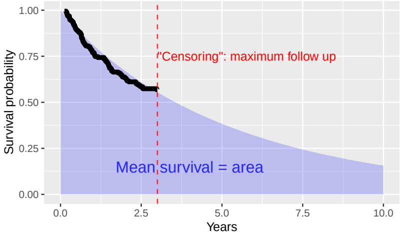

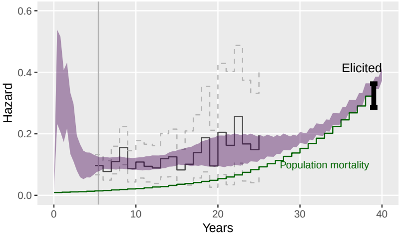

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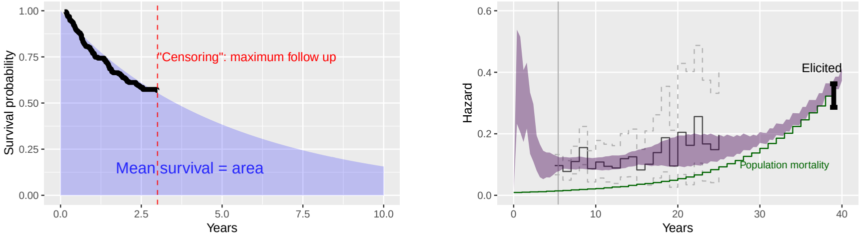

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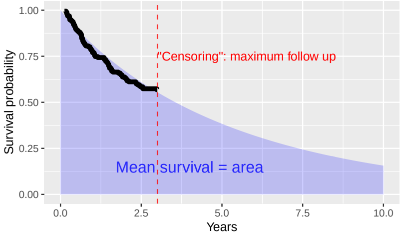

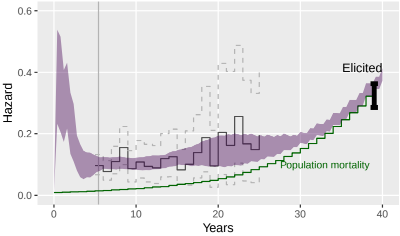

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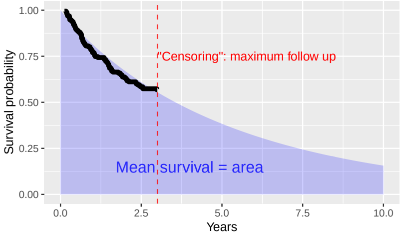
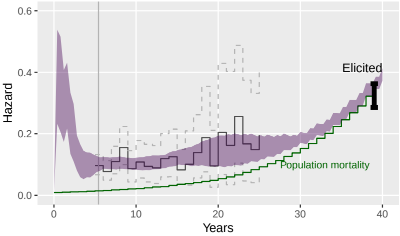


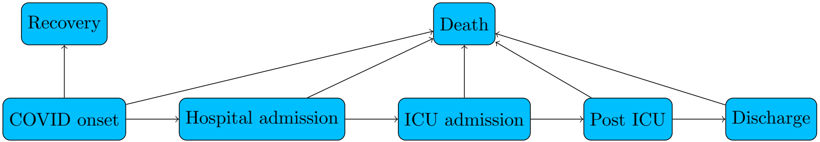


More work to do (led by Astra Zeneca, with Fatemeh Torabi) on simulation studies to build confidence in it

This model/package could form infrastructure for flexible/versatile time-to-event modelling more generally

- hierarchical models
- multistate models
- high-dimensional data (lots of covariates)

Scalability in multistate models



Each state transition is a time-to-event model: could have many covariates, and data are censored

Efficient model fitting

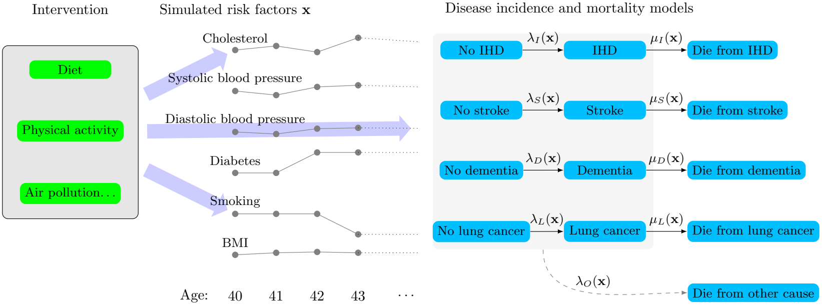
- Even 100+ parameters is challenging for identifiability
- Routinely-collected hospital data also have $n > 10000$

Efficient prediction from models

- Requires individual-level simulation, but should be fast for routine use (e.g. monitoring hospital burden)

Complex mechanistic models informed by many sources of data

Simulate from model to evaluate effect of an intervention



Microsimulation models for chronic disease prevention

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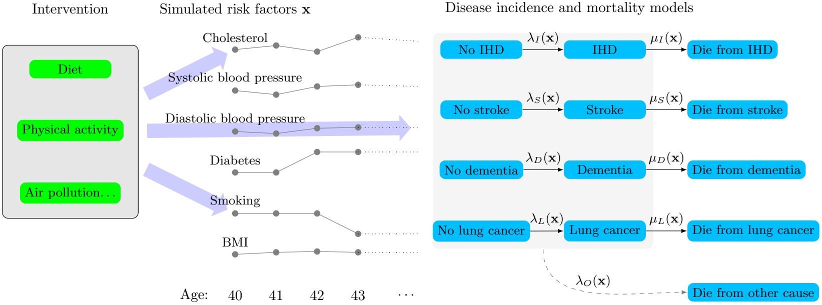

Above model motivated by mid-life health checks

Oliver Church (PhD project): Generating trajectories of multiple risk factors

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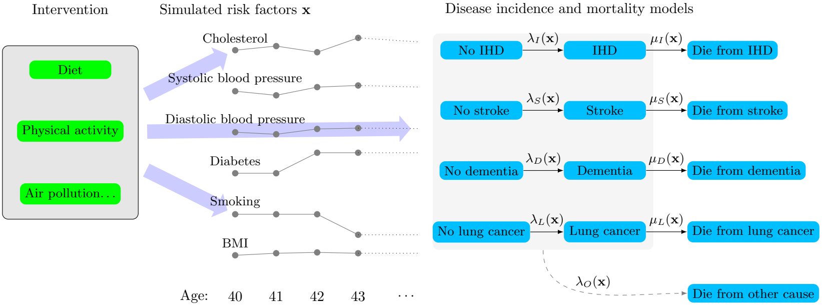

Models for health impacts of transport changes

- focus on geographical detail rather than multiple risk factors
- applications in Manchester and Melbourne (led by MRC Epi)

Mortality data to inform microsimulation models

Population mortality data is generally well recorded, however

- Limited individual-level predictors (age, gender, maybe area-level deprivation)
- Effect of having a disease not directly known: cause-specific mortality is recorded, but disease may also raise risk from other causes

Ongoing work: Bayesian synthesis of mortality data published at different levels of aggregation

- infer mortality for an individual with specific characteristics / diseases

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Other interests: applied Bayesian modelling and design

Value of Information analysis

- given a Bayesian model, determine which uncertainties have the most impact on results/decisions
- prioritise/design data collection to reduce uncertainty
- edited textbook on this topic about to be submitted

$\rightarrow$ Connects with projects proposed in QQR on

- Informative prior distributions in complex Bayesian models
  - i.e. how to quantify uncertain knowledge in the first place
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