

Smooth Constrained Mortality Forecasting with an extension to multi-population forecasts

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Outline

- 1 Motivation
- 2 P-splines for forecasting
- 3 CP-splines
- 4 Results
- 5 Subnational forecasts
- 6 Conclusions

Mortality forecasting methods: Quick overview

Parametric models

- parsimonious (for adult ages)
- large number of parameters is often necessary
- hard to disentangle physical meaning of each parameter
- simultaneous forecast of all parameters is a challenge
- rigid structure

Lee-Carter variants

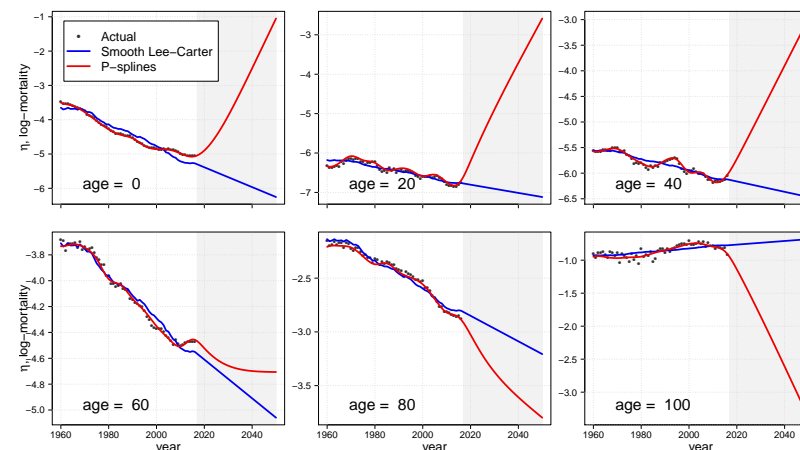
- univariate time index condenses mortality development
- fix age effect over time
- lack of smoothness in forecast
- extremely large number of parameters
- rigid structure

Nonparametric approaches, e.g. P-splines

- extremely good fit
- flexible structure
- wisely parsimonious
- purely data-driven: no demography involved !!

Outcomes from plain approaches

- USA, males, ages 0-105, years 1960-2016, forecast years 2017-2050



- Source: Human Mortality Database
 - Delwarde et al. (2007) for the smooth Lee-Carter
 - Currie et al. (2004) for the two-dimensional P-splines,

The idea

P-splines:

- flexibility (good fit)
- blind adherence extrapolation

Lee-Carter:

- rigidity (bad fit)
- past development drives future mortality

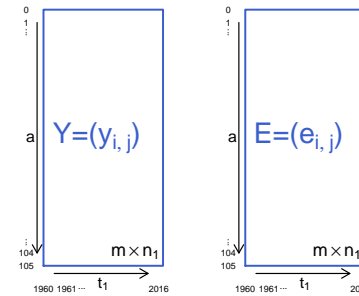
Constrained P-splines, CP-splines:

Incorporate into P-splines demographic information

- flexibility (good fit)
- future development based on prior demographic knowledge

Data structure & basic model

Observed data



Model:

$$y = \text{vec}(Y)$$

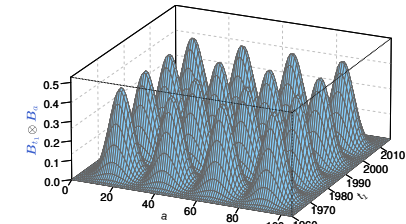
$$e = \text{vec}(E)$$

$$\ln(y) = \ln(e) + \ln(\mu) = \ln(e) + \eta$$

$$= \ln(e) + B\alpha$$

$$B = B_{t1} \otimes B_a$$

α : penalized coefficients



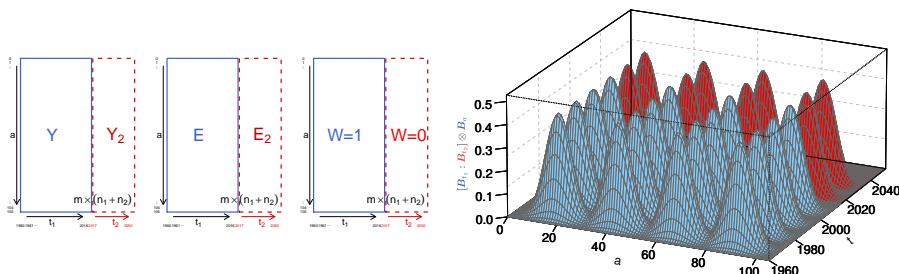
Assumption:

$$y_{ij} \sim \mathcal{P}(e_{ij} \mu_{ij})$$

- estimated by a penalized iterative weighted least-squares algorithm

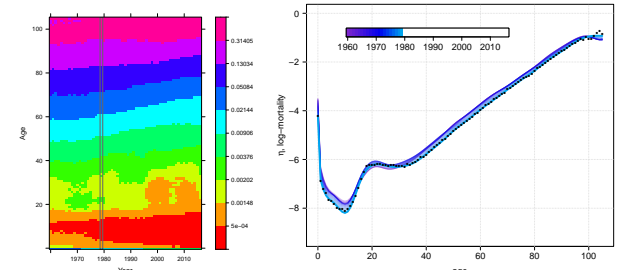
Forecasting with P-splines

- Forecasting is treated as a missing value problem
- Data are augmented with arbitrary future values and we define a weight matrix
- B-spline bases are augmented too: $B = [B_{t1} : B_{t2}] \otimes B_a$
- The original algorithm can be adapted
- No information about mortality structure is used

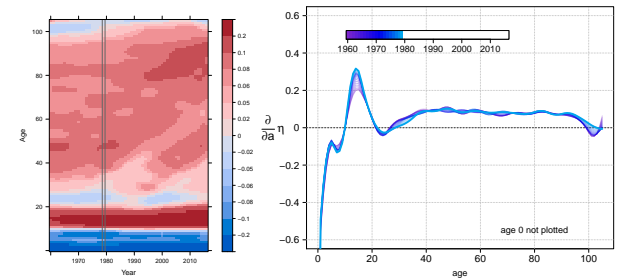


Observing mortality patterns (over ages)

Actual and Smooth log-mortality

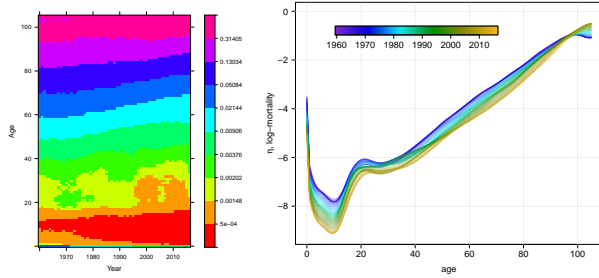


Rate-of-aging from smooth mortality

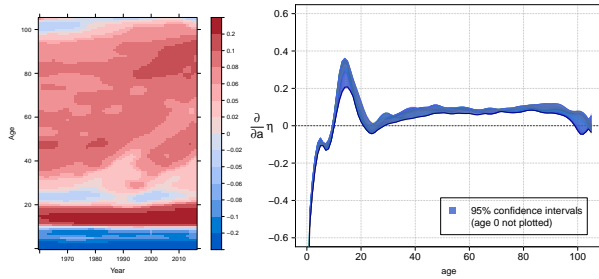


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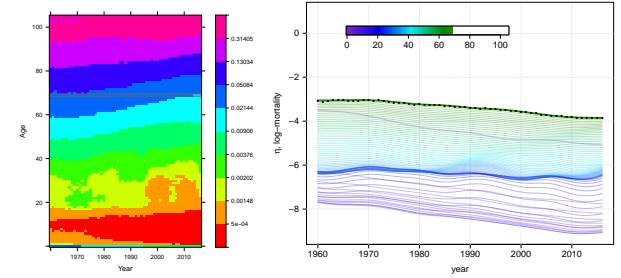


Rate-of-aging from smooth mortality

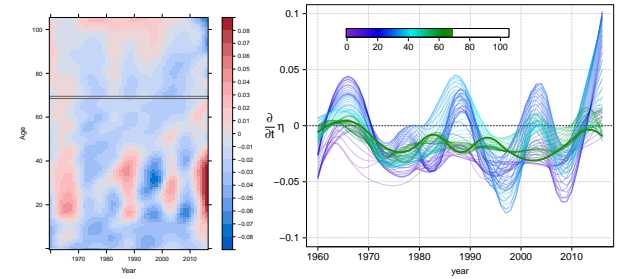


Observing mortality patterns (over years)

Actual and Smooth log-mortality

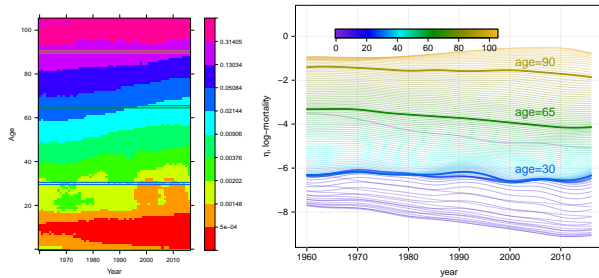


Rate-of-change from smooth mortality

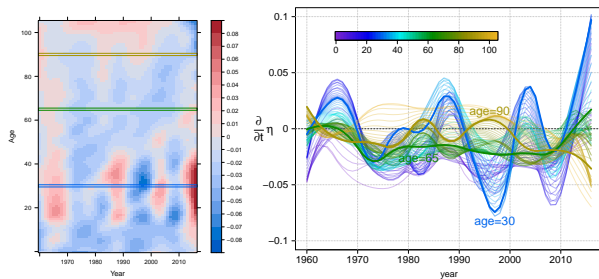


Observing mortality patterns (over years)

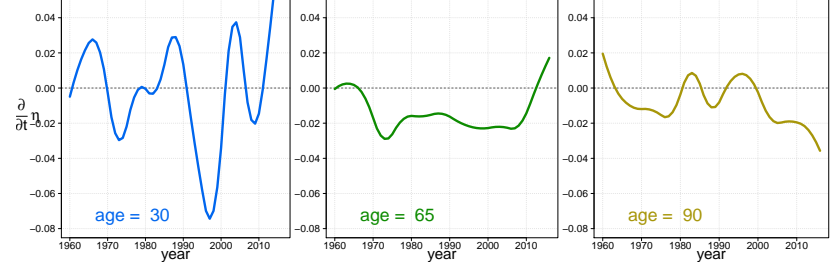
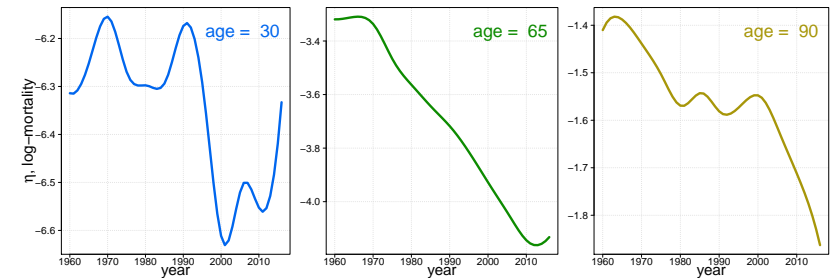
Actual and Smooth log-mortality



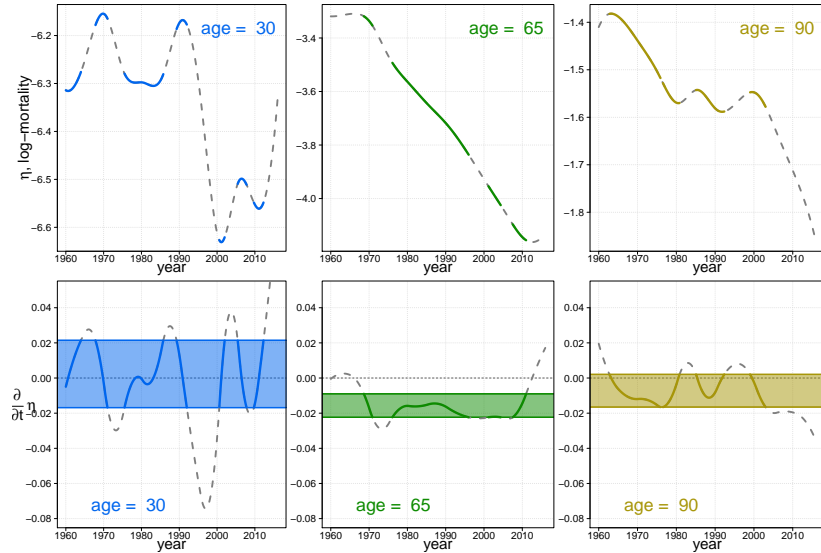
Rate-of-change from smooth mortality



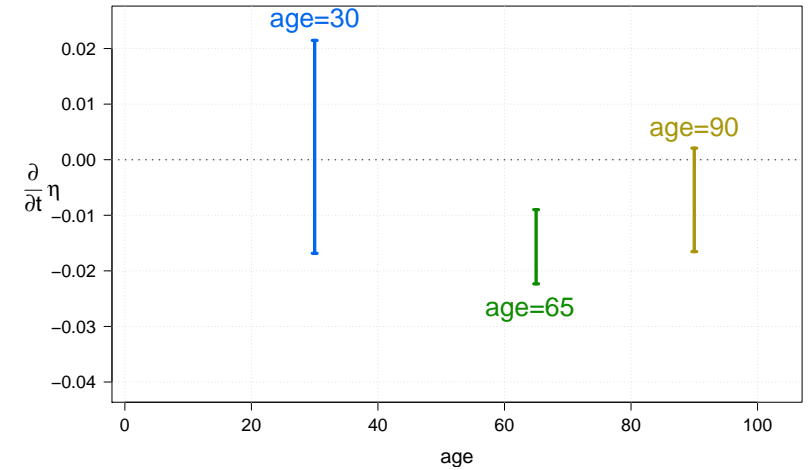
Observing mortality patterns (over years)



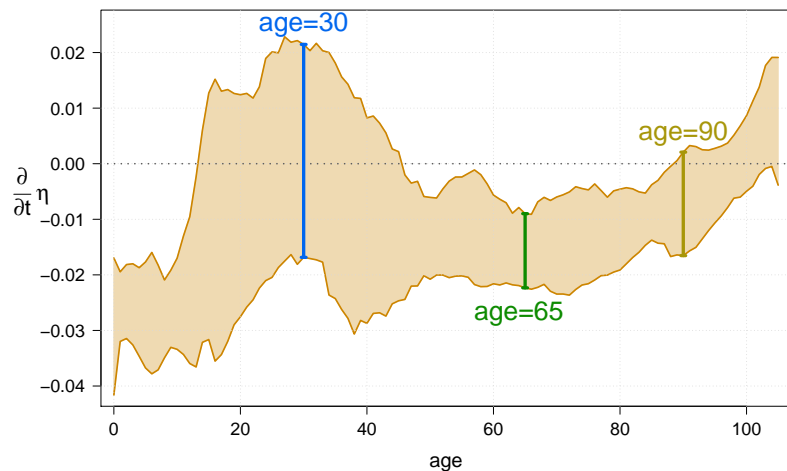
Observing mortality patterns (over years)



Observing mortality patterns (over years)



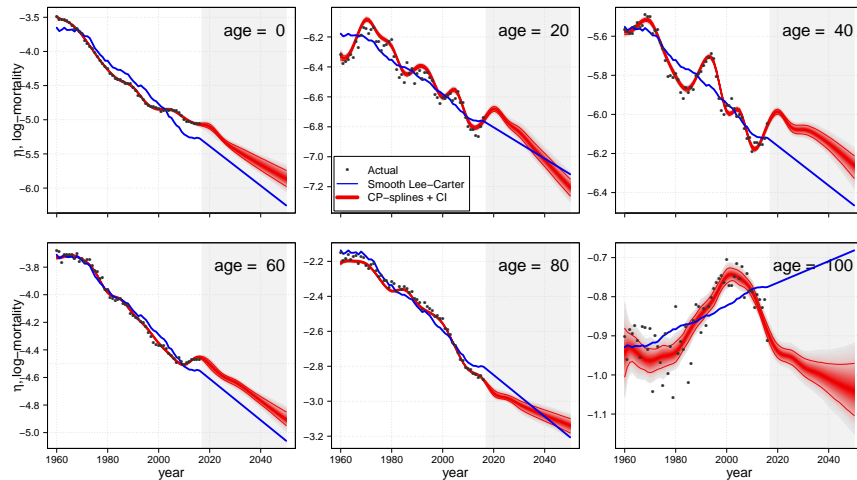
Observing mortality patterns (over years)



Working on the shape

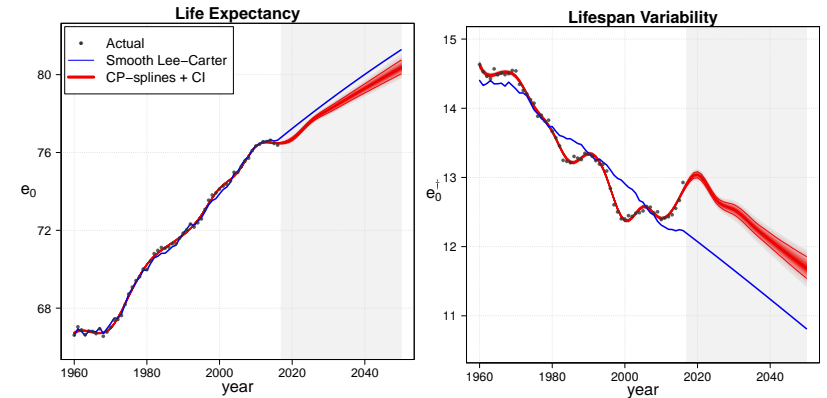
- Disregarding information about shapes seems unreasonable
- Future mortality *must* follow data-driven age-profiles and rate-of-change
- We constrain derivatives of future mortality to lay within certain confidence intervals of observed derivatives
- Asymmetric penalties are employed for this purpose:
 - within each iteration, whenever current estimations present derivatives (in future years) out of the desired intervals, a penalty intervenes
- Let's see how it works in action for a specific year (2035) and a specific age (50)

Outcomes for US, males



Log-mortality. Ages 0-105, observed years 1960-2016, forecast up to 2050

Outcomes for US, males



Life Expectancy and Lifespan variability measure (e_0^{\ddagger}).
Ages 0-105, observed years 1960-2016, forecast up to 2050

What I haven't shown here, ...

- ... but you can find in the paper below:
 - All associated equations
 - Applications to more populations
 - How infant mortality is addressed in a smoothing setting
 - Bootstrap procedure to obtain confidence intervals
 - Out-of-sample performance
 - Comparison with other alternative methods
 - Effect of changing time-window on the outcomes
 - Sensitivity analysis on confidence level in rate-of-change over t
 - Reproducible R-code

Camarda, C. G. (2019).
Smooth Constrained Mortality Forecasting.
Demographic Research. **41** (38), 1091-1130

Generalizing CP-splines

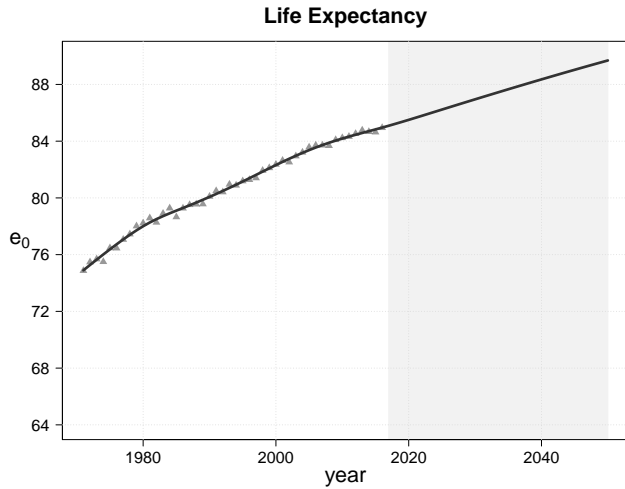
- Recently, there has been a growing strand of research on so-called *coherent* forecasting
- What does it mean? Mortality forecast of
 - males and females from the same population
 - a group of countries
 - more causes of death
 - sub-populations belonging to the same country

The idea:

given forecast values for the whole country, constrain mortality differences between each sub-population and overall country to lay within (a range of) observed past differences

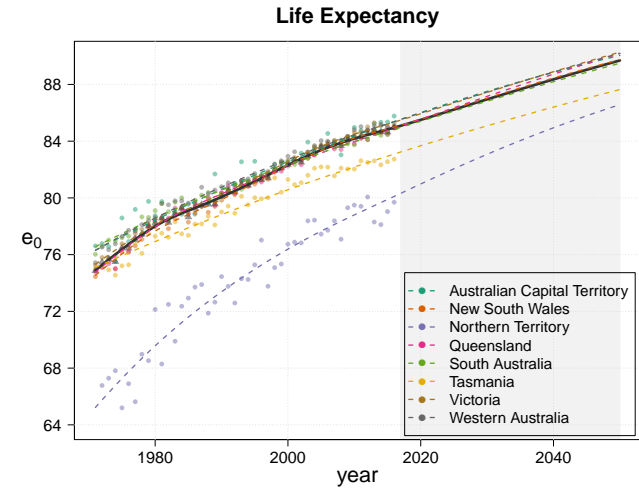
- Let's take Australia and its 8 territories/states
- Data: Females, Ages 0-100, Observed years 1971-2016, forecast up to 2050

CP-splines on Australia and its territories



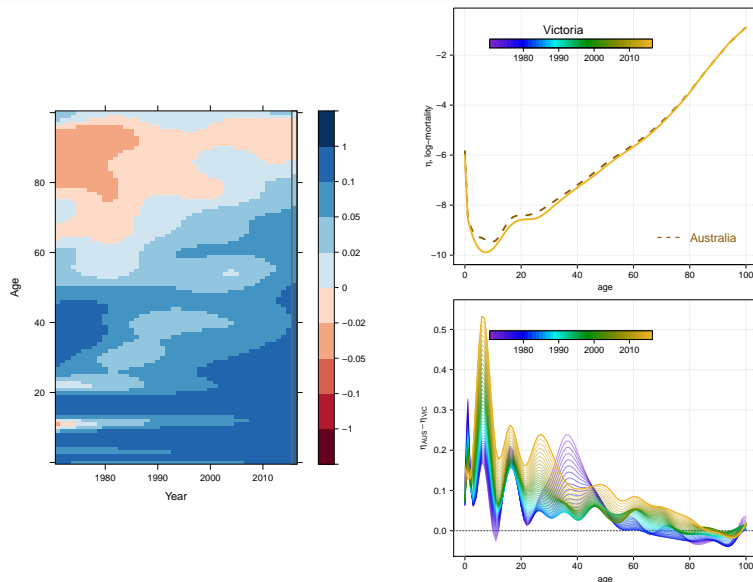
Actual, estimated and forecast life expectancy by CP-splines.
Australia

CP-splines on Australia and its territories

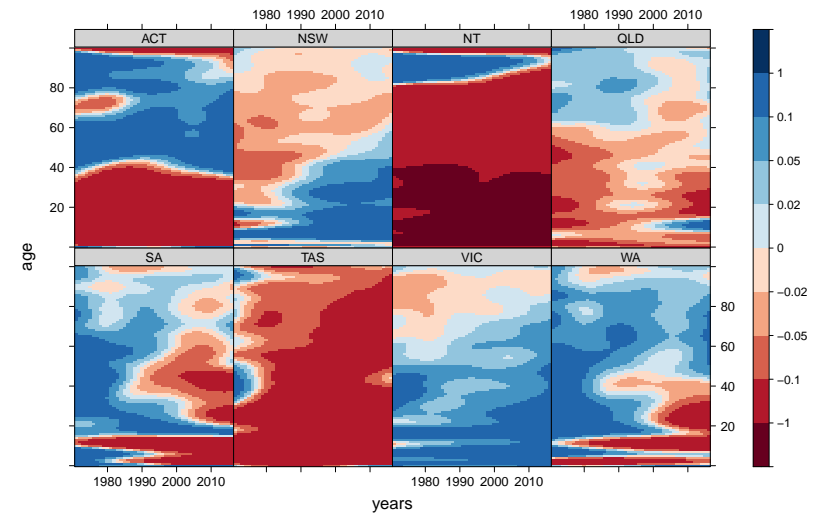


Actual, estimated and forecast life expectancy by CP-splines.
Australia and its territories

Differences in log-mortality: only Victoria

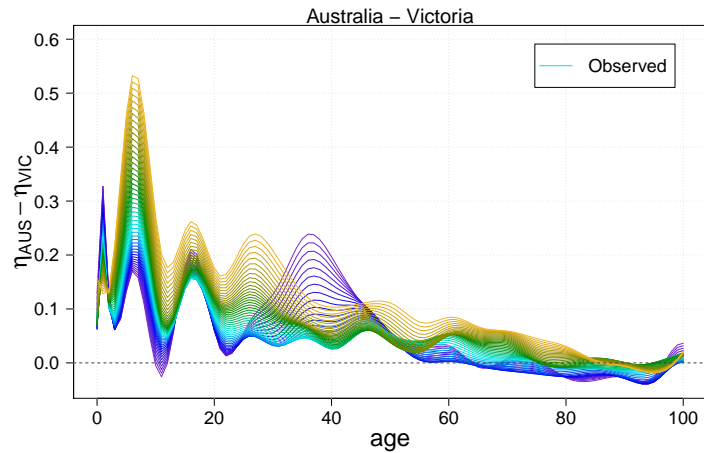


Differences in log-mortality: all territories



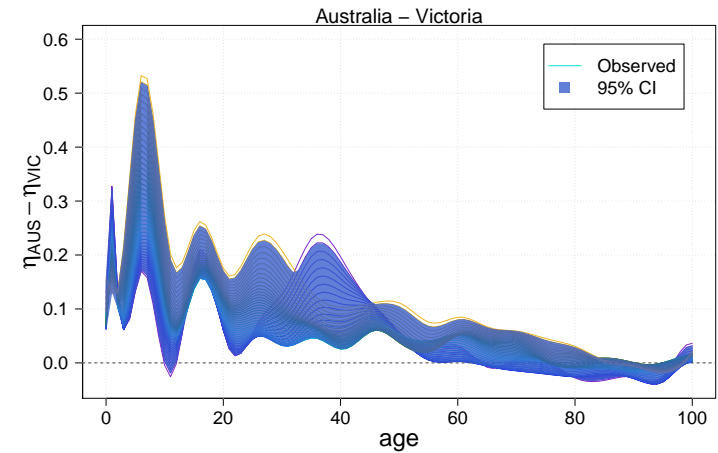
Observed differences in smooth log-mortality: Australia - each territory

Differences in future log-mortality with CP-splines



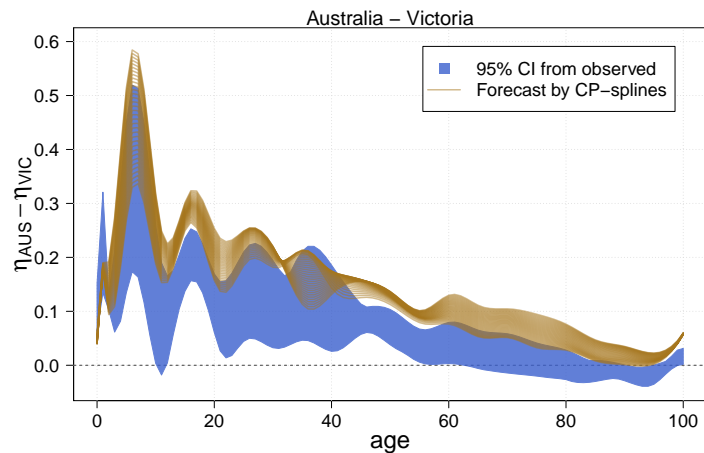
Differences in estimated smooth log-mortality

Differences in future log-mortality with CP-splines



Differences with the 95% CI in estimated log-mortality

Differences in future log-mortality with CP-splines

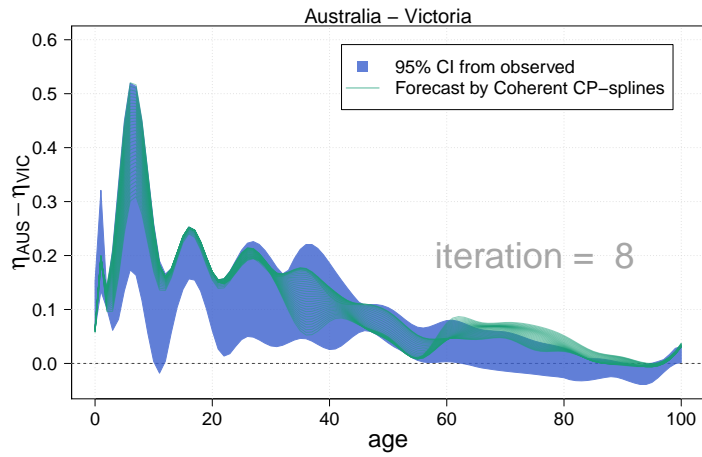


95% CI of estimated & forecast (CP-splines) differences in log-mortality

Constraining differences: Coherent CP-splines

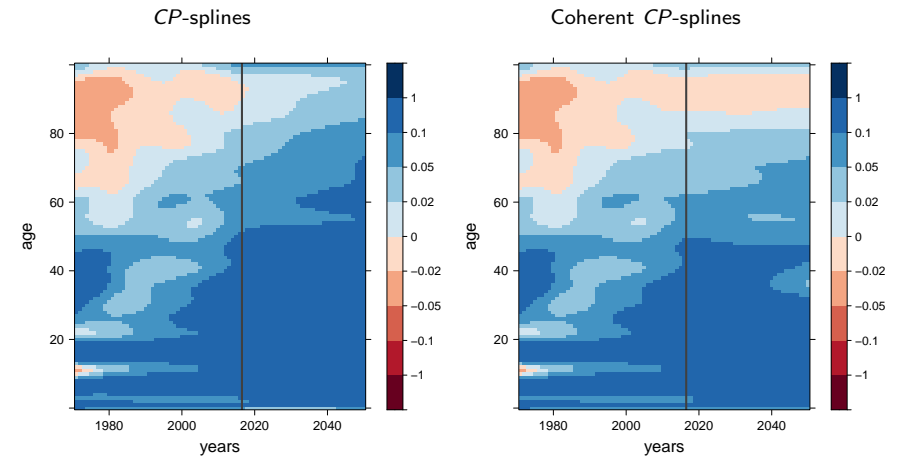
- Incorporate constraints on future differences as CP-splines do with relative derivatives
- Asymmetric penalty can be adapted
- Coherence with respect to known overall mortality preserved
- Each sub-population can be treated independently
- We achieve age-specific coherence in future years simultaneously
- Limits:
 - Knowledge about the overall future mortality is necessary
 - Range from past differences are kept in the future

Asymmetric penalty in action on differences



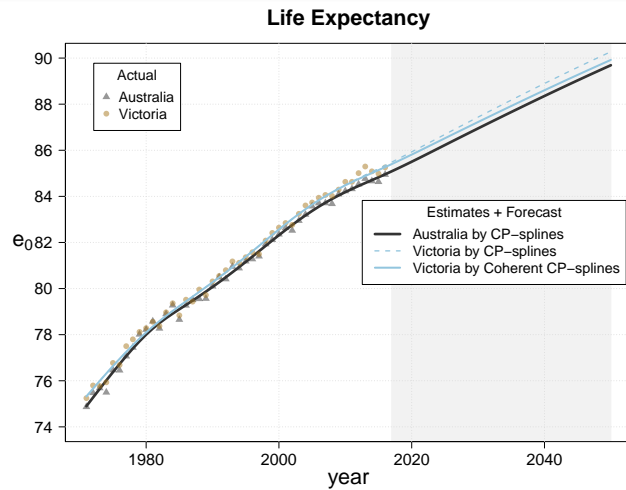
95% CI of estimated & forecast (Coherent CP-splines) differences in log-mortality

Forecast differences in log-mortality: Australia - Victoria



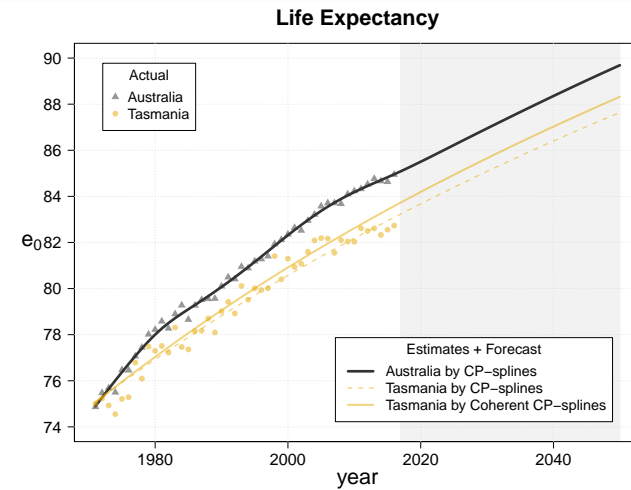
Estimated and forecast differences in log-mortality

Coherent forecast e_0 for Victoria



Actual, estimated and forecast life expectancy by (coherent) CP-splines. Australia and Victoria

Coherent forecast e_0 for Tasmania



Actual, estimated and forecast life expectancy by (coherent) CP-splines. Australia and Tasmania

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 with an extension to multi-population forecasts

Thanks for your attention.
 Comments and questions?

More info and R routines available on:
sites.google.com/site/carlogiovannicamarda

Additional slides

The Penalized IWLS

- Given data:

$$\mathbf{d} = \text{vec}(\mathbf{D})$$

$$\mathbf{e} = \text{vec}(\mathbf{E})$$

- And model

$$\ln(\mathbf{d}) = \ln(\mathbf{e}) + \ln(\boldsymbol{\mu}) = \ln(\mathbf{e}) + \boldsymbol{\eta}$$

$$= \ln(\mathbf{e}) + \mathbf{B}\boldsymbol{\alpha}$$

$$\mathbf{B} = \mathbf{B}_{y_1} \otimes \mathbf{B}_x$$

$\boldsymbol{\alpha}$: penalized coefficients

- Estimate $\boldsymbol{\alpha}$ by penalized IWLS:

$$(\mathbf{B}'\tilde{\mathbf{W}}\mathbf{B} + \mathbf{P})\tilde{\boldsymbol{\alpha}} = \mathbf{B}'\tilde{\mathbf{W}}\tilde{\mathbf{z}}$$

where

- $\tilde{\mathbf{z}} = (\mathbf{d} - \mathbf{e} * \tilde{\boldsymbol{\mu}}) / \mathbf{e} * \tilde{\boldsymbol{\mu}} + \tilde{\boldsymbol{\eta}}$
- $\tilde{\mathbf{W}} = \text{diag}(\mathbf{e} * \tilde{\boldsymbol{\mu}})$

Asymmetric penalty in formulas over ages/1

-

$$\frac{\partial}{\partial \mathbf{a}} \hat{\boldsymbol{\mu}} = \frac{\partial}{\partial \mathbf{a}} \ln(\hat{\boldsymbol{\mu}}) = \frac{\partial}{\partial \mathbf{a}} \hat{\boldsymbol{\eta}} = \mathbf{D}_a^{\dagger_1} \hat{\boldsymbol{\alpha}},$$

where

$$\mathbf{D}_a^{\dagger_1} = \mathbf{B}_{t_1} \otimes \mathbf{C}_a \quad \text{and} \quad \mathbf{C}_a = \frac{1}{h} \left[q^{-1} \mathbf{B}_a^k - q^{-1} \mathbf{B}_a^{k-1} \right]$$

with h , q and k being knot-distance, degree and positions of the original B-spline basis, \mathbf{B}_a .

- δ_L^a and δ_U^a : lower and upper bounds of CI of the derivatives
- Keep same constraints for all years \Rightarrow augment $\boldsymbol{\delta}$ over both dimensions:

$$\mathbf{g}_L^a = \mathbf{1}_{n_1+n_2} \otimes \delta_L^a$$

$$\mathbf{g}_U^a = \mathbf{1}_{n_1+n_2} \otimes \delta_U^a$$

- Similar computation is performed over years

Asymmetric penalty in formulas over ages/2

- New penalized IWLS:

$$(\check{B}' V \check{W} \check{B} + P + P^a + P^t) \check{\alpha} = \check{B}' V \check{W} \check{z} + p^a + p^t.$$

where

$$\begin{aligned} P^a &= P_L^a + P_U^a & \text{and} & & p^a &= p_L^a + p_U^a \\ P^t &= P_L^t + P_U^t & & & p^t &= p_L^t + p_U^t \end{aligned}$$

- As example, lower bounds over ages:

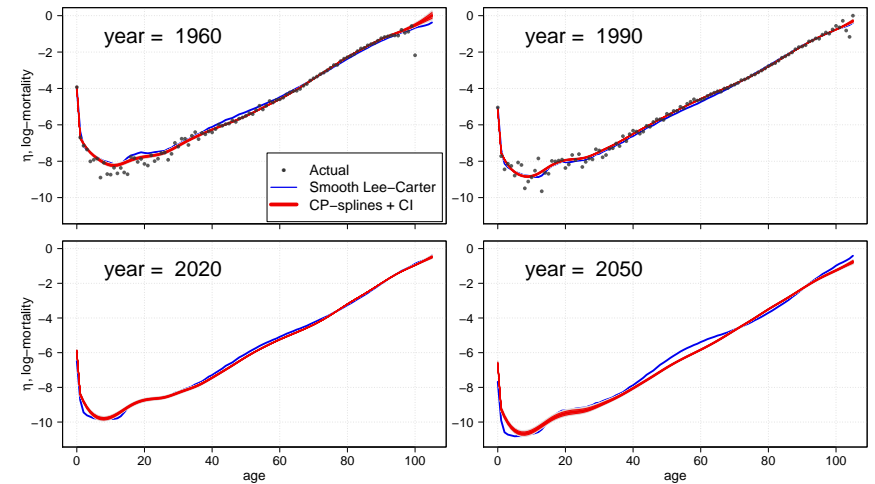
$$\begin{aligned} P_L^a &= \kappa D_a^{t_1+t_2} \text{diag}(s v_L^a) D_a^{t_1+t_2} \\ P_L^t &= \kappa D_a^{t_1+t_2} \text{diag}(s v_L^a) g_L^a \end{aligned} \quad \text{with} \quad v_L^a = \begin{cases} 0 & \text{if } D_a^{t_1+t_2} \check{\alpha} \geq g_L^a \\ 1 & \text{if } D_a^{t_1+t_2} \check{\alpha} < g_L^a \end{cases}$$

where

$$v_L^a = \begin{cases} 0 & \text{if } D_a^{t_1+t_2} \check{\alpha} \geq g_L^a \\ 1 & \text{if } D_a^{t_1+t_2} \check{\alpha} < g_L^a \end{cases},$$

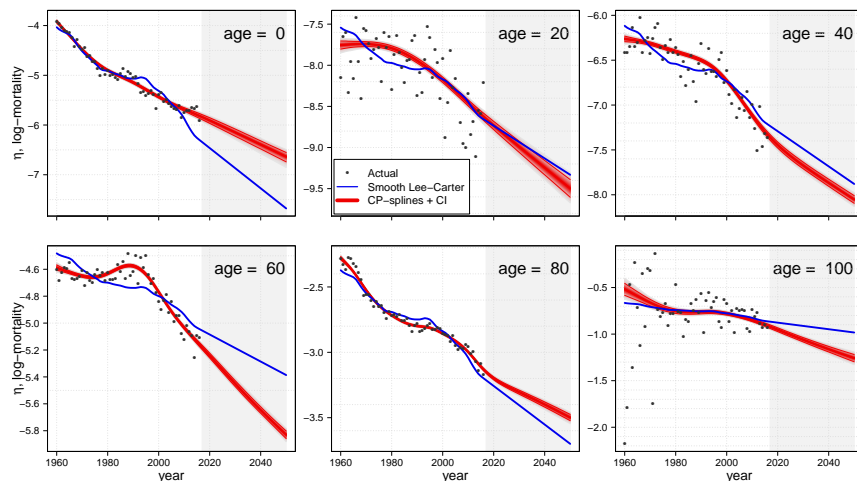
and s is a 0/1 vector equal to 1 when the constraint is to be applied (future years).

Outcomes for Denmark, females



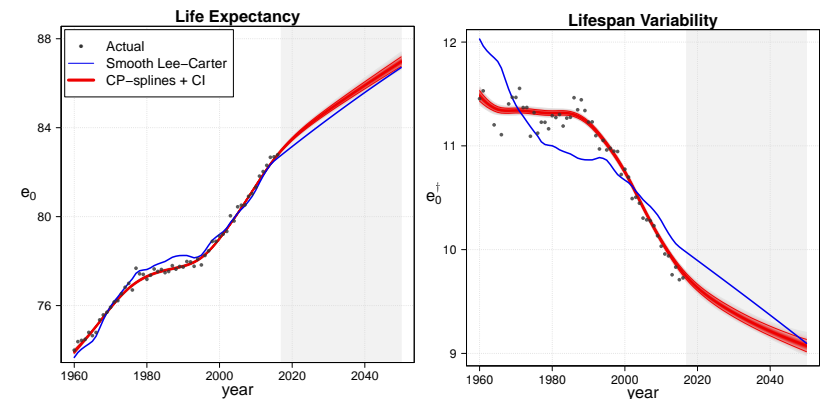
Log-mortality. Ages 0-105, observed years 1960-2016, forecast up to 2050

Outcomes for Denmark, females



Log-mortality. Ages 0-105, observed years 1960-2016, forecast up to 2050

Outcomes for Denmark, females



Life Expectancy and Lifespan variability measure (e_0^\dagger). Ages 0-105, observed years 1960-2016, forecast up to 2050

Confidence level in rate-of-change over time

