Modelling mortality trajectories for China's oldest-old

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Agenda

1. Research aims
2. Literature review
3. Data
4. Methodology
5. Empirical results
6. Limitations and contributions

Background

Demographic transition

- The global population aged over 80 is forecasted to triple from 2020 to 426 million in 2050 (UN, 2021)

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- Rising demand for LTC insurance (Crimmins and Beltran-Sanchez, 2011)

↓

Need to introduce models that can reliably project the lifespans and estimate the disability and mortality trajectories of the oldest-old

Background

Oldest-old mortality estimation issues

- Data limitation and inaccuracy restrict the analysis of oldest-old mortality

Unparalleled opportunity for studies of oldest-old mortality in China

- Developing countries are encountering more rapid population ageing
- Massive population: over 24 million people over 80 in 2020

Research aims

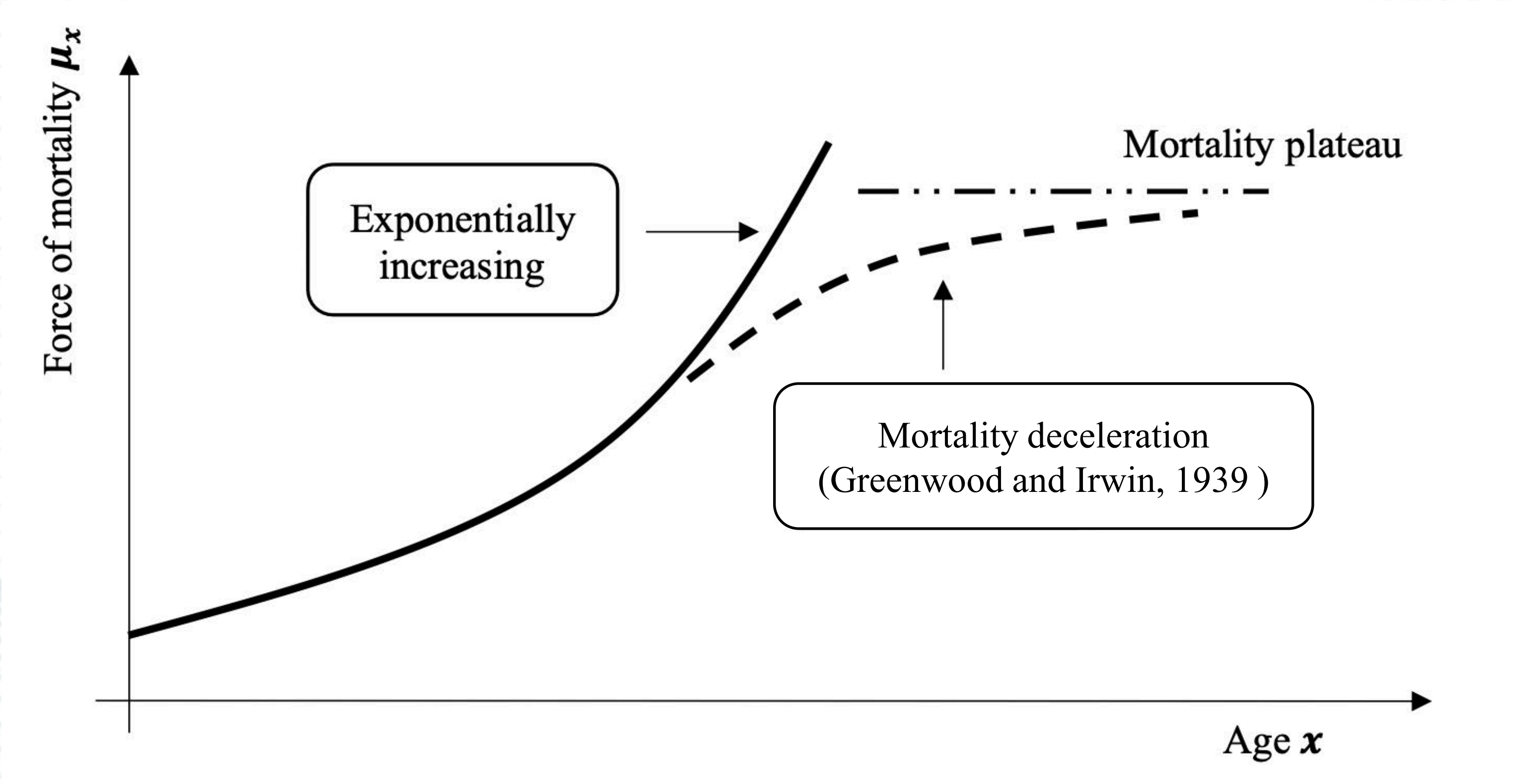
Aims

Research aims

- Comprehensively evaluating China's oldest-old mortality trajectories from 1998 to 2018.
- Propose a modelling framework that can incorporate several covariates into the mortality trajectories for the oldest-old based on left truncated right censored individual level data

Oldest-old Mortality Behaviors

Mortality deceleration or exponentially increasing



Modelling mortality differentials

Extending Parametric model

- Include covariates into Gompertz mortality law by extending parameters. (Richards, 2008)

$$\alpha_i = \alpha_{baseline} + \sum_{j=1}^{p} \alpha_j z_j$$

where z_j is the response for covariates j

Non-parametric model

- Survival tree (Ciampi et al., 1995; Davis and Anderson, 1989)
- Combined Actuarial Neural Network (CANN) (Wang et al., 2022)

Chinese Longitudinal Health Longevity Survey

The CLHLS has one of the largest samples of the oldest-old in the world.

- Baseline survey in 1998, 7 followe-up surveys in 2000, 2002, 2005, 2008, 2011, 2014, and 2018.
- Interview all possible centenarians (aged over 100) in the surveyed provinces.
- Survival data is left-truncated and right-censored (LTRC).
- Total number of observations aged from 80 to 115 in 7 survey waves is 59,171.

Data size

Wave / Time	1998-2000	2000-2002	2002-2005	2005-2008	2008-2011	2011-2014	2014-2018
Population	8,157	9,638	10,458	9,431	10,847	6,266	4,371
Deaths	3,344	3,326	5,358	4,824	5,283	2,527	2,018
Death (%)	41%	35%	51%	51%	49%	40%	46%

CLHLS data analysis

Questionaries

31 variables in the CLHLS are selected. They can be grouped into six categories.

Location
- Province
- Residency
- ......

Physical health
- ADL status
- Interviewer rated health
- ......

Psychological health
- Anxiety
- Loneliness
- Optimism
- ......

Lifestyle
- Smoke
- Drink
- ......

Demographical variable
- Occupation
- Education
- Gender
- ......

Capability test
- General ability test
- ......

Methodology

Overview

Select baseline parametric model

Combine baseline model with bagged LTRC survival tree

(extend work by Richards 2008)

Parametric Bagged Survival Tree (PBST)

- The baseline model parameters are adjusted by the terminal nodes from the survival tree

Using Integrated Brier Score with 10-folds cross validation to check model's prediction error

Baseline model selection

Six parametric mortality models are tested

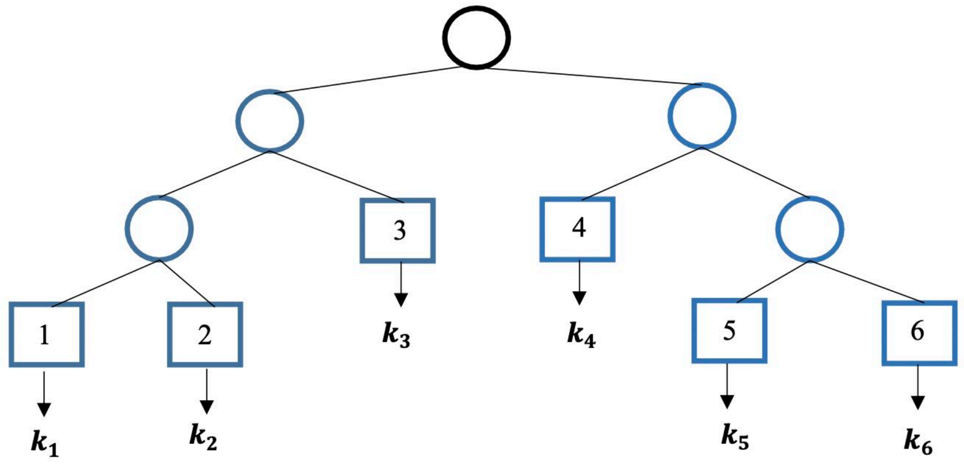
Mortality law	Force of mortality μ_x	Mortality law	Force of mortality μ_x
Gompertz	$\alpha\exp(\beta x)$	Kannisto	$\frac{\alpha\exp(\beta x)}{1+\alpha\exp(\beta x)}$
Gompertz-Makeham	$\alpha\exp(\beta x)+\lambda$	Beard	$\frac{\alpha\exp(\beta x)}{1+\alpha\exp(\beta x)}+\lambda$
Perks	$\frac{\alpha\exp(\beta x)}{1+\gamma\exp(\beta x)}+\lambda$	Thatcher	$\frac{\alpha\exp(\beta x)}{1+\gamma\exp(\beta x)}$

Based on individual level data, parametric model with least Akaike Information Criterion (AIC) is selected as the baseline model

Combine baseline model with bagging LTRC survival tree

Parametric Survival Tree (PST)

- Adjusting the baseline model parameters by the terminal nodes from the survival trees
- Assign new predictor NODE to indicate the terminal node the observation belongs



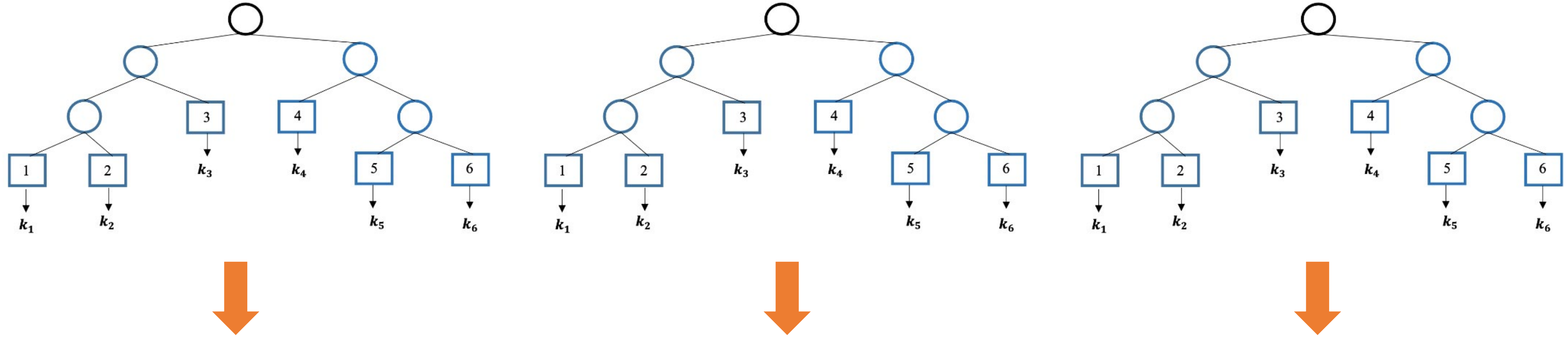
- New covariate "node" create to indicate which terminal node the observation belongs
- Parameter adjustment: $\alpha = \alpha_{baseline} + \alpha_2 k_2 + \alpha_3 k_3 + \cdots + \alpha_6 k_6$

Combine baseline model with bagging LTRC survival tree

Parametric Bagged Survival Tree (PBST)

Using bagging to reduce high variety in the survival tree

- Randomly select subset of observations to build Parametric Survival Tree (PST)

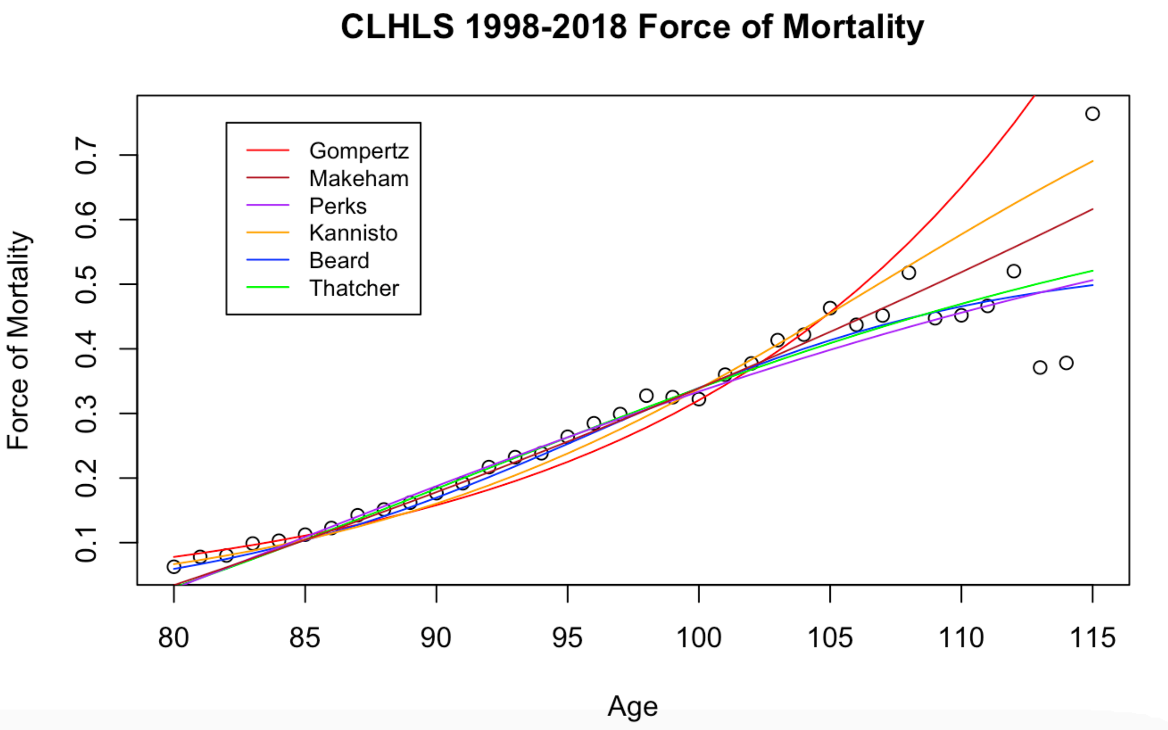


PST PST PST

- We ensemble the PST to form PBST by taking the average of the survival estimations from each PST

Age-only model fitting (1998 – 2018 CLHLS wave)

All training set observations in individual level (n=50,000) are fitted to the six candidate models. Result supports mortality deceleration at the oldest-old age.



Mortality law	AIC	No. Parameter	AIC relative to maximum	IBS (10-fold CV)
Gompertz	52,008	2	0	0.194
Gompertz-Makeham	51,945	3	-63	0.191
Kannisto	51,946	2	-62	0.191
Perks	51,958	4	-50	0.198
Beard	51,943	3	-65	0.189
Thatcher	51,947	3	-61	0.195

Test set prediction performance

Waves (Baseline model) \ IBS on test set	Test set size	Null baseline model	PBST
1998-2000 (Beard)	2,157	0.186	0.133
2000-2002 (Kannisto)	2,138	0.182	0.177
2002-2005 (Thatcher)	2,458	0.201	0.154
2005-2008 (Gompertz - Makeham)	1,931	0.180	0.163
2008-2011 (Beard)	2,847	0.188	0.129
2011-2014 (Beard)	1,266	0.159	0.145
2014-2018 (Beard)	1,371	0.140	0.107
1998-2018 (Beard)	9,168	0.171	0.158

Parametric bagging survival tree (PBST) has the greatest reduction of out-of-sample prediction error, suggesting the best prediction performance.

Further research

- Longitudinal data attrition bias
  - Build logistic model using "lost to follow-up or not" as the binary response
  - Using covariates to predict the observation's probability to attrit from surveys
  - Impose weights to the likelihood to adjust attrition bias

- Replace bagging ensemble method with random survival forest or other statistical learning methods to reduce variance
- Extend the static parametric model to stochastic parametric model (E.g., the Lee-Carter model, or the CBD model)

Contribution

- Formulating framework to analyze the mortality trajectories for China's oldest-old using individual level data
  - Most waves show mortality deceleration in the oldest-old mortality trajectories

- Combining ensemble survival trees with oldest-old parametric models
  - Allow us to incorporate unlimited numbers of factors into modelling of oldest-old force of mortalities and survival probabilities
  - Replacing the Kaplan Meier survival estimate output in survival tree with smooth parametric model

Thank You

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