

POPULATION DYNAMICS

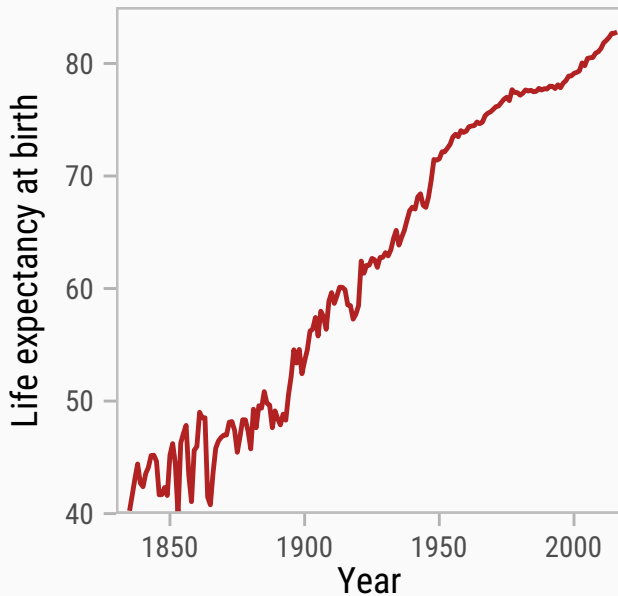
WITH EMPHASIS ON MORTALITY RESEARCH

Jesús-Adrián Álvarez

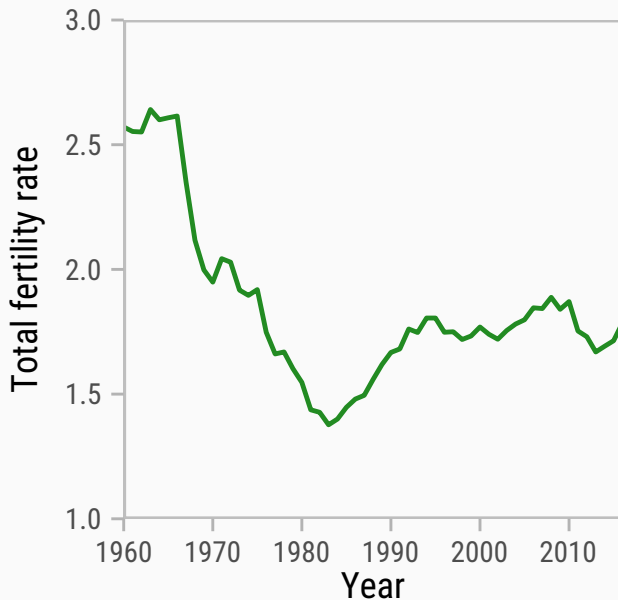
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University of Southern Denmark

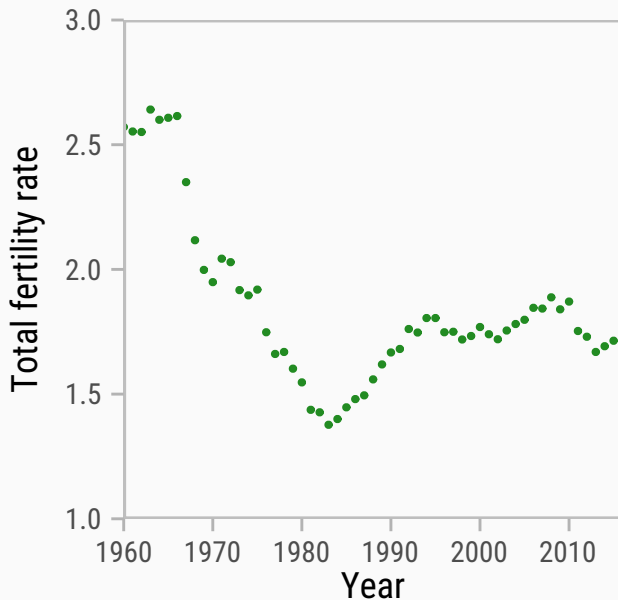
LIFE EXPECTANCY AT BIRTH, DANISH FEMALES. 1835-2017



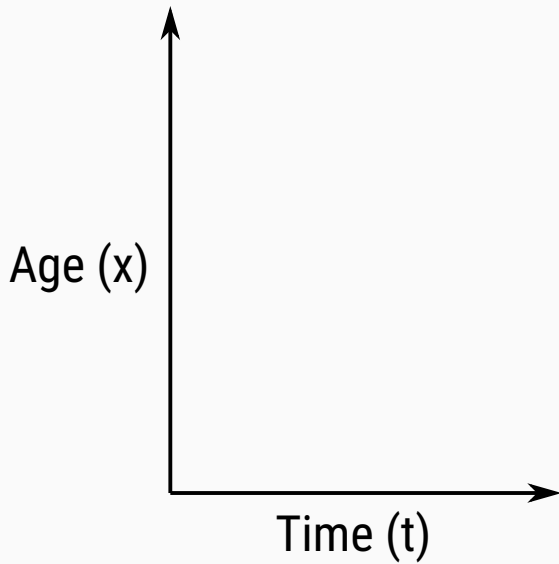
TOTAL FERTILITY RATE, DANISH FEMALES. 1960-2018

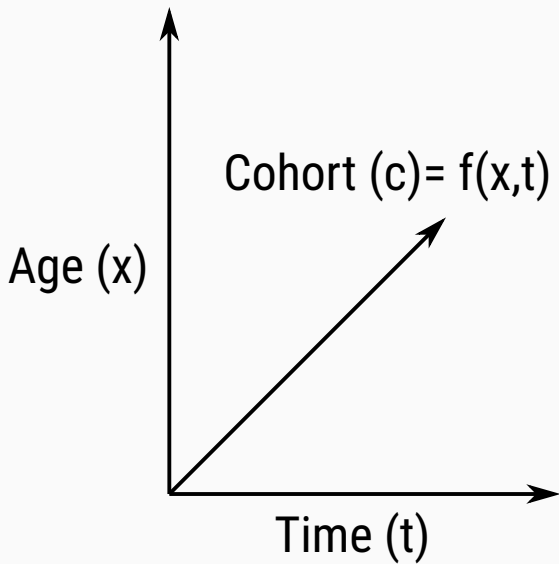


TOTAL FERTILITY RATE, DANISH FEMALES. 1960-2018



Changes over time and age





Mortality

Mortality

- Mortality hazard,

Mortality

- Mortality hazard,
- Life expectancy,

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Family demography

- Expected years ever married (Mogi and Canudas-Romo, 2018)

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- the modal age at death?

The struggle

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Limitations:

Bad approximations from discrete to continuous measures

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Discrete approach

$$e(0) = L_0 + L_1 + L_2 + \dots L_{100+}$$

How to calculate changes over time in demographic measures?

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How to apply neat continuous formulas to messy discrete data?

Data

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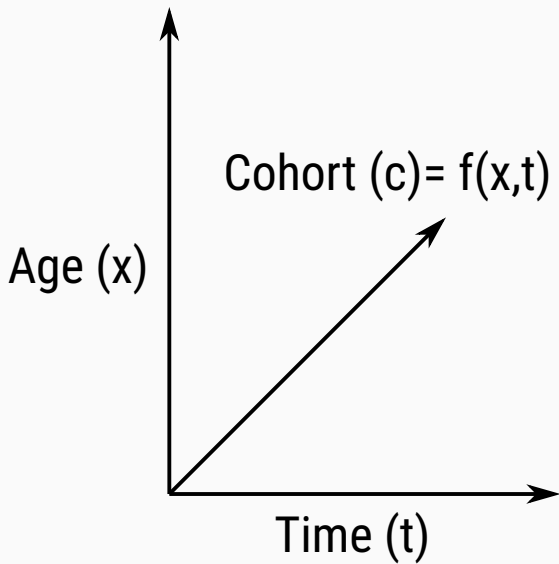
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How do we measure continuous change?

HOW DO WE MEASURE CONTINUOUS CHANGE?

$$\frac{df(x)}{dx} = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h}$$

In what direction should we derive?



IN WHAT DIRECTION SHOULD WE DERIVE?

Rate of ageing (in the age direction)

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Rate of ageing (in the cohort direction)

$$\beta(x, t) = \frac{\frac{\partial \mu(x, t)}{\partial t \partial x}}{\mu(x, t)}$$

$$\beta(x, t) = b(x, t) - \rho(x, t)$$

Approximating derivatives

$$f'(x, t) = \frac{\partial f(x, t)}{\partial t} \cong \frac{f(x, t) + f(x, t + h)}{h}$$

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The approximation depends on the size of h .

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Simpson's 3/8 rule

$$\int_a^b f(x, t) dx \cong \frac{b - a}{8} [f(a) + 3f(\frac{2a + b}{3}) + 3f(\frac{a + 2b}{3}) + f(b)]$$

Producing continuous estimates

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Discrete approximation from life tables

$$\rho(x, t + h/2) \cong \frac{\ln \left(\frac{\mu(x, t + h)}{\mu(x, t)} \right)}{h}$$

and

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- Easy to estimate from life tables,
- It can be applied to any function (changes over time and age).

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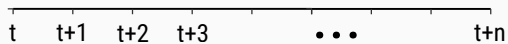
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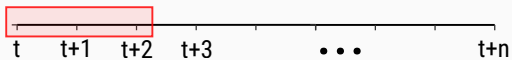
- Not very precise.

Rolling window

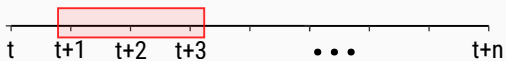
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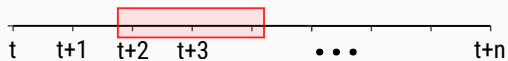
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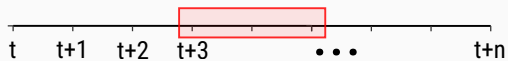
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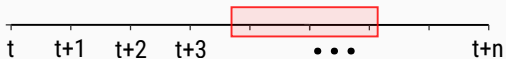
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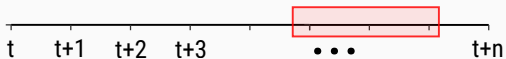
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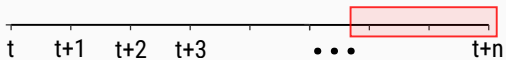
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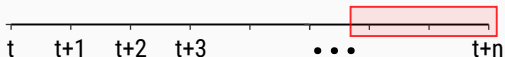


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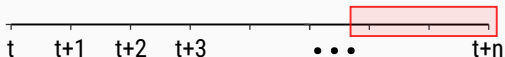
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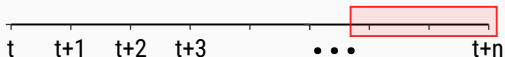
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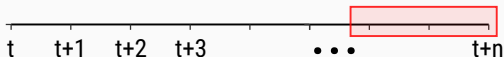


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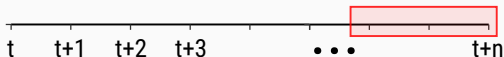


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Disadvantages

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- It requires many years/ages to provide meaningful results.

Simulating lifespans using exponential distribution with piecewise constant rate

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SIMULATING LIFESPANS

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- Simulate a great number of lifespans (>100,000) using $M(x, t)$ as the vector of rates in the function `rpexp()` of the package `msm`.

$$s(x, t) = e^{-nM(x, t)} \text{ and } \mu(x, t) = \frac{f(x, t)}{s(x, t)}$$

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- It only helps when you are looking at changes over age
- It requires a lot of RAM (and time).

Smoothing

POISSON COUNTS WITH P-SPLINES (CAMARDA, 2012)

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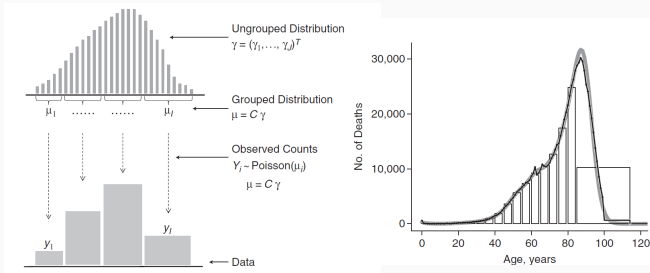
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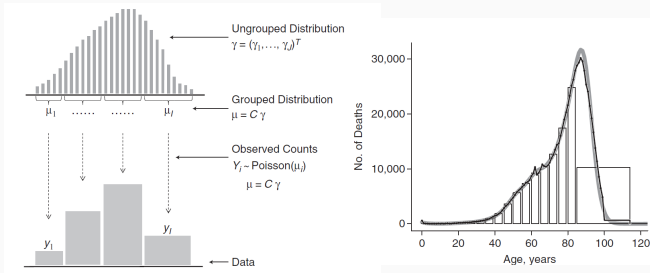


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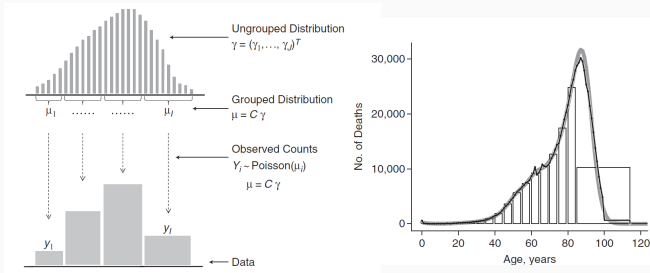


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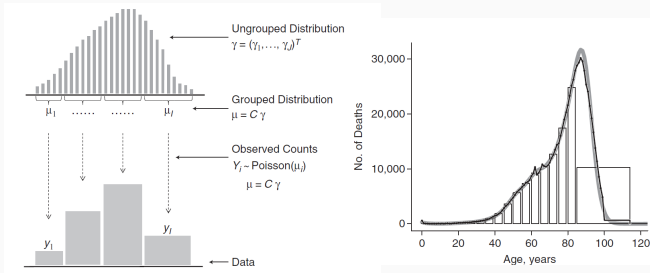
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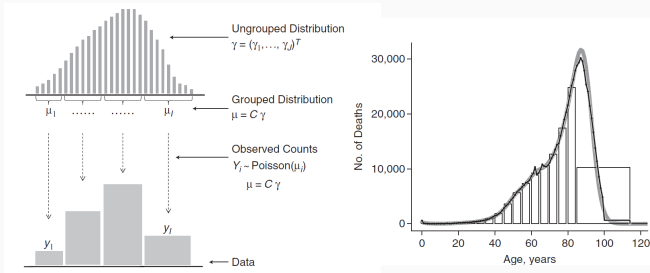
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- It is only designed for mortality data.
- Not able to produce confidence intervals (so far).

Does Demography need differential equations?

by Thomas K. Burch

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"Demographers generally were not schooled in differential equations, so we did not try to use them, and avoided topics that required their use even at the most elementary level."

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Burch, Thomas K. Model-based demography: Essays on integrating data, technique and theory. Springer Nature, 2018.

Questions?