Multi-State Health Transition Modelling Using Neural Networks

Qiqi Wang[1,2], Katja Hanewald[2,3], and Xiaojun Wang[1]

[1] Renmin University of China, School of Statistics

[2] Australian Research Council Centre of Excellence in Population Ageing Research (CEPAR)

[3] UNSW Sydney, School of Risk & Actuarial Studies

Introduction

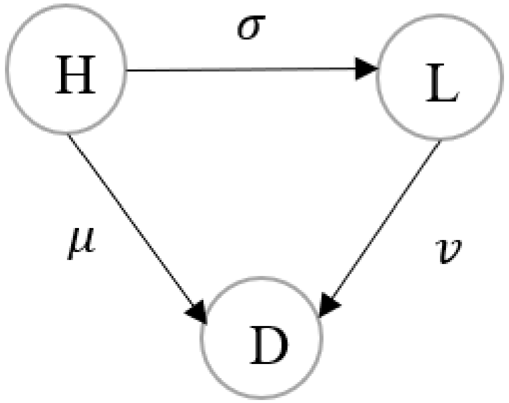
Background:

- Around the world, people are living longer
- Increasing age and longevity → higher risk of chronic diseases and disability
- Growing need for LTC in developed and developing countries
- Want to predict the chance of individuals becoming disabled and needing LTC

We propose a **new model** that **combines a neural network with a generalized linear model (GLM)** to **estimate and predict age-specific health transition intensities**

- Includes age effects, time trends, socioeconomic and lifestyle factors
- Detects and incorporates linear and nonlinear relationships among variables
- Uses transfer learning to link the different health transition processes
- **Wide range of possible applications**

Multi-State Health Transition Model



- A three-state time-inhomogeneous Markov process
- GLM framework (Fong et al., 2015, Hanewald et al., 2019)

$$\eta_x = \sum_{s=0}^{k} \beta_s x^s = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_k x^k.$$

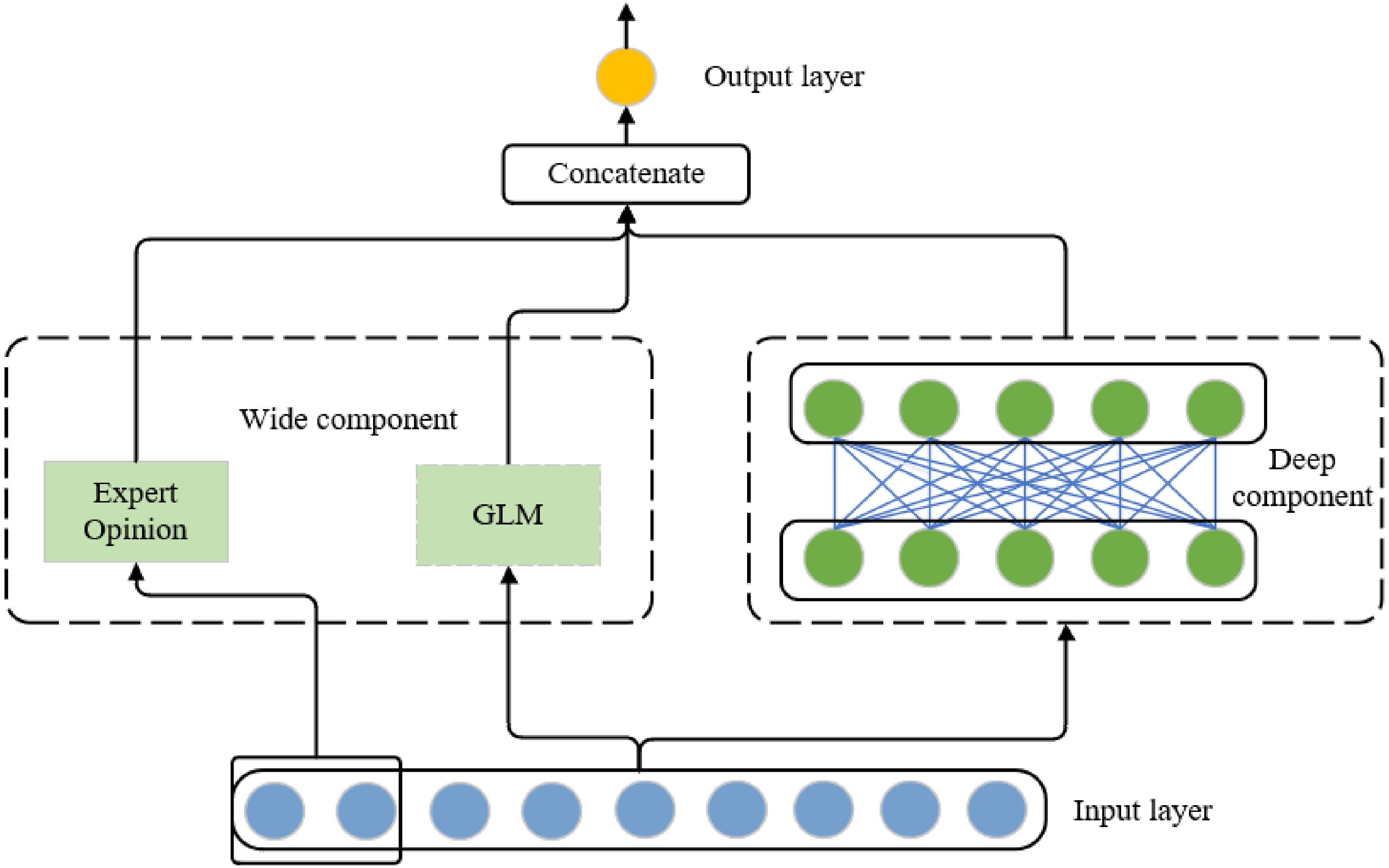
Shortcomings of previous research:

1. Only incorporate age & time
2. Need to compare different models to find relationships between variables
3. Model transitions separately

Our proposed model:

1. Incorporate socio-economic and lifestyle factors
2. Combine neural network with actuarial ideas
3. Use transfer learning to link the transitions

Our proposed model



Wide & deep architecture (Cheng et al. 2016)

- **Wide component**: a direct relationship between the input variables
- **Deep component:** indicate complex and potential links

Transfer learning: Linking transition processes

Model comparison

Data: Chinese Longitudinal Healthy Longevity Survey (CLHLS)

Methods	In-sample loss ($\times 10^{-2}$)			Out-of-sample loss ($\times 10^{-2}$)			Computing time (s)		
	σ: H→L	μ: H→D	ν: L→D	σ: H→L	μ: H→D	ν: L→D	σ: H→L	μ: H→D	ν: L→D
GLM0	158.43	77.54	45.99	125.55	63.32	66.71	0.04	0.06	0.04
NN0	129.11	59.27	30.11	145.65	18.98	53.31	10.27	14.96	9.34
GLM	80.69	86.42	56.08	95.22	96.80	55.78	0.04	0.06	0.04
NN	43.03	31.20	52.86	49.29	34.40	53.37	10.27	14.96	9.34
CM	38.54	29.29	52.04	42.78	31.70	54.10	10.48	15.39	9.68
CME	37.32	28.50	51.01	42.34	30.82	52.67	11.68	17.06	10.79
CMT	31.27	29.29	50.22	35.35	31.70	52.02	10.54	15.39	9.65
CMET	31.08	28.50	49.70	32.25	30.82	50.47	11.73	17.06	10.82

Conclusion

We propose **new model that combines a neural network with a GLM** to estimate health transition intensities

- Combined model outperforms standalone GLM and neural networks
- Identifies and incorporates socio-economic and lifestyle factors
- Incorporates expert opinion
- Links health transitions via transfer learning

✓Combination of traditional actuarial ideas and neural networks provides **better-performing health transition models**

Model has **broad applications**:

- Other health datasets and different health-related applications
  - ➢Risk classification
- Microsimulation health models
  - ➢FEM (Future Elderly Model)
- Mortality modeling using individual-level data
  - ➢Transfer learning
- Determine the causality socioeconomic variables and health transition

References

Cheng, H. T., Koc, L., Harmsen, J., Shaked, T., Chandra, T., Aradhye, H., ... & Anil, R. (2016, September). Wide & deep learning for recommender systems. *In Proceedings of the 1st workshop on deep learning for recommender systems* (pp. 7-10).

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Thank you!

Contact:

Qiqi Wang: wangqiqi_ruc@outlook.com

Katja Hanewald: k.hanewald@unsw.edu.au