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Time-Simultaneous Prediction Bands: A New Look at the Uncertainty Involved in Forecasting Mortality

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1. Introduction

- In recent years, there has been a new wave of work that is focused on the forecasting of uncertainty in mortality projections.
- Conventionally, isolated (point-wise) prediction intervals (IPI) are used to quantify the uncertainty in future mortality rates.
- A pointwise interval only reflects uncertainty in a variable at a single time point.
- In situations when the path or trajectory of future mortality rates is important, a band of pointwise intervals might lead to invalid inference.
- The primary objective of this paper is to demonstrate how simultaneous prediction bands (SPB) can be created for prevalent stochastic models.



What is IPI?

- Most time-series computer packages calculate and plot isolated (point-wise) prediction intervals (IPIs) for multiple forecasts.
- The following example shows an output from a standard forecasting package.
- 95% prediction intervals are included.
- What is the meaning of the confidence level 95% here?





What is SPB?

• SPB is a time-simultaneous prediction band with coverage probability 0 $<1-\alpha\leq 1$ for a random trajectory ${\bf y}$ if

$$\Pr(\mathbf{y} \in \mathbf{SPB}) = \Pr\left(\bigcap_{s=1}^{S} (I_s \leq y_{T+s} \leq h_s)\right) = 1 - \alpha.$$

- SPB is useful when the whole path (or trajectory) of future mortality rates is important.
- The following graph shows a hypothetical 95% SPB.





Why IPI \neq SPB?

- Unless all trajectories develop very orderly (say, perfectly correlated), the probability that a trajectory lies completely inside all ISI would be less than 1α .
- It can be seen from an extreme example that if the forecasts are uncorrelated to each other, the probability of S consecutive predictions are within the ISI is $(1 \alpha)^S$.
- For S = 20 and $\alpha = 5\%$, this probability becomes 35.85%!
- In general, predictions from a stochastic mortality model are neither perfectly correlated nor totally uncorrelated; therefore, we cannot use IPI to replace SPB.



2. Data

- Historic mortality data for US and Canadian (unisex) populations from age 60 to 99 and from year 1951 to 2004.
- The required data, death counts and exposures-to-risk, are obtained from the Human Mortality Database (2010).
- Note that the methods we propose do not require a specific choice of a sample age range and a sample period. They are chosen just purely for illustration purposes.



3. Mortality Models

- We provide a brief review of two mortality models which we use to illustrate the concept of time-simultaneous prediction bands (SPB).
- They are the Cairns-Blake-Dowd (CBD) model and the generalized CBD model with a cohort effect (GCBD).
- Note that the methods we propose do not require a specific choice of stochastic mortality models. They are chosen just purely for illustration purposes.



The Cairns-Blake-Dowd (CBD) Model

• Cairns et al. (2006) propose a two-factor stochastic mortality model

$$\ln\left(\frac{q_{x,t}}{1-q_{x,t}}\right) = \kappa_t^{(1)} + \kappa_t^{(2)}(x-\bar{x}), \tag{1}$$

where $q_{x,t}$ is the realized single-year death probability at age x and time t, \bar{x} is the average age over the age range we consider, and $\kappa_t^{(1)}$ and $\kappa_t^{(2)}$ are period indexes.

• The maximum likelihood estimates (MLE) of $\kappa_t^{(1)}$ and $\kappa_t^{(2)}$, $t = 1950, \ldots, 2004$, for Canada and US, are shown in the following graphs.



MLE of the CBD Model — Canada





MLE of the CBD Model — US





The Cairns-Blake-Dowd (CBD) Model

• After fitting equation (1) to historic death probabilities, the period indexes $\kappa_t^{(1)}$ and $\kappa_t^{(2)}$ are modeled by a bivariate random walk with drift, that is,

$$\kappa_{t+1} = \kappa_t + \mu + CZ(t+1) \tag{2}$$

where $\kappa_t = (\kappa_t^{(1)}, \kappa_t^{(2)})'$, $\mu = (\mu_1, \mu_2)'$ is a constant 2×1 vector, C is a constant 2×2 upper triangular matrix, and Z(t) is a 2-dimensional standard normal random vector.



The Cairns-Blake-Dowd (CBD) Model

 Trajectory of mortality predicted rates for a particular birth cohort (age x in year T) can be obtained by

$$\ln\left(\frac{\hat{q}_{x+s,T+s}}{1-\hat{q}_{x+s,T+s}}\right) = \kappa_T^{(1)}(s) + \kappa_T^{(2)}(s)(x+s-\bar{x}),$$

where $\kappa_T^{(1)}(s)$ and $\kappa_T^{(2)}(s)$ are the minimum sqaure error (MMSE) forecasts of $\kappa_{T+s}^{(1)}$ and $\kappa_{T+s}^{(2)}$, respectively.



The GCBD Model

 To model cohort effects, we may consider the following generalization of the CBD model:

$$\ln\left(\frac{q_{x,t}}{1-q_{x,t}}\right) = \kappa_t^{(1)} + \kappa_t^{(2)}(x-\bar{x}) + \kappa_t^{(3)}((x-\bar{x})^2 - \hat{\sigma}_x^2) + \gamma_{t-x}^{(4)},$$
(3)

where $\kappa_t^{(1)}$, $\kappa_t^{(2)}$, and $\kappa_t^{(3)}$ are period risk factors, $\gamma_{t-x}^{(4)}$ is a cohort risk factor, and $\hat{\sigma}_x^2$ is the mean of $(x - \bar{x})^2$ over the age range we consider.

• The maximum likelihood estimates (MLE) of $\kappa_t^{(1)}$, $\kappa_t^{(2)}$, $\kappa_t^{(3)}$ and $\gamma_{t-x}^{(4)}$, $t = 1950, \ldots, 2004$, for Canada and US, are shown in the following graphs.



MLE of the GCBD Model — Canada





MLE of the GCBD Model — US





The GCBD Model

• Having fitted equation (3) to historic data, the period indexes are modeled by a trivariate random walk with drift:

$$\kappa_{t+1} = \kappa_t + \mu + CZ(t+1), \tag{4}$$

where $\kappa_t = (\kappa_t^{(1)}, \kappa_t^{(2)}, \kappa_t^{(3)})'$, $\mu = (\mu_1, \mu_2, \mu_3)'$ is a constant 3×1 vector, *C* is a constant 3×3 upper triangular matrix, and Z(t) is a 3-dimensional standard normal random vector.



The GCBD Model

 Trajectory of mortality predicted rates for a particular birth cohort (age x in year T) can be obtained by

$$\ln\left(\frac{\hat{q}_{x+s,T+s}}{1-\hat{q}_{x+s,T+s}}\right) = \kappa_T^{(1)}(s) + \kappa_T^{(2)}(s)(x+s-\bar{x}) + \kappa_T^{(3)}(s)((x+s-\bar{x})^2 - \hat{\sigma}_x^2) + \gamma_{T-x}^{(4)},$$
(5)

where $\kappa_T^{(i)}(s) = \kappa_T^{(i)} + s\mu_i$, i = 1, 2, 3, is the MMSE forecast of $\kappa_{T+s}^{(i)}$.



4. Simulation-Based SPB

Consider the cohort of individuals who are aged x at the forecast origin T. Assuming that the forecast horizon is S, the trajectory of interest would be m = (m_{x+1,T+1},..., m_{x+S,T+S}). From the stochastic components of the mortality models, we simulate a learning sample of size N (we use N = 5000 in this paper):

$$\mathbf{M} = \{\mathbf{m}^{(n)}\}_{n=1}^{N} = \{(m_{x+1,T+1}^{(n)}, \dots, m_{x+S,T+S}^{(n)})\}_{n=1}^{N}$$

 Note that CBD models is based on q_{x,t} rather than m_{x,t}. To obtain central death rates, we apply the constant force of mortality (CFM) assumption:

$$m_{x,t}=-\ln(1-q_{x,t}),$$



Method 1: Adjusted Intervals

- Our goal is to construct a time-simultaneous prediction band such that $\lceil (1 \alpha)N \rceil$ of the trajectories in **M** are completely inside the band at every time point, while $\lfloor \alpha N \rfloor$ are outside the band at one or more points of time.
- Let PI_s = [I_s, h_s] be a pointwise prediction interval for m_{x+s,T+s} with coverage probability 1 − α. Then the limits I_s and h_s are set to the ⌊α/2⌋th lowest and highest values in the sample, respectively.
- Kolsrud (2007) proposes a three-step iterative method, which he calls 'adjusted intervals,' to construct a time-simultaneous prediction band from a learning sample.



Method 1: Adjusted Intervals

- The iterative algorithm:
 - Step 1: For each s = 1, ..., S, widen the interval uniformly to include the nearest sample point above and the nearest sample point below.

$$PI_s^* = [I_s - \delta_s, h_s + \delta_s]$$

- Step 2: Check the simultaneous coverage of all intervals in the learning sample **M**.
- Step 3: If the simultaneous coverage is less than the prescribed level 1α , go to Step (1). Otherwise, terminate the algorithm.
- The resulting band of intervals would contain no less than 1α of the trajectories in the learning sample.



Illustration of Adjusted Intervals — Canada



Generalized Cairns-Blake-Dowd





Illustration of Adjusted Intervals - US



Generalized Cairns-Blake-Dowd





Method 2: Chebyshev Bands

- The envelope of a (sub)sample is defined as the tightest band that contains all trajectories in the (sub)sample.
- As an example, the envelope of the learning sample M can be expressed as ([min_n m⁽ⁿ⁾_{x+s,T+s}, max_n m⁽ⁿ⁾_{x+s,T+s}])^S_{s=1}.
- The idea behind Chebyshev bands is that we construct a time-simultaneous prediction band as the envelope of a subsample M* that contains [(1 α)N] trajectories with the shortest distance to the mean trajectory

$$\bar{\mathbf{m}}=(\bar{m}_{x+1,T+1},\ldots,\bar{m}_{x+S,T+S}).$$



Method 2: Chebyshev Bands

• It is suggested that we measure the distant by the the weighted Chebyshev distance, which can be expressed as:

$$\mathcal{D} = \max_{s=1,\dots,S} \left(\frac{|m_{x+s,T+s} - \bar{m}_{x+s,T+s}|}{\sigma_s} \right),$$

where

$$\sigma_{s} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(m_{x+s,T+s} - \bar{m}_{x+s,T+s}\right)^{2}}$$

is the pointwise standard deviation s steps beyond the forecast origin.



Illustration of Chebyshev Bands — Canada



Generalized Cairns-Blake-Dowd





Illustration of Chebyshev Bands — US



Generalized Cairns-Blake-Dowd





5. Further Research

- Model Risk: Denuit (2009)
- Parameter Method: Li and Chan (2011)
- Non-linear Model: Azaïs et al. (2010)

Thank You!

