LSTM-based Coherent Mortality Forecasting for Developing Regions

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Presentation Overview

Our Work

Human Mortality Forecasting for Developing Countries/Regions

- Many developing countries/regions have experienced a rapid mortality decline over the past few decades.
- Their recent mortality development trends are **NOT** necessarily driven by the same factors as their long-term behaviours.
- We propose a **time–varying mortality forecasting model** based on the **life expectancy** and **lifespan disparity** gap between these developing countries and a selected benchmark group (developed countries).
- We use a deep neural network model with an LSTM architecture to project the life expectancy and lifespan disparity difference, which further controls the rotation of the time-varying Lee-Carter (LC) model for three developing countries.

LSTM-based Time-varying LC Model

Time-Varying LC model

Let the logarithm of central death rate $m^j_{x,t}$ for a particular developing country j at age x and year t satisfieds

$$\begin{aligned} \ln m^j_{x,t} &= a^j_x + b^j_{x,t} k^j_t + \varepsilon_{x,t}, \\ k^j_t &= d^j_t + k^j_{t-1} + \epsilon_t, \end{aligned} \tag{1}$$

The **main differences** between (1) and the classical LC method:

- the time–varying $b^j_{x,t}$ that measures a time–dependent age effect on mortality at different periods;
- the time-varying d^j_t describes a time-dependent drift in the random walk model used to project the period effect k^j_t.

Projection of Time-varying Factors

The age effect and drift terms of the period effect in the time-varying LC model are projected as

$$\begin{aligned} b_{x,t+1}^{j} &= (1-\omega_t^b)\hat{b}_x^j + \omega_t^b \widehat{B}_x \\ d_{t+1}^{j} &= (1-\omega_t^d)\hat{d}^j + \omega_t^d \hat{d}_0, \end{aligned} \tag{2}$$

- $\hat{b}_x^j$ and $\hat{d}^j$ are the estimated LC parameters for country j;
- $\widehat{B}_x$ and $\hat{d}_0$ are the estimated parameters of the Li-Lee model for the benchmark group.
- The key of such a time-varying LC model is the projection of the time-varying weights ω_t^b and ω_t^d.

Projection of Time-varying Factors

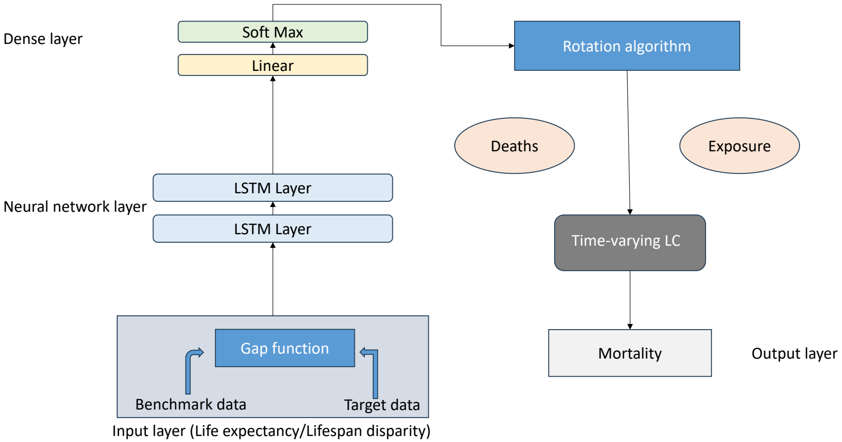
For simplicity, let $\omega_t^d = \omega_t^b = \omega_t$, for all $t \geq T$ (T is the maximum time for training in the data),

$$\omega_t = \left\{ \frac{1}{2}\left(1 + \sin\left[\frac{\pi}{2}\left(2\max\left(\frac{g_T - g_t}{g_T}, 0\right) - 1\right)\right]\right)\right\}^p, \tag{3}$$

where g_t is the life expectancy and lifespan disparity gap at time t between the target country/region and the benchmark group.

- ω_t increases smoothly to 1 if the life expectancy/life disparity gap decreases in the projection phase.
- $p \in [0, 1]$ is a tuning parameter, we choose $p = 1$ such that ω_t has low rate of change close to 0 and 1.
- The life expectancy/life disparity gaps g_t are projected using a unified neural network model with LSTM architecture.

LSTM-based Mortality Forecasting Model



Mortality Data

Data Information

- Benchmark group: Denmark, Finland, France, the Netherlands, Switzerland, Sweden, the U.K., the U.S., and Japan.
- The central death rates in the one–age and one–year blocks, ages equal to 0, 1, 2, 3, ... , 97, 98, 99, and years ranging from 1950 to 2019 (remove COVID-19 effects).
- The mortality data of developing countries/regions (e.g., Mainland China) is obtained from the United Nations population division.
- Note that a necessary condition for the application of our method is that the life expectancy or lifespan disparity of the target countries/regions converges to the ones of the benchmark group.

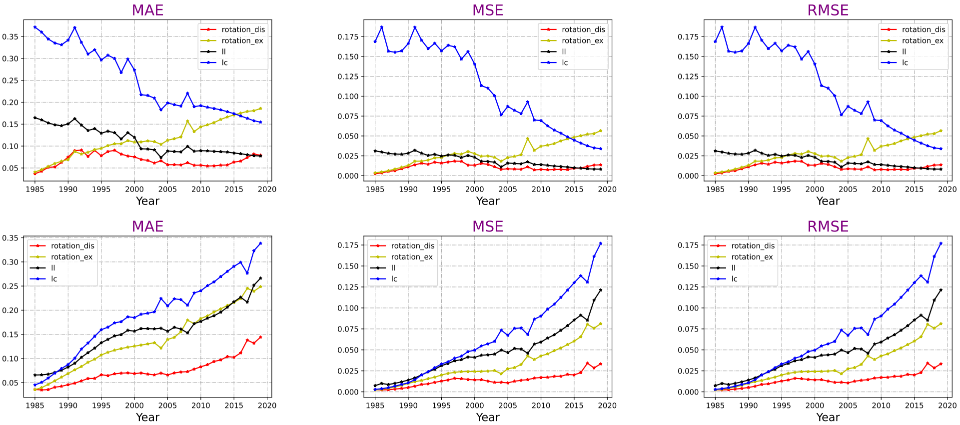
Empirical Results

Empirical Results for China (6-year Avg. Prediction Errors)

	Year	85-91	92-98	99-05	06-12	13-19	Total
MSE	LC	0.0878	0.0965	0.0854	0.0794	0.0904	0.0879
	Li-Lee	0.0202	0.0279	0.0314	0.0355	0.0509	0.0332
	LSTM-ex	0.0078	0.0214	0.0245	0.0375	0.0588	0.0301
	LSTM-disp	0.0055	0.0146	0.0123	0.0121	0.0179	0.0125
MAE	LC	0.2104	0.2293	0.2129	0.2145	0.2327	0.2201
	Li-Lee	0.1146	0.1312	0.1293	0.1305	0.1541	0.1321
	LSTM-ex	0.0575	0.0998	0.1194	0.1565	0.2003	0.1267
	LSTM-disp	0.0496	0.0738	0.0681	0.0682	0.0933	0.0706
RMSE	LC	0.2481	0.2902	0.2885	0.2816	0.2888	0.2939
	Li-Lee	0.1382	0.1669	0.1732	0.1791	0.2008	0.1781
	LSTM-ex	0.0881	0.1462	0.1565	0.1935	0.2417	0.1731
	LSTM-disp	0.0731	0.1205	0.1109	0.1082	0.1308	0.1116

Prediction Errors (in Years) for China

(Females at the top, males on the bottom.)



Thank You!

Questions?